A Two-Stage Cooperative Dispatch Model for Power Systems Considering Security and Source-Load Interaction

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Abstract: In modern power systems with more renewable energy sources connected, the consideration of both security and economy becomes the key to research on power system optimal dispatch, especially when more participants from the source and load sides join in the interaction response activities. In this paper, we propose a two-stage dispatch model that contains a day-ahead multi-objective optimization scheduling sub-model that combines a hyper-box and hyper-ellipse space theory-based system security index in the first stage, and an intraday adjustment scheduling sub-model that considers active demand response (DR) behavior in the second stage. This model is able to quantitatively analyze the relationship between the security and economy of the system dispatch process, as well as the impacts of the interaction response behavior on the wind power consumption and the system’s daily operating cost. The model can be applied to the evaluation of the response mechanism design for interactive resources in regional power systems.

Keywords: power system optimal dispatch; security assessment; source-load interaction and response

1. Introduction

With the advancement of green electricity, more clean and renewable power sources have been brought into global power systems. However, most renewable energy sources have notable uncertainties in their power output [1], which inevitably results in dispatch issues. In addition, the composition structure from not only the source side but also the load side has changed. Power loads are not merely passive, rigid loads. With flexible characteristics, active DR components, such as smart household appliances, energy storage, and electric vehicles, can cooperate with renewable energy sources in power system operation [2], which can promote the consumption of renewable energy and achieve peak-shaving and valley-filling targets.

Most of the research on power system cooperative dispatching has focused on economic influences. An improved distributed robust optimization approach is proposed in [3], with the aim of minimizing the overall costs of flexible resources, including conventional generators, energy storage systems, and renewable energy curtailments. The proposed model in [4] is given as a multi-objective optimization problem with different economic objective functions, such as the fuel consumption cost, fuel transportation cost, and penalty cost of hydropower stations’ disposable water. However, the impacts of the increasing penetration of renewable energy on power system security are becoming apparent. At the same time, the source-load interaction and response environment make the system operation state more complex, which further aggravates its influence on system security.

Regarding the influence and treatment methods of the security factors in optimal dispatch issues, most of the existing studies can be classified into two categories. In the first category, security is taken as a constraint condition, so that a security constraint economic dispatch (SCED) model is reformulated [5]. In [6], an SCED model based on anticipated
accident checking is established that can select corresponding multi-stage scheduling schemes according to different security constraints. The research in [7] introduces a solution to the problem of stochastic security-constrained unit commitment by considering extreme scenarios of wind power output. In [8], a horizontal time decomposition strategy for reducing the computation time of security-constrained economic dispatch is presented that formulated a local SCED for each sub-horizon with respect to the constraints of internal and overlapping intervals. To account for frequency stability constraints, a look-ahead dynamic SCED model is designed in [9] to optimize the cost of power generation, subject to operation and frequency stability constraints under normal and contingency conditions. In the second category, security is taken as a part of the objective function in the optimal dispatch model, and a multi-objective optimization function is constituted along with the economic objective in order to transform the power system optimization dispatch into a multi-objective optimization problem (MOP) for consideration. Ref. [10] quantifies the system security level according to risk theory, based on which a power system dispatch framework is built that aims to balance the system security level and real-time operation costs. In [11], a risk-based multi-objective economic dispatch model is formulated in which the minimizations of both the operation risk and the fuel cost are considered to be objective functions. The Conditional Value-at-Risk assessment measure is employed in [12], and both the solution and the model robustness, through original multi-objective risk-based robust mixed-integer linear programming, are guaranteed. Since the status of the security is further improved with a source-load interaction and response environment, it is of great importance to consider both economy and security in a power system dispatch model. Additionally, DR from the load side plays an important role in interaction and response activities, cooperating with source-side components, including thermal units and renewable energy. In [13], a dynamic interaction and response control strategy for electric vehicles that improves the consumption level of distributed energy resources is proposed, with the aim of solving the problem of synergistic utilization between electric vehicles and a high-penetration photovoltaic system. Ref. [14] integrates a base load, dispatchable load, electric vehicle load, and energy storage load, forming an interaction and response strategy that considers the clustering of electricity consumption behavior. Ref. [15] builds a flexible resource optimization dispatch model, including DR, energy storage, and electric vehicles, as well as designing a flexible ramp market based on interaction and response activities. Similarly, a flexible security-constrained structure for the purposes of meeting the superior flexibility via the coordination of generation and demand sides is proposed in [16]. Ref. [17] presents a flexible load-side resource pricing mechanism through the calculation of the economic benefits and shared compensation for the demand resource providers. In [18], electric vehicles are modeled as a virtual energy storage component; then, cooperative operation with wind power is achieved through an intelligent electric vehicle charging strategy.

The interaction and response behavior of DR is accompanied by uncertainties. Ref. [19] applies the variation law of the deviation interval caused by the uncertainty of DR to the modeling of price-based DR behavior, and forms an incentive DR mechanism that combines rigid and elastic constraints based on the uncertainty model of wind power prediction, a load agent decision model, and a dispatch control center decision model. Ref. [20] presents a decision evaluation method that takes into account the load adjustment for an uncertain wind power scenario. To overcome the uncertainties stemming from the predicted prices and the energy demands, a real-time incentive-based DR algorithm for smart grid systems with reinforcement learning and a deep neural network is proposed in [21]. Ref. [22] presents a strategy for transactive energy in networked microgrids, and various uncertainties, such as renewable generations, loads, and market prices, are taken into account in the model. However, the impacts of DR’s interaction and response activities on wind power consumption and system operation cost should be quantitatively analyzed, especially when DR’s behavior itself is accompanied by uncertainties.
To deal with the aforementioned issues, we proposed a two-stage cooperative dispatch model for power systems that considers security as well as a source-load interaction and response environment. The novel contributions of this work include: (1) a day-ahead multi-objective optimization model is established by extending the application of a hyper-box and hyper-ellipse space theory-based system security index; (2) an active DR model is formed according to different interaction and response characteristics in peak/valley load periods; and (3) by including the active DR model, the intraday rescheduling model is extended, which can conduct wind power consumption.

The rest of the paper is organized as follows. Section 2 presents a day-ahead multi-objective optimization dispatch model through a combined hyper-box and hyper-ellipse space theory-based system security index. Section 3 describes how different types of active DRs’ interaction response modes are designed, and how an intraday adjustment scheduling model is proposed based on these modes. Section 4 verifies the effectiveness of the proposed two-stage scheduling model with simulations. Finally, Section 5 draws conclusions from the presented studies.

2. Day-Ahead Multi-Objective Optimization Scheduling

In this section, we introduce a system security index based on hyper-box and hyper-ellipse space theory. In addition, we build a multi-objective optimization scheduling model through combining economic objectives that can be applied on the day-ahead scheduling process. Here, we also define the scheduling process as Stage I.

2.1. System Security Index Based on Hyper-Box and Hyper-Ellipse Space Theory

A hyper-box is a multidimensional closed space formed by value ranges of variables, which uses a vector to reflect the location of each variable in the space. The spatial location characterized by a vector in the hyper-box can be changed into a scalar value by approximately inscribing a hyper-ellipse space in the hyper-box space. In practical application, if the space in the hyper-ellipse has been defined, the location in the hyper-ellipse could be quickly determined according to the scalar value. In this way, hyper-box and hyper-ellipse space theory can be applied in a scenario for which the states of an entire multidimensional variable group need to be easily reflected [23]. Thus, a system security index can be established based on hyper-box and hyper-ellipse space theory. In [23], the system security index included the bus voltage security index and the line flow security index. In this study, only the line flow security index is utilized as the system security index, under the condition that the optimization scheduling is based on the DC power flow model. However, it does not mean that the proposed model is incompatible with voltage-related indices. Making the above simplification is from the perspective of computational efficiency.

$A_{P,j}$ and $S_{P,j}$ are the alarm and security limits of the active power flow of the $l$th transmission line, respectively. Then, the power flow deviation of the $l$th line, $d_{P,j}$, can be defined as:

$$
\begin{align*}
    d_{P,j} = \left( \left| P_j \right| - A_{P,j} / P_{Base} \right) & \quad \left| P_j \right| \geq A_{P,j} \\
    d_{P,j} = 0 & \quad \left| P_j \right| < A_{P,j}
\end{align*}
$$

where $\left| P_j \right|$ is the larger absolute value of the bidirectional active power flow on the $l$th transmission line and $P_{Base}$ is the base value of the $l$th line power flow. The deviation of the security value and the early alarm value of the $l$th line active power flow, $g_{P,j}$, can be defined as:

$$
    g_{P,j} = (S_{P,j} - A_{P,j}) / P_{Base}.
$$

Hence, the line flow security index can be obtained based on hyper-box and hyper-ellipse space theory:

$$
    P_{IP} = \left[ \sum_{j} \left( d_{P,j} / g_{P,j} \right)^{2n} \right]^{1/2n},
$$

where $2n$ is the scalar value of the line flow security index.
where \( n \) is typically set to 2 when considering both the accuracy of fit and the computing efforts.

2.2. Day-Ahead Multi-Objective Optimization Scheduling Model

In the day-ahead scheduling stage, the multi-objective optimization function contained two objects: economy and security.

The economy objective is focused on reducing the system’s operation cost. Assuming that only the fuel cost of the thermal units is considered, the economy objective function can be expressed as:

\[
\min F_1 = \min \sum_{t=1}^{T} \sum_{i=1}^{N_F} \left[ a_i \left( p_{i,t}^F \right)^2 + b_i p_{i,t}^F + c_i \right],
\]

(4)

where \( T \) is the total optimization period (24 h) and \( N_F \) is the total number of the thermal units. \( a_i, b_i, \) and \( c_i \) are the consumption characteristic coefficients of the \( i \)th thermal unit. \( p_{i,t}^F \) is output of the \( i \)th thermal unit in time period \( t \).

The security objective is focused on improving the system security. The calculation of the system security index involved in this study is based on the \( N-1 \) scenario. In addition, \( P_{IP} \), as described in (3), is considered to be the system security index. Accordingly, the security objective function can be expressed as:

\[
\min F_2 = \frac{1}{T} \sum_{t=1}^{T} \left\{ \frac{1}{M} \sum_{L_i=1}^{M} \left\{ \sum_{j=1, j \neq L_i}^{M} \left[ \left( d_{P,j}/g_{P,j} \right) \right]^{2n} \right\}^{1/2n} \right\},
\]

(5)

where \( M \) is the amount of the transmission lines. It should be noted that the calculation of the system security index in (5) is associated with all of the \( N-1 \) scenarios of the \( M \) lines. However, the range of lines involved in the optimization process can be decided according to the actual case. In a large-scale system, pre-processing can be conducted so that the key lines that have a significant influence on the system security are identified. Then, the range of lines can be applied to the aforementioned security objective function. The main constraints in Stage I are described below.

The system power balance constraint in each time period is:

\[
\sum_{i=1}^{N_F} p_{i,t} = \sum_{s=1}^{N_W} p_{W,s,t} + P_{D,t},
\]

(6)

where \( N_W \) is the amount of wind farms, \( p_{W,s,t} \) is the output of the \( s \)th wind farm in a time period, \( t \), and \( P_{D,t} \) is the total load in time period \( t \).

The output constraint of the thermal unit in each time period, \( t \), is:

\[
p_{i,t}^F_{\text{min}} \leq p_{i,t}^F \leq p_{i,t}^F_{\text{max}},
\]

(7)

where \( p_{i,t}^F_{\text{max}} \) and \( p_{i,t}^F_{\text{min}} \) are the upper limit and the lower limit of the \( i \)th thermal unit output, respectively.

The ramp rate constraint of the thermal unit is:

\[
\begin{cases} 
  p_{i,t}^F - p_{i,t-1}^F & \leq R_{i,\text{dn}}^F \\
  p_{i,t}^F - p_{i,t-1}^F & \leq R_{i,\text{up}}^F 
\end{cases}
\]

(8)

where \( R_{i,\text{dn}}^F \) and \( R_{i,\text{min}}^F \) are the downward and upward ramp rates of the \( i \)th thermal unit, respectively.

The capacity constraint of the transmission line is:

\[
|P_l| \leq \text{Limit}_l,
\]

(9)
where $|P_l|$ and $\text{Lim}_{li}$ are the actual transmitted power and upper capacity limit on the $l$th transmission line, respectively.

3. Intraday Adjustment Scheduling in the Interaction Response Mode

In this section, we first design an active DR model with four types of interaction response modes. Then, the intraday adjustment scheduling process, denoted herein as Stage II, contains the active DR model. In addition, we update the constraints that can be used in the rescheduling process.

3.1. Active DR Model

In the intraday adjustment scheduling stage, the interactive resources are required to maintain the dynamic balance of the system power. Additionally, the cost brought by coordinating the interactive resources is expected to be reduced as far as possible. In this study, we propose an active DR model that can actively change the load within a certain range. The active DR can coordinate with the thermal units to achieve the goal of the dynamic balance of the system power. Furthermore, it can promote wind power consumption.

It is assumed that the electricity price and the base value of the load on the bus where the active DR is located in time period $t$ are $C_{0,t}$ and $D_{0,t}$, respectively. When the active DR is not involved in the interaction response process, the cost paid by the active DR to the electric power company at the time interval ($\Delta t = 1$ h) can be expressed as:

$$\Pi_{\text{ini},t} = C_{0,t} \cdot D_{0,t}. \quad (10)$$

To stimulate the active DR’s participation in the interaction response process, the electric power company is supposed to conduct incentives based on two aspects: the electricity price and the response subsidy. Thus, when the active DR participated in the process, the cost can be expressed as:

$$\Pi_{\text{act},t} = K_t \cdot C_{0,t} \cdot (D_{0,t} + \Delta D_t) - R_t |\Delta D_t|, \quad (11)$$

where $K_t$ is the price discount coefficient in time period $t$, $R_t$ is the compensation coefficient of the active DR in time period $t$, and $\Delta D_t$ is the response quantity of the active DR in time period $t$ ($\Delta D_t > 0$ represents the load being increased with the active DR’s participation, while $\Delta D_t < 0$ represents the load being lowered). Therefore, the profit gained by the active DR can be expressed as:

$$\Pi_t = \Pi_{\text{ini},t} - \Pi_{\text{act},t}. \quad (12)$$

By substituting (10) and (11) into (12), we have

$$\Pi_t = (1 - K_t)C_{0,t}D_{0,t} - K_t C_{0,t} \Delta D_t + R_t |\Delta D_t|, \quad (13)$$

which indicates that both the price discount coefficient, $K_t$, and the compensation coefficient, $R_t$, affect the enthusiasm of the active DR candidates to participate in the interaction response process. Additionally, given that the configuration of the active DR in the system had to promote peak shaving and valley filling, it is necessary to design an appropriate response scheme based on the above characteristics of the active DR.

According to the peak and valley periods as well as the active DR’s positive response (load increase)/negative response (load reduction) behaviors, the active DR modes can be divided into four types, as shown in Table 1, in which the + and − symbols represent the positive response and the negative response behaviors of the active DR, respectively.
Table 1. Four types of the active DR modes.

| Mode 1 | Mode 2 | Mode 3 | Mode 4 |
|--------|--------|--------|--------|
| Peak load periods | + | - | + | - |
| Valley load periods | + | - | - | + |

- **Mode 1:** Because of the positive response behavior of the active DR in the peak load period, the gap between the peak load and the valley load is further widened. Thus, the active DR candidates are not recommended to experience an electricity price discount. Setting $K^{(1)}_t = 1$, we can reform (13) as follows:

$$
\Pi^{(1)}_t = -C_{0,t} \Delta D_t + R^{(1)}_t \Delta D_t,
$$

where $K^{(1)}_t$ and $R^{(1)}_t$ represent the price discount coefficient and the response compensation coefficient in Mode 1, respectively. According to (14), it can be found in this mode that $\Pi^{(1)}_t \geq 0$ should be satisfied to ensure that the active DRs are encouraged to participate in the interaction response process. Thus, $R^{(1)}_t$ should be no more than $C_{0,t}$.

- **Mode 2:** Compared with Mode 1, the negative response behavior of the active DR in the peak load period can narrow the gap between the peak load and the valley load. Thus, the active DR candidates can enjoy an appropriate electricity price discount. $K^{(2)}_t$ herein is set to 0.8, hence, (13) can be reformed as:

$$
\Pi^{(2)}_t = 0.2C_{0,t} \Delta D_t - 0.8C_{0,t} \Delta D_t - R^{(2)}_t \Delta D_t,
$$

where $K^{(2)}_t$ and $R^{(2)}_t$ represent the price discount coefficient and the response compensation coefficient in Mode 2, respectively. $\Pi^{(2)}_t$ in (15) is always non-negative. Since Mode 2 is helpful to peak shaving and valley filling, $R^{(2)}_t$ can be greater than $R^{(1)}_t$.

- **Mode 3:** Similar to Mode 2, the positive response behavior of the active DR in the valley load period can narrow the gap between the peak load and the valley load. Thus, the active DR candidates can also experience an appropriate electricity price discount. $K^{(3)}_t$ herein is set to 0.8; hence, (13) can be reformed as follows:

$$
\Pi^{(3)}_t = 0.2C_{0,t} \Delta D_t - 0.8C_{0,t} \Delta D_t + R^{(3)}_t \Delta D_t,
$$

where $K^{(3)}_t$ and $R^{(3)}_t$ represent the price discount coefficient and the response compensation coefficient in Mode 3, respectively. To ensure that the active DRs are encouraged to participate in the interaction response process, $\Pi^{(3)}_t \geq 0$ should be satisfied and $\Pi^{(3)}_t$ should increase along with $\Delta D_t$. Thus, $R^{(3)}_t$ must be more than 80% of $C_{0,t}$.

- **Mode 4:** The negative response behavior of the active DR in the valley load period can widen the gap between the peak load and the valley load. Thus, the active DR candidates are not recommended to experience an electricity price discount. Setting $K^{(4)}_t = 1$, we can reform (13) as follows:

$$
\Pi^{(4)}_t = -C_{0,t} \Delta D_t - R^{(4)}_t \Delta D_t,
$$

where $K^{(4)}_t$ and $R^{(4)}_t$ represent the price discount coefficient and the response compensation coefficient in Mode 4, respectively. $\Pi^{(4)}_t$ in (17) is always non-negative. Since Mode 4 is helpful to peak shaving and valley filling, $R^{(4)}_t$ can be smaller than $R^{(3)}_t$. 
3.2. Intraday Adjustment Scheduling Model

The optimization goal of Stage II is to minimize the adjustment cost based on the day-ahead scheduling plan of Stage I, which includes the adjustment cost of the thermal units, the response cost of the active DR candidates, and the wind-abandoning penalty cost. The optimization function can be expressed as:

$$\min F = \min \left( F_f + F_a + F_w \right),$$

(18)

$$F_f = \sum_{t=1}^{T} \sum_{i=1}^{N_T} \left[ a_i \left( \Delta P_{i,t}^F \right)^2 + \left( 2a_i \cdot P_{i,t}^F + b_i \right) \Delta P_{i,t}^F + \lambda_i \Delta P_{i,t}^F \right],$$

(19)

$$F_a = \sum_{t=1}^{T} \sum_{j=1}^{N_A} v_{j,t} \left( \left( 1 - K_{j,t} \right) C_{0,j,t} D_{0,j,t} - K_{j,t} C_{0,j,t} \Delta D_{j,t} + R_{j,t} \left| \Delta D_{j,t} \right| \right) \Delta t,$$

(20)

$$F_w = \sum_{t=1}^{T} \sum_{s=1}^{N_W} \omega_{s,t} \Delta p_{s,t}^W \Delta t,$$

(21)

where $F_f, F_a,$ and $F_w$ represent the adjustment cost of the thermal units, the response cost of active DR candidates, and the wind-abandoning penalty cost, respectively. $N_A$ in (20) is the amount of the active DR candidates. $P_{i,t}^F$ in (19) is the output of the $i$th thermal unit in time period $t$ in Stage I. $\Delta P_{i,t}^F$ and $\lambda_i$ are the active power adjustment amount and the adjustment compensation coefficient of the $i$th thermal unit in time period $t$ in Stage II, respectively. $F_a$ in (20) integrates each active DR candidate’s response cost. $v_{j,t}$ is a 0/1 variable that represents whether the $j$th active DR candidate in time period $t$ participated in the interaction response process ($v_{j,t} = 1$ represents the active DR participation, while $v_{j,t} = 0$ represents the active DR quitting). $\Delta D_{j,t}$ is the response quantity of the $j$th active DR candidate in time period $t$. $C_{0,j,t}, D_{0,j,t}, K_{j,t},$ and $R_{j,t}$ are the initial electricity price, load, discount coefficient, and response compensation coefficient of the $j$th active DR candidate in time period $t$. $N_W$ in (21) is the amount of the wind farms. $\Delta p_{s,t}^W$ and $\omega_{s,t}$ are the wind-abandoning amount and the penalty coefficient of the $s$th wind farm in time period $t$. Then, the main constraints in Stage II can be described as shown below.

The updated system power balance constraint in each time period is:

$$\sum_{i=1}^{N_T} \Delta P_{i,t}^F - \sum_{j=1}^{N_A} \Delta D_{j,t} + \sum_{s=1}^{N_W} \left( p_{s,t}^{W*} - p_{s,t}^W - \Delta p_{s,t}^W \right) = 0,$$

(22)

where $p_{s,t}^{W*}$ and $p_{s,t}^W$ are the predicted outputs of the $s$th wind farm in time period $t$ in Stage II and Stage I, respectively. $\Delta p_{s,t}^W$ represents the wind-abandoning amount that only exists in a scenario in which the thermal units and the active DR candidates can not completely absorb wind power.

The upper and lower limits of the thermal unit output adjustment can be defined as:

$$p_{i,t}^F - p_{i,t}^{F,\text{min}} \leq \Delta P_{i,t}^F \leq p_{i,t}^{F,\text{max}} - p_{i,t}^F.$$

(23)

The upper and lower limits of the active DR adjustment can be defined as:

$$\Delta D_{j,t}^{\text{min}} \leq \Delta D_{j,t} \leq \Delta D_{j,t}^{\text{max}},$$

(24)

where $\Delta D_{j,t}^{\text{max}}$ and $\Delta D_{j,t}^{\text{min}}$ are the upper and lower limits of the response quantity at the $j$th active DR candidate in time period $t$, respectively.
In addition, considering the impacts of the uncertainty of the active DR’s behavior in the interaction response process, the chance constraints of the system regulation capacity are added, as shown in (25) and (26):

\[
\text{Pr}\left\{ \sum_{i=1}^{N_c} \Delta P^F_{i,t} - \sum_{j=1}^{N_R} \left( \Delta D^\mu_{j,t} + \Delta D^\text{delta}_{j,t} \right) - \sum_{s=1}^{N_W} \left( \Delta P^W_{s,t} \right) \geq - \sum_{s=1}^{N_W} \left( p^W_{s,t} - p^W_{s,t}^\star \right) \right\} \geq \alpha_{up}, \quad (25)
\]

\[
\text{Pr}\left\{ \sum_{i=1}^{N_c} \Delta P^F_{i,t} - \sum_{j=1}^{N_R} \left( \Delta D^\mu_{j,t} + \Delta D^\text{delta}_{j,t} \right) - \sum_{s=1}^{N_W} \left( \Delta P^W_{s,t} \right) \leq - \sum_{s=1}^{N_W} \left( p^W_{s,t} - p^W_{s,t}^\star \right) \right\} \geq \alpha_{dn}, \quad (26)
\]

In (25), \( \sum_{s=1}^{N_W} \left( p^W_{s,t}^\star - p^W_{s,t} \right) \leq 0 \) is associated with the constraint within the wind power overestimation time period. Similarly, \( \sum_{s=1}^{N_W} \left( p^W_{s,t} - p^W_{s,t}^\star \right) \leq 0 \) in (26) is associated with the constraint within the wind power underestimation time period. \( \Delta D^\mu_{j,t} \) and \( \Delta D^\text{delta}_{j,t} \) represent the expected value and deviation of the response quantity of the active DR candidate in time period \( t \), respectively. \( \alpha_{up} \) and \( \alpha_{dn} \) represent the confidence coefficients associated with the chance constraints in (25) and (26), respectively.

4. Case Study

To demonstrate the correctness and effectiveness of the proposed method, the verification studies are carried out for a 6-bus test system, a modified IEEE 118-bus test system, and a modified IEEE 300-bus test system. The simulation time horizon is set to 24 h with intervals of 1 h, and all the simulations are based on a MATLAB environment.

4.1. Six-Bus Test System

The six-bus test system is modified from the system in [24]. The system has three thermal power units (G1, G2, and G3) and seven transmission lines, as shown in Figure 1. It is assumed that a wind farm and an active DR were located on Bus 4 and Bus 5, respectively. In addition, the total power load is assigned to Bus 3, Bus 4, and Bus 5 based on the distribution factors (0.5, 0.3, and 0.2, respectively). The forecast daily load and the wind power output are shown in Figure 2.

Figure 1. Topology of the modified six-bus test system.
4.1.1. Stage I: Day-Ahead Multi-Objective Optimization Scheduling

With the multi-objective optimal model described in Section 2.2, the generation schedule of each thermal power unit can be obtained according to the wind power outputs and the daily load forecast in the ground-state scenario, which provides the thermal power units with an adjusting generating range for scenarios containing the active DR and the wind power forecast uncertainties. The fluctuation of the wind power output is set to ±30% of its predicted base value [25,26], and the fluctuation of each load bus is set to ±5% of its predicted base value [27]. In the optimization process of Stage I, a non-dominated sorting genetic algorithm II (NSGA-II) method is used to solve the established multi-objective optimization model. The maximum iteration number is set to 1000, and the variation rate in addition to the crossover rate are set to 0.2 and 0.8, respectively. In addition, the initial population size is set to 200. Figure 3 shows the boundary of the Pareto optimal solution set. The computing time is 67.34 s.

![Figure 2. The predicted wind power output and load in a typical day.](image)

**Figure 2.** The predicted wind power output and load in a typical day.

It can be observed from Figure 3 that the Pareto optimal front searched by the NSGA-II method is relatively dispersed and continuous, which indicates that this algorithm searches for as many Pareto optimal solutions as possible. According to the above solution set, results of two schemes are compared:

- Scheme I: give top priority to economy, which refers to the rightmost point in Figure 3;
- Scheme II: give top priority to security, which refers to the leftmost point in Figure 3.

Under Scheme I, the daily system operation cost is USD 476,520 and the system security index value is 0.6417, whereas the daily system operation cost is USD 477,692
and the system security index value is 0.6048 under Scheme II. Compared with Scheme II, the economic index under Scheme I is reduced by USD 1172 (0.25 percent) while the security index is increased by 0.0369 (6.10 percent). According to the definition in [21], the smaller the security index value is, the more secure the system is. Therefore, the security index value of Scheme I is larger than that of Scheme II, indicating a decrease in the system security.

To consider the influence of both economy and security, all of the solutions from the Pareto optimal front are sorted according to the economy and security indices. Then, the median point (477022, 0.6190) is selected on behalf of the solution set as the base value for the following scenarios. The corresponding thermal unit output scheduling is listed in Table 2, and the adjustment range of each thermal unit is shown in Figure 4.

Table 2. Thermal unit output scheduling in Stage I (MW).

| Time | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| G1   | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 108.9 | 129.2 | 152.9 | 168.8 |
| G2   | 50.0  | 50.0  | 50.0  | 50.0  | 50.0  | 50.0  | 56.3 | 82.8 | 100.0 | 100.0 | 100.0 | 100.0 |
| G3   | 95.3  | 88.2  | 85.9  | 79.5  | 77.5  | 82.8  | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| Time | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  | 24  |
| G1   | 176.9 | 178.8 | 184.5 | 191.8 | 184.1 | 155.9 | 144.8 | 135.2 | 137.1 | 143.0 | 100.0 | 109.9 |
| G2   | 100.0 | 100.0 | 100.0 | 100.0 | 98.2  | 100.0 | 100.0 | 100.0  | 100.0 | 87.1  | 71.6  | 70.0  |
| G3   | 100.0 | 100.0 | 100.0 | 100.0 | 98.2  | 100.0 | 100.0 | 100.0  | 100.0 | 87.1  | 100.0 | 80.2  |

Figure 4. The adjustment range of each thermal unit.

4.1.2. Stage II: Intraday Adjustment Scheduling in the Interaction Response Mode

In Stage II, the interactive resources in the system are mobilized to address the fluctuations of the wind power output, maintaining the dynamic balance of the system power. Additionally, the economic cost of coordinating the interactive resources of various parties in the interaction response process is expected to be reduced as far as possible. It is assumed that the adjustment cost of the active power output of each thermal power unit is USD 100/MW·h. The basic electricity price of the active DR is USD 80/MW·h during the time period from 08:00 to 20:59 and USD 45/MW·h during the time periods from 00:00 to 07:59 as well as 21:00 to 23:59. The adjustment boundary of the active DR in each period is set to ±10% of the base load demand at each active DR location, and the fluctuation of the interaction response for each active DR candidate is set to ±10% of the expected response value. In addition, the wind abandonment penalty coefficient is set to USD 500/MW·h. According to the active DR model described in Section 3.1, during the peak period the price discount coefficient is set to 1 and the response compensation coefficient is set to 1.1 times the price at the moment when the active DR is in a positive response. Furthermore, the
price discount coefficient is set to 0.8 and the response compensation coefficient is set to 1.2 times the price at the moment when the active DR is in a negative response. During the valley period, the price discount coefficient is set to 0.8 and the response compensation coefficient is set to 90% of the price at the moment when the active DR is in a positive response. Additionally, the price discount coefficient is set to 1 and the response compensation coefficient is set to 80% of the price at that moment when the active DR is in a negative response.

To explore the influence of the response behaviors of interactive resources for different wind power output scenarios on the intraday adjustment scheduling, the following three scenarios are designed:

**Scenario 1**: No large overestimation/underestimation of wind power output.

In this scenario, the predicted value of the wind power output is generated randomly according to the probability distribution of the wind power output and the fluctuation of the wind power output in each period does not exceed ±30% of the expected value, as shown in Figure 5.

![Figure 5. The predicted intraday wind power output.](image)

By solving the model designed in Section 3.2, the output adjustment quantity of each thermal unit and the response quantity of each active DR candidate can be obtained in the process of Stage II. Figure 6 compares the output of the thermal units in this scenario and the ground-state scenario in Stage I. In addition, Table 3 lists the response quantity of the active DR candidate in each period. With the interaction response of the active DR, the operating cost of the whole system in the process of balancing the wind power fluctuation is increased by USD 4313; among that cost, the adjustment cost of the three thermal units is increased by USD 3601 and the active DR cost is USD 712.

![Figure 6. The comparison of the thermal unit output in Stage I and Stage II (Scenario 1).](image)
In this scenario, it is assumed that the wind power output is reduced to 0 in time periods 16 and 17. However, in other time periods, the wind power output remains the same as that in Scenario 1. It is obvious that the wind power output is significantly overestimated in time periods 16 and 17. By solving the same model described in Section 3.2, the output quantity of each thermal power unit after adjustment scheduling can be obtained, as shown in Figure 7. The response quantity of the active DR candidate is listed in Table 4. The system’s operating cost for Scenario 2 is increased by USD 14,154; among that cost, the increased cost of the thermal power units in the process of adjustment is USD 11,358 and the increased cost of the active DR is USD 2796. It should be noted that there is no wind-abandoning phenomenon in this scenario.

We also verify the status of the active DR candidate not participating in the adjustment process. Accordingly, the operating cost of the system is increased by USD 5102, which is determined by the three thermal units. Compared with the active DR participation case, the system’s daily operation cost is increased by USD 789. It should be noted that no wind-abandoning penalty cost is generated in this scenario, whether the active DR participates in the interaction response activities or not.

**Scenario 2**: Large overestimation of wind power output.

In this scenario, it is assumed that the wind power output is reduced to 0 in time periods 16 and 17. However, in other time periods, the wind power output remains the same as that in Scenario 1. It is obvious that the wind power output is significantly overestimated in time periods 16 and 17. By solving the same model described in Section 3.2, the output quantity of each thermal power unit after adjustment scheduling can be obtained, as shown in Figure 7. The response quantity of the active DR candidate is listed in Table 4. The system’s operating cost for Scenario 2 is increased by USD 14,154; among that cost, the increased cost of the thermal power units in the process of adjustment is USD 11,358 and the increased cost of the active DR is USD 2796. It should be noted that there is no wind-abandoning phenomenon in this scenario.

| Time | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|------|---|---|---|---|---|---|---|---|---|----|----|----|
| D0   | 0 | −1.03 | 0 | 0 | −0.68 | −1.90 | 0 | −1.67 | 0 | 0 | 0 | 0 |

| Time | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|------|----|----|----|----|----|----|----|----|----|----|----|----|
| D0   | 0  | 1.83 | 0 | 0 | 0 | 6.08 | 0 | 0 | 1.02 | 0.45 | −1.96 | −0.64 |

**Table 3.** Response quantity of the active DR candidate in Scenario 1 (MW).

**Figure 7.** The comparation of the thermal unit output in Stage I and Stage II (Scenario 2).

**Table 4.** Response quantity of the active DR candidate in Scenario 2 (MW).

| Time | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|------|---|---|---|---|---|---|---|---|---|----|----|----|
| D0   | 0 | −1.03 | 0 | 0 | −0.68 | −1.90 | 0 | −1.67 | 0 | 0 | 0 | 0 |

| Time | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|------|----|----|----|----|----|----|----|----|----|----|----|----|
| D0   | 0  | 1.83 | 0 | 0 | 0 | 6.08 | 0 | 0 | 1.02 | 0.45 | −1.96 | −0.64 |

Via comparison with Scenario 1, it can be found that the thermal power units cannot fully fill the power shortage caused by the wind power output overestimation due to the limitation of their regulation range in time period 17. Thus, the active DR in this period reduces part of the load in the interaction response process and coordinates with the thermal power units to complete the purpose of filling the power shortage. In contrast, the
active DR does not participate in the interaction response process in time period 16 when the power shortage is completely made up by the upward adjustment of the thermal units. **Scenario 3**: Large underestimation of wind power output.

It is assumed the wind power output surges to three times that in Scenario 1 in time periods 2, 5, and 6. However, in other time periods, the wind power output remains the same. In this scenario, it is necessary to coordinate the thermal power units and the active DR to balance the exceeded wind power as much as possible. The output of each thermal unit is shown in Figure 8 and the response quantity of the active DR in each period is shown in Table 5. The computing time is 2.16 s. In Scenario 3, the daily operating cost of the system is increased by USD 16,621; among that cost, the cost of the three thermal units is increased by USD 9,108 during the adjustment process, the cost of the active DR is increased by USD 1,922, and the cost of the wind-abandoning penalty is USD 5,591. It can be found that the system cannot completely balance the exceeded wind power due to the adjustment range of both the thermal units and the active DR, which results in the wind-abandoning phenomenon.

![Figure 8. The comparison of the thermal unit output in Stage I and Stage II (Scenario 3).](image)

**Table 5.** Response quantity of the active DR candidate in Scenario 3 (MW).

| Time | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9   | 10   | 11   | 12   |
|------|------|------|------|------|------|------|------|------|-----|------|------|------|
| D0   | 0    | 0    | 0    | 0    | 3.86 | 3.99 | 0    | −1.67| 0   | 0    | 0    | 0    |
| Time | 13   | 14   | 15   | 16   | 17   | 18   | 19   | 20   | 21  | 22   | 23   | 24   |
| D0   | 0    | 1.83 | 0    | 0    | 6.08 | 0    | 0    | 1.02 | 0.45| −1.96| −0.64|      |

To further analyze the impact of the active DR on the wind power consumption and system’s daily operating cost in this scenario, Table 6 lists the comparison of the relevant data for two schemes (① represents the scheme without the active DR, and ② represents the scheme with the active DR). It can be found that when the active DR does not participate in the response process, the wind-abandoning quantity is increased from 11.18 MW to 23.13 MW and the corresponding wind-abandoning penalty cost is increased from USD 5,591 to USD 11,567. The adjustment cost of the thermal units is increased from USD 9,108 to USD 10,045. Accordingly, the system’s daily operation adjustment cost is increased from USD 16,621 to USD 21,612.
Table 6. Impacts of active DR behavior on system operation in the modified six-bus test system.

|                              | 1             | 2             |
|------------------------------|---------------|---------------|
| Wind-abandoning quantity (MW)| 23.13         | 11.18         |
| Wind-abandoning penalty (USD)| 11,567        | 5591          |
| Adjustment cost of thermal units (USD) | 10,045 | 9108      |
| Response cost of active DR (USD) | 0             | 1922          |
| System’s daily operation adjustment cost (USD) | 21,612 | 16,621 |

4.2. IEEE 118-Bus Test System

To verify the adaptability of the established model on a system with large-scale buses, a modified IEEE 118-bus test system is selected for the simulation. The system consists of 19 thermal units, 5 wind farms, 186 transmission lines, and 91 load buses (including 5 active DR candidates). The distribution of the thermal units, wind farms, and active DR locations in the system is shown in Figure 9. The forecasting base values of the five wind farms’ outputs are set to 80%, 90%, 100%, 110%, and 120% of the wind farm output shown in Figure 2. The peak and valley load forecasting base values are set to 5092 MW and 2083 MW, respectively. In addition, the daily load curve shape remains the same as that shown in Figure 2; in other words, the load value in each period is enlarged in proportion to the peak and valley values.

Figure 9. Topology of the modified IEEE 118-bus test system.

4.2.1. Stage I: Day-Ahead Multi-Objective Optimization Scheduling

The fluctuation of each wind farm output and each load bus is set to ±30% and ±5% of their predicted base values, respectively. Considering the computation efficiency for the larger-scale system, the pre-processing for the security objective in (5) is conducted based on the security assessment method. Then, the key lines that have significant influence on the system security are selected. In the pre-processing of the test system, the ranking of all lines according to their degree of influence on the system’s security can be obtained. The lines ranked in the top 20 are selected for the subsequent optimization process. The computing time is 1429.68 s. Similar to the computation in the six-bus test system, according to the Pareto optimal solution set, the median point (3009691, 0.6686) is selected on behalf of the solution set as the base value for the following scenarios.
4.2.2. Stage II: Intraday Adjustment Scheduling in the Interaction Response Mode

It is also assumed that the upward/downward adjustment cost of the thermal unit output is USD 100/MW. The adjustment range, the price discount coefficient, and the response compensation coefficient of the active DR remain unchanged. In the six-bus test system, there is no wind-abandoning phenomenon in either Scenario 1 or Scenario 2; the phenomenon only occurs in Scenario 3. Furthermore, in Scenario 2, the active DR has to participate in the power balance adjustment process due to the large overestimation of wind power output. However, in a system with large-scale buses, it is generally considered that the system has a large enough upward reserve capacity to fulfill the power shortage of the system. Therefore, for the 118-bus test system, the following two scenarios are designed from the perspective of the wind-abandoning phenomenon. These scenarios have the aim of analyzing the impacts of the response behavior on the adjustment of the intraday scheduling.

**Scenario 1**: No wind-abandoning phenomenon occurs.

In this scenario, the predicted output value of each wind farm is generated randomly according to the probability distribution of the wind power outputs, and the fluctuation of the wind power output in each time period does not exceed ±30% of the expected value, as shown in Figure 10. The output adjustment quantity of each thermal power unit and the response quantity of each active DR candidate can be obtained.

![Figure 10. The predicted intraday wind power output.](image)

With the participation of the active DR, the system’s operation cost of balancing the wind power fluctuation is increased by USD 7085; among this cost, the adjustment cost of the thermal units is increased by USD 5244 and the active DR response cost is USD 1841. Additionally, the simulation is carried out for the active DR not participating in the interaction response process. At that point, the daily system operation cost is increased by USD 8389; this increased cost only contains the increased adjustment cost of the thermal units. Compared with the active DR participating in the interactive response process, the daily system operation cost is increased by USD 1304. It should be noted that no wind-abandoning penalty cost is generated whether the active DRs participate in the interaction response process or not.

**Scenario 2**: Wind-abandoning phenomenon occurs.

It is assumed that the output of each wind farm surges to twice that of Scenario 1 in time periods 4 and 5. However, in the other time periods, the wind power output remains the same. In other words, the wind power output is significantly underestimated in the aforementioned time periods. Thus, it is necessary to coordinate the thermal units and active DRs to balance the exceeded wind power as much as possible. The computing time is 16.43 s. The daily system operating cost is increased by USD 26,536, including USD 14,929 for the thermal units in the adjustment process, USD 6134 for the active DR, and USD 5473 for the wind-abandoning penalty. Compared with Scenario 1, it can be found that due to the adjustment range of the thermal units and the active DRs, the system cannot
completely absorb the sudden increase in the wind power output in some time periods, resulting in the wind-abandoning phenomenon.

The impacts of the active DRs on the wind power consumption and system’s daily operating cost are also analyzed in this scenario. Table 7 lists the comparison of the relevant data for two schemes (① represents the scheme without the active DR, and ② represents the scheme with the active DR). It can be found that when the active DR candidates do not participate in the response process, the wind-abandoning quantity is increased from 10.95 MW to 54.87 MW, and the corresponding wind-abandoning penalty cost is increased from USD 5473 to USD 27,435. The adjustment cost of the thermal units is increased from USD 14,929 to USD 17,396. Accordingly, the system’s daily operation adjustment cost is increased from USD 26,536 to USD 44,831.

Table 7. Impacts of active DR behavior on system operation in the modified IEEE 118-bus test system.

|                                | ①       | ②       |
|--------------------------------|---------|---------|
| Wind-abandoning quantity (MW)  | 54.87   | 10.95   |
| Wind-abandoning penalty (USD)  | 27,435  | 5473    |
| Adjustment cost of thermal units (USD) | 17,396  | 14,929  |
| Response cost of active DR (USD) | 0       | 6134    |
| System’s daily operation adjustment cost (USD) | 44,831  | 26,536  |

4.3. IEEE 300-Bus Test System

We also verify the adaptability of the established model on a modified IEEE 300-bus test system. The system consists of 56 thermal units, 10 wind farms, 411 transmission lines, and 199 load buses (including 10 active DR candidates). The forecasting base value of the 10 wind farms’ outputs is set to six times of the wind farm output shown in Figure 2. The peak and valley load forecasting base values are set to 28,239 MW and 11,552 MW, respectively. The other parameters remain unchanged. Additionally, the key lines that have significant influence on the system security are selected. In this test system, the lines ranked in the top 50 are selected for the subsequent optimization process. In Stage I, according to the Pareto optimal solution set, the median point (15430685, 0.6578) is selected on behalf of the solution set as the base value. In Stage II, we design a scenario in which wind-abandoning phenomenon occurs. Table 8 lists the comparison of the relevant data for two schemes (① represents the scheme without the active DR, and ② represents the scheme with the active DR). It can be also found that the system’s daily operation adjustment cost is decreased, and wind curtailment is reduced as active DR candidates participate in the rescheduling process. The computing time in Stage I and Stage II is 4687.06 s and 53.82 s, respectively. Although more computing time in Stage I is needed, it is still adaptive to the day-ahead scheduling process. Compared with Stage I, the computing time in Stage II increased slightly. For a system with a larger scale, the computation efficiency can be improved by parallel computing on high-performance servers.

Table 8. Impacts of active DR behavior on system operation in the modified IEEE 300-bus test system.

|                                | ①       | ②       |
|--------------------------------|---------|---------|
| Wind-abandoning quantity (MW)  | 425.34  | 79.06   |
| Wind-abandoning penalty (USD)  | 212,672 | 39,530  |
| Adjustment cost of thermal units (USD) | 62,973  | 52,628  |
| Response cost of active DR (USD) | 0       | 34,383  |
| System’s daily operation adjustment cost (USD) | 275,645 | 126,541 |

5. Conclusions

In this paper, a two-stage cooperative dispatch model for power systems that considers security with a source-load interaction and response environment is proposed. First, a day-ahead multi-objective optimization dispatch model with a combined hyper-box and
hyper-ellipse space theory-based system security index is established. Second, different types of active DR interaction response modes are designed, based on which an intraday adjustment scheduling model is proposed. Finally, through the two-stage cooperative dispatch model, the output scheduling of the thermal units and response values of active DR candidates are obtained and demonstrated with several case studies.

Based on the work presented in this paper, following contributions are made:

1. This work extends the application of a hyper-box and hyper-ellipse space theory-based system security index in a power system dispatch. The day-ahead multi-objective optimization model provides a quantitative approach for analyzing the relationship between the security and economy of the system dispatch process;
2. The interaction response activities of the active DR can be coordinated with thermal power units to maintain the dynamic power system balance and effectively reduce the wind-abandoning phenomenon;
3. This two-stage cooperative dispatch model can support power system security assessment and an active DR strategy; therefore, it is able to help operators effectively evaluate the system state and design interaction response mechanisms.

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