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Multi-Time-Scale Dispatching Method for Power System Source-Load Considering Wind Power Correlation

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Abstract. In view of the challenges of intermittency, volatility, and spatial correlation between wind farms brought about by wind power's expasion, this paper improved the multi-time scale source-load scheduling method. The joint probability distribution of wind farms is constructed using covariance analysis and Copula model to capture the correlation characteristics of wind power fluctuations and generate multiple wind power scenarios. The paper optimized the multi-time scale framework of long-term planning, day-ahead scheduling and real-time scheduling. The LSTM is integrated to enhance wind power prediction, and the prediction results are adjusted to meet the correlation criteria through joint distribution. The charging and discharging of energy storage is optimized through dynamic programming, and the demand response strategy is adjusted in real time through the load aggregation model to dynamically configure flexible resources. The 30-day comparative test verifies the effectiveness of the improved method: the average reserve demand adequacy ratio reaches 0.9, the proportion of unmet load time is only 2.08%, and the wind power utilization rate and flexible resource utilization rate are 87.64% and 77.13% respectively. Based on simulation and numerical optimization, this paper proposed an improved solution to enhance the adaptability of the power system to large-scale wind power access.

Key words. Wind power forecasting, Copula model, Multi-time scale framework, Demand response strategy, Energy storage optimization

Nomenclature

Abbreviations	
LSTM	Long Short-Term Memory
MILP	Mixed-Integer Linear Programming
ERA5	Fifth Generation ECMWF Atmospheric Reanalysis of The Global Climate
NREL	National Renewable Energy Laboratory
MPC	Model Predictive Control
Formula Parameters	
P_i	The missing value
t_i	The time corresponding to the missing value P_i
$\tilde{P}_i$	The smoothed power data
N	The window width
ρ_{ij}	The correlation coefficient
u_i	The mean of the power of wind farm i
σ_i	The standard deviation of the power of wind farm i
f_i	The marginal probability density function of wind farm i
P_i^x	The power outputs of wind farm x at time i
P_i^y	The power outputs of wind farm y at time i
$\bar{P}^x$	The means of P_i^x
$\bar{P}^y$	The means of P_i^y
d_i	The ranking difference of wind farms
$C_{\text{start}}^{(m,t)}$	The start and stop cost of the unit in scenario m and period t
$C_{\text{res}}^{(m,t)}$	The reserve capacity cost
$C_{\text{stor}}^{(m,t)}$	The energy storage equipment's operating cost
$P_{\text{total}}^{(m,t)}$	The total power generation
D_t	The system load demand
$P_i^{(m,t)}$	The power generation of wind farm i in scenario m and time period t
$P_j^{(m,t)}$	The output of traditional generator set j
$P_{\text{stor}}^{(m,t)}$	The energy storage equipment's net power output

1. Introduction

As wind power generation technology advances, wind energy has become an essential part of the global power system [1]. Wind power has been increasingly convenient recently, and more and more countries and regions regard it as an essential means to achieve low-carbon transformation and optimize energy structure

[2]. However, the spatial connectivity between wind farms and the instability and unpredictability of wind power generation have brought unprecedented challenges to power system dispatching [3,4]. The volatility of wind power leads to uncertainty in grid operation, which affects the economy and reliability of the system [5,6]. Traditional power system dispatch methods often assume that wind power can be accurately predicted and that the power generation capacity of different wind farms is independent of each other, leading to a lack of coordination in dispatching at various time scales and difficult to effectively respond to the uncertainty brought about by fluctuations in wind power in the system [7]. In addition, the allocation of flexible resources including energy storage and demand response in the traditional dispatch framework has also failed to fully consider the correlation between wind farms [8,9], resulting in the failure of flexible resources to maximize their benefits in the rapid changes of wind power fluctuations, affecting the economy and reliability of the overall system dispatch. The current research key issues is to consider the correlation between wind farms in power system dispatching and improving the coordination and flexibility effectively.

The impact of wind power correlation and uncertainty on power system dispatch has attracted widespread attention in recent years [10,11]. Scholars have carried out numerous studies on wind power prediction models [12,13] to improve prediction precision and reduce the impact of wind power uncertainty [14,15], providing a more reliable dispatch basis for the power system. Most studies concentrated on enhancing the power prediction model of a single wind farm, including time series model-based short-term prediction [16,17] and machine learning-based wind power prediction [18,19]. These studies do not consider the influence of spatial correlation between wind farms on the dispatch of the entire system. Others on the optimization design of multi-time-scale dispatch frameworks, improving the flexibility of dispatch plans and the ability to cope with wind power fluctuations by integrating coordination mechanisms [20,21]. However, most of the existing multi-time-scale dispatch methods fail to fully consider the correlation between wind farms and lack an effective mechanism for the dynamic allocation of flexible resources. Therefore, effectively incorporating the correlation between wind farms into the dispatch optimization model and dynamically coordinating the resource allocation in various time periods through a multi-time-scale dispatch framework are still significant difficulties in current research.

To cope with the challenges of wind power volatility and correlation to power system dispatch, this paper constructs the joint probability distribution between wind farms through covariance analysis and the Copula model, captures the correlation characteristics, and designs a multi-time-scale optimization framework, covering long-term planning, day-ahead dispatching, and real-time dispatching. In wind power prediction, the LSTM model is combined, and the prediction results are corrected through joint distribution. This paper also optimizes the energy storage charging and discharging strategy through dynamic programming, optimizes the demand response by combining the load aggregation model, and realizes the dynamic allocation of flexible resources, improving the system's adaptability to wind power fluctuations.

2. Related Work

Wind power is an essential renewable energy source, but its unpredictability and volatility pose a major threat to power system stability and economic efficiency [22,23]. Researchers have proposed various methods to model the correlation of wind power and its impact on power system dispatch to deal with the volatility of wind power effectively, mainly focusing on spatial correlation modeling between wind farms [24,25] and time-scale-based dispatch optimization [26,27].

Spatial correlation modeling is a key direction in the modeling of wind power correlation. Traditional wind power correlation modeling usually relies on simplified correlation coefficients or statistical methods to describe the correlation between wind farms [28,29]. However, these methods often ignore the complex nonlinear relationships and dependencies between wind farms, resulting in an inaccurate description of the correlation. The Copula model has gradually been utilized for modeling the correlation between wind farms recently [30,31]. Unlike traditional methods, this model can handle spatial correlation and flexibly simulate the complex associations between wind farms. By constructing a joint probability distribution, this model can provide more accurate prediction data for power system dispatching so that the stability and dispatching efficiency of the system under wind power fluctuations can be improved.

The dispatch problem of power system has been widely studied, especially the multi-time-scale dispatching optimization technology based on wind power correlation modeling. Huang J proposed a multi-time scale coordinated control framework, which optimized the dispatching and frequency regulation performance of wind turbines through minute-level and second-level control strategies, and verified its effectiveness. However, he did not fully consider the system complexity when large-scale wind power is connected, and the long-term impact analysis of different unloading methods was insufficient. The universality of practical application needs to be further verified [32]. Zhang S proposed a multi-time scale flexibility evaluation method using empirical mode decomposition to analyze the flexibility supply and demand of integrated energy systems under different wind power installed capacity ratios. This method quantifies the flexibility gap through model prediction and decomposition algorithms, providing a basis for system planning. However, the simplified assumptions and insufficient case verification limit the universality of the conclusions [33].

In short-term dispatch, many studies adopt optimized dispatch algorithms to improve the power system's operation efficiency to reduce the power gap. Hu Y introduced the non-deterministic optimization whale optimization algorithm for wind power forecasting, and proposed a fast global optimization algorithm based on bee population conversion to achieve dynamic economic dispatch. This research improved the wind power forecasting accuracy and dispatching efficiency, but did not consider other key indicators such as environmental factors and voltage deviation, and the universality and long-term stability of large-scale wind power access need to be further verified [34]. SeyedGarmroudi S D solved the economic dispatch and joint economic emission dispatch problems by improving the Pelican optimization algorithm, showing superior performance. The lack of universality and parameter sensitivity analysis of this study limits its applicability in complex scenarios [35]. They combine the dispatch strategy of flexible resources to cope with the uncertainty and volatility of wind power. In addition, some studies also explore the impact of wind power prediction errors on dispatch optimization results and propose adjustment methods based on real-time data and rolling dispatch to improve the emergency response capability of the system. For long-term dispatch, the research focuses more on the seasonal changes of wind power and the balance between power demand and power generation capacity on a longer time scale. Such studies typically use interannual data for modeling to optimize long-term investment and planning of energy storage systems and ensure the power system stability and economic efficiency under different seasonal and climatic conditions.

Previous studies have attempted to apply Copula models to capture the interdependencies between wind farms and then optimize power system dispatch to effectively integrate the spatial correlation between wind farms and power system dispatch. Based on this, this paper constructs the joint probability distribution between wind farms by means of the Copula model and designs the allocation strategy of flexible resources in combination with multi-time-scale dispatch optimization.

3. Power System Source-Load Dispatch Method

A. Wind Farm Correlation Modeling

In this study, the core objective of wind farm correlation modeling is to establish a high-precision joint probability distribution model through the historical power data of multiple wind farms and their meteorological data. Figure 1 presents its framework.

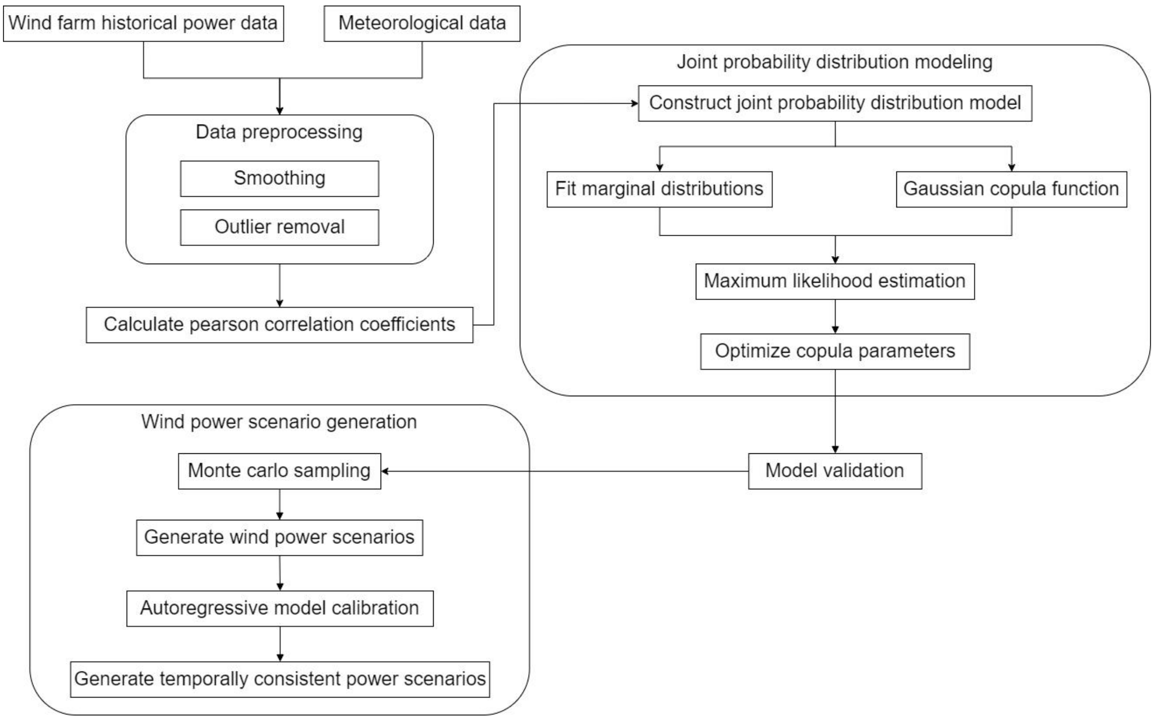

Figure 1. Wind farm power prediction joint probability distribution model framework.

The data used to build the model comes from meteorological data from the ERA5 (Fifth Generation ECMWF Atmospheric Reanalysis of The Global Climate) database and wind farm power data provided by NREL (National Renewable Energy Laboratory).

When preprocessing the data, linear interpolation is first utilized to fill in the missing power values [36]. Through this method, for each missing power data point, the existing data points before and after it are used to estimate and generate a continuous time series. The estimation formula for each missing value is as shown in formula (1).

$$P_i = P_{i-1} + \frac{P_{i+1} - P_{i-1}}{t_{i+1} - t_{i-1}}\left(t_i - t_{i-1}\right) \quad (1)$$

t_i indicates the time corresponding to the missing value P_i.

The interquartile range method is used to remove data when dealing with outliers [37]. This method uses the interquartile range of the data to find extreme values that deviate from the typical fluctuation range.

In addition, the historical power data is smoothed utilizing the sliding average method to eliminate high-frequency noise and more effectively extract the wind power change trend [38]. 24 hours are taken as the window period. The average value of the power data within 24 hours around each data point is calculated, the calculation formula is shown in formula (2).

$$\tilde{P}_i = \frac{1}{N}\sum_{j=i-\frac{N}{2}}^{i+\frac{N}{2}} P_j \quad (2)$$

$\tilde{P}_i$ represents the smoothed power data, and N denotes the window width.

The preprocessing process of meteorological data is similar to that of power data. Two vital factors impacting wind power generation are wind direction and speed. These data are also missing or noisy. During the processing, the missing wind speed and wind direction data are first filled using linear interpolation. Then, the meteorological data is smoothed using the sliding average method to eliminate short-term noise caused by meteorological fluctuations.

The correlation analysis mainly aims to identify and quantify the linear and nonlinear dependencies between wind farms. First, the Pearson correlation coefficient matrix between each pair of wind farm power data is calculated to quantify the linear correlation between wind farms [39]. The calculation basis of the Pearson correlation coefficient is the ratio of the covariance between the wind farm power data and its standard deviation, which can reflect the synchronization of the power output of different wind farms. The closer the element value of this matrix is to 1, the more synchronized the power output between wind farms. Conversely, a value close to -1 indicates that the power output shows an opposite trend. The correlation coefficient is defined as formula (3):

$$\rho_{ij} = \frac{\mathrm{Cov}\left(P_i, P_j\right)}{\sigma_i \sigma_j} = \frac{\mathbb{E}\left[\left(P_i - u_i\right)\left(P_j - u_j\right)\right]}{\sigma_i \sigma_j} \quad (3)$$

u_i and σ_i are the mean and standard deviation of the power of wind farm i.

When constructing the joint probability distribution model, the Gaussian Copula function is used to describe the dependency structure between wind farms. In this process, the marginal distribution is fitted for the power output data of each wind farm. The distribution parameters are determined using maximum likelihood estimation, as shown in formula (4).

$$\hat{\theta}_i = \arg\max_{\theta_i} \prod_{j=1}^{N} f_i\left(P_{ij};\theta_i\right) \quad (4)$$

f_i is the marginal probability density function of wind farm i.

Then, the Gaussian Copula function is used to combine these marginal distributions into a joint distribution [40], and the Copula parameters are optimized by the maximum likelihood estimation method. Finally, the numerical gradient descent method is used to iteratively optimize the correlation structure to ensure that the model can accurately reflect the correlation between wind farms.

The Kolmogorov-Smirnov test is adopted to evaluate the fitting precision and screen the optimal marginal distribution model. After determining the marginal distribution, the marginal distribution of each wind farm is expanded to a joint distribution through the Gaussian Copula function. The Copula parameters are optimized through the maximum likelihood estimation method, and the correlation structure is iteratively optimized using the numerical gradient descent method [41]. The model verification is completed by comparing the probability distribution and correlation structure of the historical data with the generated samples. The Kullback-Leibler divergence and distribution deviation statistics are used as evaluation indicators to quantitatively analyze the fitting precision of the model-generated samples.

After the joint distribution model is established, the wind power scenario is generated through the Monte Carlo sampling method. Through the Cholesky decomposition of the joint distribution, the independent normal distribution samples are transformed into samples that conform to the correlation structure, and the wind power output scenario is generated through the inverse transformation of the marginal distribution. The autoregressive model trained on historical data is applied to perform time series correction on the scenario sequence to ensure that the generated power scenario has temporal consistency and physical feasibility, further retaining the temporal correlation characteristics of wind power.

B. Improvement of Wind Power Prediction

Historical power output data and meteorological data from several wind farms are used and preprocessed in the wind power prediction improvement process. Figure 2 presents the wind power prediction improvement framework.

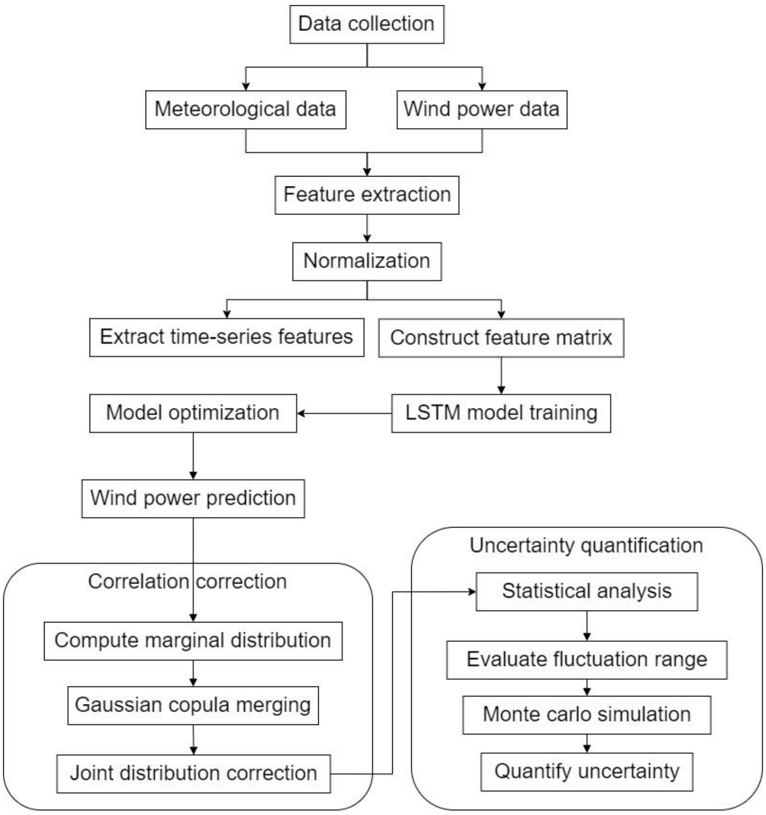

Figure 2. Wind power prediction improvement framework.

In data feature extraction, time series features of wind power and meteorological variables are extracted from historical data, such as daily average power value, the relationship between wind speed and power, etc. All input features are standardized.

In the implementation of the single wind farm power prediction model, LSTM is used for modeling [42]. The input layer of the LSTM model receives standardized data, which is the model's feature input to help the network capture the wind power output's temporal pattern. The LSTM network's hidden layer consists of multiple LSTM units, through which the model can learn the long-term and short-term dependencies in the data. Finally, the predicted value for the corresponding time period is generated in the output layer. During model training, the model parameters are continuously adjusted to reduce the prediction error gradually.

In the correlation correction stage, the wind farm power output marginal distributions are first calculated. The Gaussian Copula function is applied to merge them into a joint distribution to capture the dependency structure between wind farms. Then, the predicted values are corrected to ensure that they conform to the actual spatial correlation.

Through statistical analysis of historical data, the fluctuation range of wind power is evaluated, and the corresponding confidence interval is calculated to quantify the uncertainty of the prediction results. The Monte Carlo method is utilized to produce numerous samples of simulations, and the confidence interval of predictions is evaluated using these samples. By analyzing these samples, the potential range of wind power output fluctuations can be determined, and the uncertainty of the predicted value can be quantified.

C. Multi-Time-Scale Dispatching Framework

1) Implementation of Long-term Planning

In implementing long-term planning, the input data include wind farm correlation scenarios, technical parameters of power generation equipment and system load data. Wind farm correlation scenarios are generated from historical wind power data through covariance analysis and the Copula model. The relationship between wind farms is examined using Pearson and Spearman correlation coefficients to calculate linear and nonlinear correlations between wind farms [43,44].

The calculation formula of Pearson correlation coefficient is formula (5).

$$\rho_{xy} = \frac{\sum_{i=1}^{n}\left(P_i^x - \bar{P}^x\right)\left(P_i^y - \bar{P}^y\right)}{\sqrt{\sum_{i=1}^{n}\left(P_i^x - \bar{P}^x\right)^2 \sum_{i=1}^{n}\left(P_i^y - \bar{P}^y\right)^2}} \quad (5)$$

P_i^x and P_i^y are the power outputs of wind farm x and wind farm y at time i, and $\bar{P}^x$ and $\bar{P}^y$ are the means of the corresponding power sequences.

The Spearman rank correlation coefficient is a correlation calculated based on the order of the data, the calculation formula is as shown in formula (6).

$$\rho_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n\left(n^2 - 1\right)} \quad (6)$$

d_i is the ranking difference of wind farms.

Then, the univariate probability distribution of each wind farm is expanded into a joint probability distribution through the Gaussian Copula function, and the joint output power distribution of multiple wind farms is obtained. These joint distributions reflect the dependencies between wind farms and provide the necessary basis for the generation of wind power fluctuation scenarios.

The objective of the optimization model construction stage is to reduce the costs associated with flexible resource allocation and reserve capacity. The reserve capacity cost is mainly the additional power generation capacity required to ensure the system's stable operation under the condition of wind power fluctuations. The flexible resource allocation cost considers the dispatching of energy storage equipment and demand response resources. The constraints include system power balance constraints, equipment constraints, energy storage capacity limitations, and technical constraints on the start and stop of generator sets.

Based on the system power balance constraint, the system's total power generation in each time period should be greater than or equal to the total load demand. Specifically, the power generation of all wind farms and the power output of traditional generators and energy storage equipment must meet the system load requirements. Equipment constraints include restrictions on the capacity and minimum output of generators and restrictions on the energy storage equipment's charging and discharging rates. The output power of the generator set must be between its maximum capacity and minimum output. The energy storage equipment's charging and discharging rates are also limited and cannot exceed the maximum charging and discharging rate set in the technical parameters.

The optimization problem is solved using the mixed-integer linear programming (MILP) method [45]. MILP can process both integer decision variables and continuous decision variables. The generator set's start and stop status is represented by integer decision variables. The energy storage equipment's power generation, charging, and discharging powers are represented by continuous decision variables. By converting the objective function and constraints into standard linear expressions, all decision variables involving the generator set and the energy storage equipment are used in the model. The wind power fluctuation scenario is used as input. Multiple wind power scenarios are generated through Monte Carlo sampling. The model is dispatched and optimized in combination with the system load data. The model is solved to obtain the optimal reserve capacity allocation plan by determining the generator set's start and stop status and the energy storage equipment's charging and discharging strategy.

The specific solution process includes initializing the input data and building an optimization model and then using the solver to solve. The solver uses an efficient optimization algorithm and heuristic search method to calculate the approximate optimal solution. The solution results output the start and stop status of the generators in each period, the dispatching plan of demand response resources, etc. The results of these solutions ensure that the system satisfies the load demand while reducing the cost of dispatching flexible resources and reserve capacity when wind power changes.

2) *Implementation of Day-Ahead Dispatching*

Scenario generation in day-ahead dispatching is according to wind power prediction results, historical power output, and meteorological conditions of wind farms to predict future power output. A multi-scenario generation method is used, and a joint distribution between wind farms is constructed through covariance analysis and the Copula model to cope with the inevitable volatility and uncertainty in wind power prediction. For each wind farm, based on the relationship between its historical power output and meteorological conditions, the Gaussian Copula expands the single variable power distribution into a multidimensional joint distribution. Multiple wind power scenarios are generated from the joint distribution through the Monte Carlo sampling method to reflect the possible states of different wind power outputs while considering the correlation between wind farms. Each generated scenario represents a possible wind power output state, covering the temporal and spatial correlation of wind power fluctuations.

In dispatching optimization, the objective is to reduce the system's overall operating cost. Its expression is shown in formula (7):

$$\min \mathbb{E}\left[C_{\text{total}}\right] = \frac{1}{M}\sum_{m=1}^{M}\left(\sum_{t=1}^{T}\left(C_{\text{start}}^{(m,t)} + C_{\text{res}}^{(m,t)} + C_{\text{stor}}^{(m,t)}\right)\right) \quad (7)$$

$C_{\text{start}}^{(m,t)}$ is the start and stop cost of the unit in scenario m and period t; $C_{\text{res}}^{(m,t)}$ is the reserve capacity cost; $C_{\text{stor}}^{(m,t)}$ is the energy storage equipment's operating cost.

Considering the uncertainty of wind power, the key constraints of the optimization model include power balance constraint and wind power fluctuation confidence interval constraint. The power balance constraint requires that the total power generation $P_{\text{total}}^{(m,t)}$ in each time period t meets the system load demand D_t, the total power calculation is shown in formula (8):

$$P_{\text{total}}^{(m,t)} = \sum_{i=1}^{N} P_i^{(m,t)} + \sum_{j=1}^{G} P_j^{(m,t)} + P_{\text{stor}}^{(m,t)} \geq D_t \quad (8)$$

$P_i^{(m,t)}$ is the power generation of wind farm i in scenario m and time period t; $P_j^{(m,t)}$ is the output of traditional generator set j; $P_{\text{stor}}^{(m,t)}$ is the energy storage equipment's net power output.

The confidence interval constraint of wind power fluctuation requires that within each dispatching period, the units' start and stop decisions and the energy storage dispatching can adapt to the wind power fluctuation range.

In solving the scenario optimization algorithm, the expected cost of multiple wind power fluctuation scenarios is optimized. The operating cost of each scenario consists of the unit start and stop cost, energy storage charging and discharging cost, and reserve capacity allocation cost. In multiple scenarios, the expected operating cost is calculated by a weighted average of all scenarios. The optimization algorithm uses scenario optimization technology and combines stochastic programming and dynamic programming methods to deal with the uncertainty of wind power effectively. The constraints and objective functions are linearized to adapt to the solution of MILP problems so that the optimization process can adapt to the computing needs of large-scale systems.

In solving the model, the stochastic optimization method is combined with the rolling time domain optimization method to solve multiple scenarios. Each time the optimization is performed, multiple wind power scenarios are first generated according to historical data and wind power prediction results. For each generated scenario, the dispatching optimization model optimizes the start and stop decision of the generator set and the charging and discharging strategy of the energy storage system according to the objective function of minimizing the total operating cost. The optimization process involves the processing of multiple scenarios and dynamically adjusting the start and stop status of the unit and the energy storage equipment's charging and discharging strategy.

3) Implementation of Real-time Dispatching

In implementing real-time dispatching, data input is the basis of system operation. The system continuously monitors power output and system load data through the energy management system. All raw data is input into the real-time dispatching model after standardization, noise filtering, and outlier correction. Based on these real-time data, the dispatching system can dynamically update the power system's operating status, precisely calculate the power gap in the current period, and compare it with the actual load demand of the system in real time. Figure 3 presents the real-time dispatching system framework.

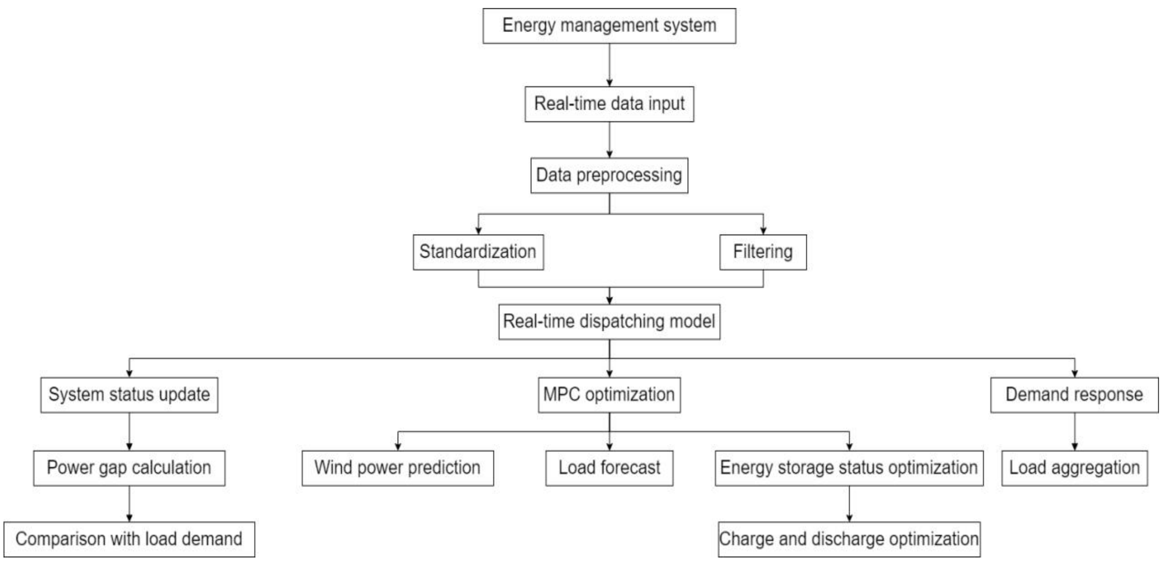

Figure 3. Real-time dispatching system framework.

The model predictive control (MPC) method is adopted to perform rolling updates on the dispatching plan to achieve dynamic adjustment [46]. In each optimization period, MPC uses the real-time data of the current period as input and optimizes the dispatch decision for several future periods based on wind power prediction results, load forecast information, and energy storage equipment status. The optimization objective function mainly includes the system's power generation and energy storage costs. The constraints include physical output limitations of wind farms, system load demands, and the availability of flexible resources. During the optimization process, the problem is converted into a linear programming problem and solved by the optimal algorithm to ensure real-time calculation of the optimal energy storage charging and discharging strategy and demand response dispatching plan.

The real-time dispatching algorithm considers the energy storage equipment's current charging and discharging status and remaining capacity when adjusting its charging and discharging. The energy storage equipment's charging and discharging are limited by its maximum capacity and charging and discharging rates. In the dispatching model, the optimization algorithm reasonably arranges the charging and discharging operations of energy storage equipment based on the real-time power gap, the energy storage equipment's remaining power, and the wind power output prediction. When the system faces a power gap, the energy storage equipment gives priority to providing power supplements. When the wind power is higher than the load demand, the energy storage system starts to charge and store the remaining power. The dynamic programming algorithm is utilized to the optimization of energy storage charging and discharging to solve the charging and discharging cycle and loss problems of energy storage, maximizing the energy storage system's benefits and extend the equipment service life.

Regarding demand response, the real-time dispatching system combines real-time load data and uses a load aggregation model to integrate multiple demand response resources. The load aggregation model combines different types of demand response resources into a virtual load pool to optimize dispatch decisions. During the dispatch process, real-time loads are combined with the demand response potential of adjustable load resources, and optimization algorithms are applied to determine the optimal load reduction and transfer strategies. When the system load demand exceeds the power supply capacity, priority is given to calling demand response resources with fast response speeds, such as load transfer for commercial users or industrial load dispatch. These response measures can quickly adjust load demand and alleviate the power gap problem faced by the power system during wind power fluctuations.

The core of the real-time dispatching strategy is to respond quickly to wind power fluctuations, especially when wind power fluctuates greatly. Based on the rolling time domain optimization strategy, the real-time dispatching system continuously adjusts the energy storage equipment's charging and discharging plan and the dispatch strategy of demand response to balance the impact of wind power fluctuations on load demand. Through the optimization algorithm, the dispatching plan for each time period is calculated in real time according to multiple factors including real-time wind power data, load demand, energy storage status, and future wind power prediction. This solution realizes the power system's dynamic adaptation under the condition of wind power fluctuations, ensuring that the system can operate stably under the uncertainty of wind power, meet load demand, and achieve a balance between economy and reliability.

D. Dynamic Allocation of Flexible Resources

The energy storage system optimization relies on real-time monitoring of state-space models to precisely control the energy storage equipment's charging and discharging status. The model represents the charging and discharging process as a discrete-time system. The state variables include remaining power and charging and discharging power. At each moment, the state of the energy storage system is affected by the charging and discharging power, equipment characteristics, and load demand. The inputs include system load demand, wind power prediction, energy storage capacity, and charging and discharging constraints. The optimization objective comprehensively considers the charging and discharging cost, equipment maintenance cost, and reserve capacity requirements. The charging and discharging and cycle constraints are used in the objective function to extend the equipment service life. Finally, the charging and discharging strategy is optimized through dynamic programming methods.

Demand response optimization effectively manages demand response resources within the system through a load aggregation model. The model aggregates different types of load resources, such as industrial loads, commercial loads, and residential loads, to form a virtual load pool so that various types of loads can be flexibly adjusted when needed to achieve system resource balance. The model inputs include real-time load data, wind power output, load regulation requirements, and resource response characteristics. The model prioritizes load resources with faster response speeds and stronger regulation capabilities based on the response time, response amplitude, and cost-effectiveness of the load type. When the system load demand exceeds the power supply capacity, the response capability and priority of the load resources determine the strategy of load reduction and transfer. In situations where wind power fluctuates dramatically, the call of demand response resources can effectively alleviate the power gap and reduce the demand for reserve capacity.

The optimization model considers the dynamic characteristics of demand response resources and energy storage equipment, realizes the joint optimization of energy storage and demand response, coordinates charging and discharging and load adjustment, and maximizes the utilization efficiency of flexible resources. The model constraints cover the energy storage equipment's charging and discharging rate, capacity limitations, response rate, and time constraints of demand response resources, etc. The objective of joint optimization is to fully meet load demand and power balance while minimizing system operating costs. Through this optimization, the system can dynamically dispatch energy storage equipment and demand response resources according to real-time wind power fluctuations and load demand and reasonably arrange energy storage charging and discharging and load reduction strategies. The MILP method is adopted to solve this joint optimization problem. The energy storage charging and discharging plan and demand response strategy are solved based on the objective function and constraints. By applying this optimization model, the system can maintain the balance and coordination of flexible resources in a changing operating environment.

4. Simulation Application and Performance Evaluation

A. Simulation Application Experiment

The experimental setting of this paper is based on the IEEE 39-node power system. The experimental period is 30 days, a total of 720 hours. The experiment includes three wind farms, located at Bus 5, Bus 15 and Bus 30 in the IEEE 39-node power system, and their installed capacities are shown in Table 1:

Table 1. Wind farm settings.

Wind Farm Number	Bus Number	Installation Capacity (MW)
1	Bus 5	100
2	Bus 15	150
3	Bus 30	120

The experimental environment is shown in Figure 4.

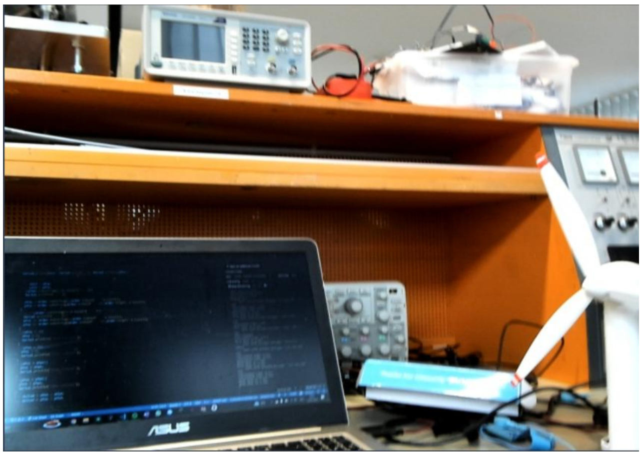

Figure 4. Experimental environment.

The experiment is divided into three stages: long-term planning, day-ahead dispatching, and real-time dispatching. In the long-term planning stage, the reserve capacity allocation within a week is optimized. During day-ahead dispatching, daily unit start and stop plans and energy storage equipment charging and discharging plans are formulated. In the real-time dispatching stage, the dispatching strategy of flexible resources is adjusted according to power prediction data. The wind power fluctuation data in the experiment is collected in units of five minutes. The load demand data is collected in units of one hour. The status of the energy storage equipment and adjustable load is updated in units of fifteen minutes.

The experimental setting includes an experimental group and control groups. The experimental group adopts the method in this paper, considering the correlation between wind farms and performing multi-time-scale dispatching optimization. The control groups include three methods. Control group 1 adopts single-time-scale dispatching based on deterministic prediction, ignoring the correlation between wind farms, with fixed reserve capacity and dispatching plan [47]. In control group 2, the correlation of wind farms is ignored, and dispatching is performed through independent scenario optimization without considering multi-time-scale coordination [48]. Control group 3 adopts a simple time series averaging method, dispatching according to the average value of historical data, ignoring wind power uncertainty and dynamic adjustment [49]. The operating costs, dispatching reliability, flexible resource utilization, and other indicators of each group in the experiments are compared to confirm the effectiveness of the method in this paper.

B. Application Effect

1) Economic Efficiency

In this paper, economic efficiency is the total operating cost directly calculated through the optimization model, covering key components including reserve capacity cost, start and stop cost, and energy storage operating cost. By comparing the cost changes under different dispatch strategies, the role of the optimization method in reducing system operating costs and improving economic benefits is evaluated. This indicator verifies the actual effect of the method in this paper in optimizing power system dispatch and flexible resource allocation.

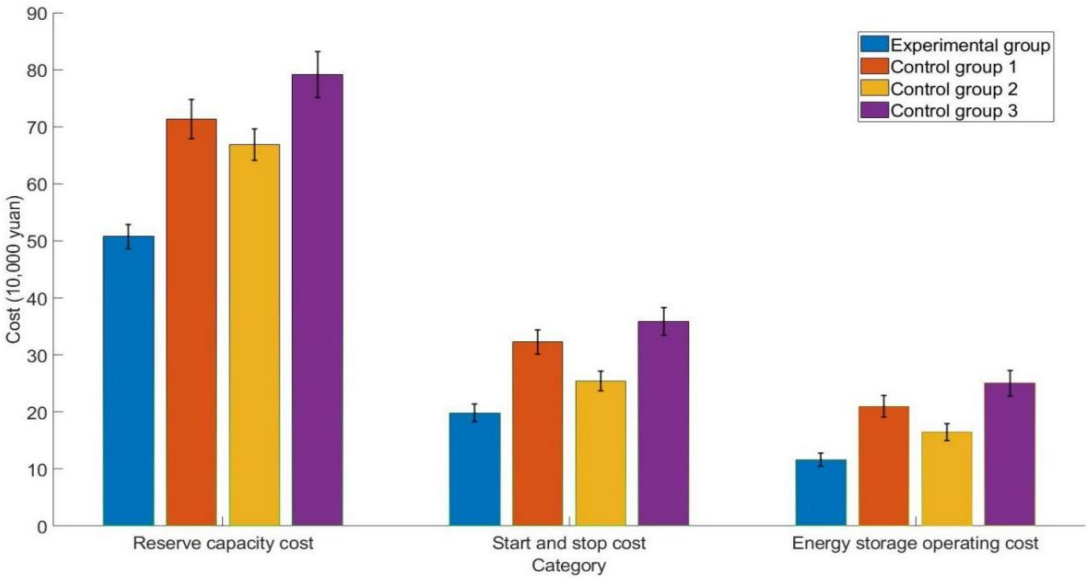

Figure 5. Comparison of economic efficiency between the experimental group and control groups.

Figure 5 compares the reserve capacity cost, start and stop cost, and energy storage operating cost. The reserve capacity cost of the experimental group is 507,800 yuan, while that of the control groups 1, 2, and 3 are 713,400 yuan, 669,200 yuan, and 791,500 yuan, indicating that the experimental group has more advantages in cost control. Similarly, the start and stop cost and energy storage operating cost are also significantly lower than those of the control groups, which are 198,400 yuan and 116,700 yuan, respectively, in the experimental group. The standard deviation of the experimental group is lower than that of each item in the control groups, showing the stability and consistency of the costs of the experimental group under different circumstances.

2) Reserve Demand Adequacy

The adequacy of reserve demand is measured by comparing wind power fluctuations with reserve capacity allocation and counting the proportion of reserve demand met in each period. This indicator can be used to evaluate the effectiveness of the system's reserve capacity in responding to wind changes. It reflects the system's ability to meet reserve capacity requirements in different scenarios. By analyzing the proportion of time periods in which reserve demand is met, the reliability of the optimized dispatching strategy in dealing with uncertainty and wind power fluctuations is quantified.

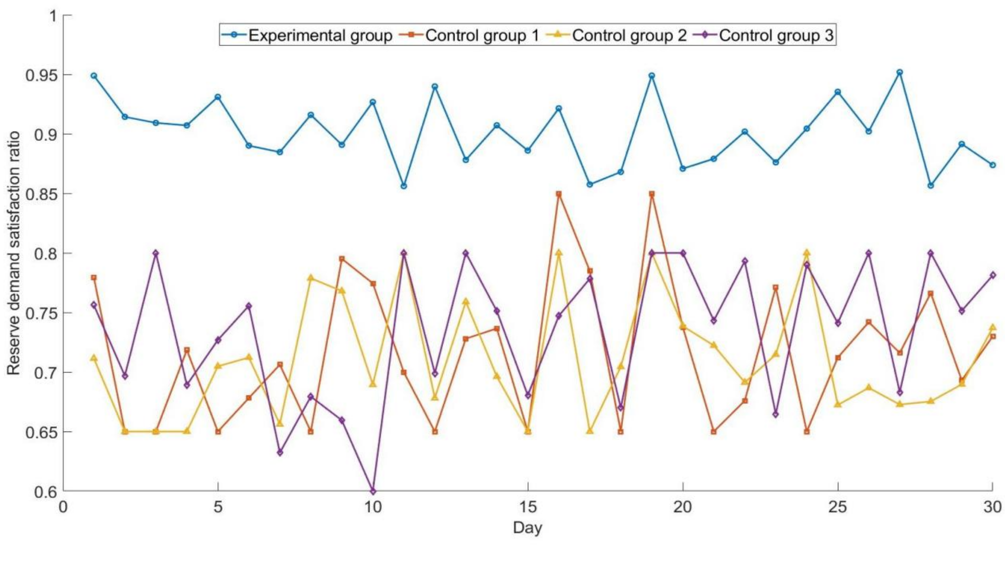

Figure 6. Comparison of the adequacy of each method's reserve demand.

The paper compared each group's reserve demand adequacy in Figure 6. From the overall trend, the experimental group has the highest reserve demand adequacy. The average adequacy of the experimental group is 0.9, showing strong stability and small fluctuations. The adequacy value of control groups is generally lower. By comparison, it can be found that the experimental group has apparent advantages in the reserve demand adequacy and can better cope with changes in system demand.

3) *Dispatching Reliability*

The dispatching reliability is measured by counting the number of times the load demand is not met and calculating its proportion in the total period. Specifically, the optimization model's dispatch results are compared with the actual load demand, and the total duration and number of times the load demand is not met are counted. Indicators such as the average and maximum unmet load duration are further analyzed. This indicator reflects the stability and adaptability of the dispatch plan in dealing with load fluctuations and wind power uncertainties.

The paper compared load groups satisfaction in Table 2. In the experimental group, the load is not met 16 times in 720 time periods. The proportion of unmet load duration is 2.08%. The average duration is 0.94 hours, with a maximum duration of 1.53 hours. Loads of control groups 1, 2, and 3 are not met 33 times, 28 times, and 36 times, and the proportion of unmet load duration is 5.17%, 4.96%, and 5.58%, respectively. Overall, the method in this paper is better than control groups in terms of load satisfaction and duration, showing better system stability.

4) *Wind Power Utilization and Flexible Resource Utilization*

The wind power utilization rate is calculated by the ratio of the actual power consumption of the wind farm to the total output to evaluate the effective utilization of wind energy resources. The flexible resource utilization rate is calculated by counting the energy storage equipment's charging and discharging capacity and the call volume of demand response and calculating its proportion to the total capacity, thereby measuring the regulation capacity of flexible resources in the power system.

Table 2. Comparison of dispatching reliability between the experimental group and control groups.

		Experimental Group	Control Group 1	Control Group 2	Control Group 3
Total duration		720	720	720	720
Number of times the load demand is not met		16	33	28	36
Unmet load duration	Proportion	2.08%	5.17%	4.96%	5.58%
	Mean	0.94	1.13	1.28	1.12
	Maximum	1.53	2.02	1.81	2.98

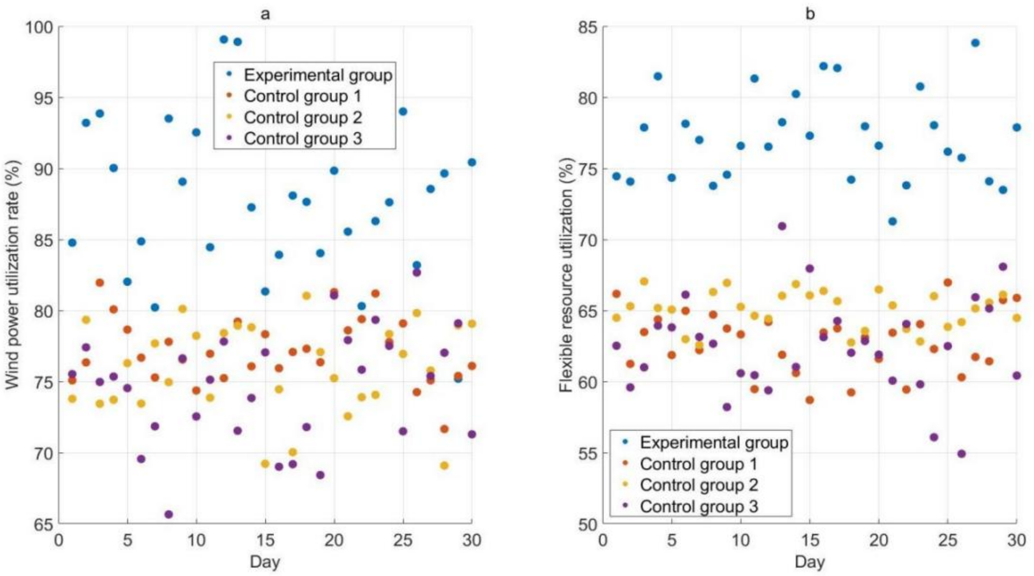

Figure 7. Comparison of wind power utilization and flexible resource utilization.

The differences between the experimental and control groups is shown in Figure 7 regarding wind power utilization and flexible resource utilization, with the experimental group performing more stably overall. The average wind power utilization of the experimental group is 87.64%, which is higher than 77.17% of control group 1, 75.89% of control group 2, and 74.55% of control group 3. Regarding flexible resource utilization, the average utilization rate of the experimental group is 77.13%, which is also higher than the other three groups. The data demonstrates significant advantages of the method in this paper in wind power utilization and flexible resource dispatching.

5. Conclusion

This study achieved reliable, economical and efficient operation of the power system under the condition of large-scale wind power access by constructing a joint probability distribution model of wind farms and an optimization scheduling framework. The scientific innovation of the study lies in capturing the correlation characteristics of wind power fluctuations through covariance analysis and Copula model, and optimizing wind power prediction and energy storage charging and discharging strategies by combining LSTM model and dynamic programming. Practical innovation is reflected in the coordination of long-term planning, day-ahead scheduling and real-time scheduling through a multi-time scale scheduling framework, dynamic configuration of flexible resources, and significant improvement of the adaptability and economy of the system. Through a 30-day comparative test, it was verified that this method has significant advantages in reducing operating costs, improving wind power utilization and resource flexibility, enhancing the system's adaptability to wind power fluctuations, and ensuring scheduling reliability. Despite this, the current method still faces the challenge of computational complexity when dealing with large-scale wind farm group scheduling, and has high requirements for the accuracy and timeliness of real-time data. Future research will focus on exploring more efficient computing methods, optimizing scheduling processes, reducing computing resource usage, and combining data fusion technology to improve data quality, so as to ensure the stability and reliability of scheduling strategies in practical applications, and further promote the efficient integration and utilization of renewable energy in the power system.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Author Contribution

Yidong Hu: Drafted and revised the manuscript critically for important intellectual content.

Yunfeng Yang, Hui Chen: Contributed to the acquisition, analysis, and interpretation of data.

Jian Gao, Zhangyong Wei: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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