Research on Multi-Timescale Coordinated Method for Source-Grid-Load with Uncertain Renewable Energy Considering Demand Response

Jia Ning 1,*, Sipeng Hao 1, Aidong Zeng 1, Bin Chen 2 and Yi Tang 3

1 School of Electric Power Engineering, Nanjing Institute of Technology, Nanjing 211167, China; hsnpnjit@126.com (S.H.); zengaidong@foxmail.com (A.Z.)
2 State Grid Changzhou Power Supply Company, Changzhou 213003, China; chenbinseu@163.com
3 School of Electrical Engineering, Southeast University, Nanjing 210096, China; tangyi@seu.edu.cn
* Correspondence: ningjia@njit.edu.cn

Abstract: The high penetration of renewable energy brings great challenges to power system operation and scheduling. In this paper, a multi-timescale coordinated method for source-grid-load is proposed. First, the multi-timescale characteristics of wind forecasting power and demand response (DR) resources are described, and the coordinated framework of source-grid-load is presented under multi-timescale. Next, economic scheduling models of source-grid-load based on multi-timescale DR under network constraints are established in the process of day-ahead scheduling, intraday scheduling, and real-time scheduling. The loads are classified into three types in terms of different timescale. The security constraints of grid side and time-varying DR potential are considered. Three-stage stochastic programming is employed to schedule resources of source side and load side in day-ahead, intraday, and real-time markets. The simulations are performed in a modified Institute of Electrical and Electronics Engineers (IEEE) 24-node system, which shows a notable reduction in total cost of source-grid-load scheduling and an increase in wind accommodation, and their results are proposed and discussed against under merely two timescales, which demonstrates the superiority of the proposed multi-timescale models in terms of cost and demand response quantity reduction.

Keywords: renewable energy; multi-timescale; source-grid-load; demand response

1. Introduction

With the intensification of the traditional energy crisis and the increasingly prominent environmental problems, coupled with the declining cost of renewable energy generation in recent years, the installed capacity and generated energy of renewable energy have been growing rapidly [1,2]. When the total amount of wind power and photovoltaic power generation accounts for a small proportion of the total grid power generation, the uncertainty of wind power and photovoltaic power generation has no significant impact on the grid. With the continuous expansion of renewable energy, the complexity of power supply side situation changes is enhanced, which is not conducive to the active power balance and voltage adjustment of the grid and increases the difficulty of power market planning and scheduling and power grid operation control. For example, the ‘duck curve’ [3] caused by the rapid increase of photovoltaic power generation in California: the overall load curve shows a ‘trough’ characteristic in the original period of ‘peak’ due to the occurrence of photovoltaic power during the day, but when the solar power generations stop generating power in the evening, the power demand rises sharply, and the thermal power unit causes a large power shortage due to the ramp limitation. Wind power not only increases the amplitude and rate of unbalanced power fluctuation in the power system due to its volatility and intermittence [4], but also brings difficulty to power control of the power system due to the timescale characteristics of wind power prediction error.
In response to the above challenges, energy storage equipment [5], pumped storage power plants [6], gas turbines [7], and compressed air energy storage [8] could be used to mitigate the impact of randomness and volatility of renewable energy, but there is a problem of high economic costs. Compared with traditional power generation resources, demand response (DR) has many advantages in operation control [9,10]. Firstly, there is a lot of load participating in DR programs. Taking the United States as an example, the report of the Federal Public Utilities Regulatory Commission shows that DR could offset 20% of the peak load [11]. Secondly, DR resources could quickly respond to scheduling and control instructions, and there is no regulation inertia of conventional generators. Finally, the decentralized distribution of DR resources is conducive to the formulation of accurate control schemes in emergencies [12]. Because there are many types of responsive load, their dynamic response characteristics and action characteristics reflect the characteristics of multi-timescales [13]. In the scheduling process, on the one hand, it is necessary to classify the customer loads according to the multi-timescale characteristics of DR [14], and on the other hand, it is imperative to consider the level of responsive load participating affected by various factors, such as user comfort [15], regret probability, and time-varying DR potential [16]. Therefore, it is of great significance to master the multi-timescale characteristics of power supply side and load side, and comprehensively consider the demand response and security risk constraints, such as the over-limit of power flow and node voltage instability.

With the continuous expansion of renewable energy connected to grid, the coordinated control methods only relying on power supply side have been unable to meet the requirements of renewable energy accommodation. Therefore, more and more studies have proposed the DR control as an active control method to participate in the source-grid-load coordinated control. In the existing models and methods, the scheduling of DR resources is mostly concentrated on a single timescale [17–19], ignoring the multi-timescale characteristics of DR resources. Reference [20] proposes a new method to unleash the potential of DR in real-time. A dynamic energy balancing cost model is presented for day-ahead market scheduling under generation uncertainties and demand response penetration in Reference [21]. Reference [22] presents a novel robust framework for the day-ahead scheduling to minimize the expected energy cost. In Reference [23], a peer–peer energy trading platform among residential houses is presented to coordinate DR schemes and level OFF potential generation/consumption disturbances in the hour-ahead intraday context. An effective strategy is proposed to improve the security and economy considering the uncertainty of wind power and electric vehicles (EVs) and a dispatch interval coefficient is presented in Reference [24]. Moreover, wind power generation also has multi-timescale characteristics, where its precision of prediction is higher when timescale is smaller and the prediction time is closer to the actual time [25]. Therefore, multi-timescale DR have great potentials in addressing wind power generation variabilities more effectively.

This paper proposes an improved coordinated method for source-grid-load, which considers the multi-timescale characteristics of both wind power forecasting and DR resources. In other words, we build multi-timescale models in the day-ahead market, intraday market, and real-time market to optimize the benefit and maximize the wind accommodation considering the wind generation variabilities of source side, the security risk constraints of grid side, and the end users’ uncertainty and DR resources’ diversity of load side.

The rest of this paper is organized as follows. In Section 2, the framework of the multi-timescale coordinated method is described. Section 3 presents the economic scheduling models of source-network-load with uncertain renewable energy considering multi-timescale DR under network constraints, including day-ahead scheduling, intraday scheduling, and real-time scheduling. The solution methodology is proposed in Section 4. Case studies are developed in Section 5, and Section 6 concludes the paper.
2. Multi-Timescale Coordinated Framework of Source-Grid-Load Considering DR

This paper proposes a coordinated framework for multi-timescale scheduling of power system comprising generators, wind generations, interconnected smart users, and loads. The multi-timescale scheduling includes day-ahead scheduling, intraday scheduling, and real-time scheduling. Loads are divided into controllable loads and non-controllable loads [26,27]. The presented coordinated method consists of three procedures which are realized in day-ahead, intraday, and real-time markets, respectively. The optimization objectives of all three procedures are to minimize the total cost. The optimal results of the previous step are beneficial to the realization of the latter step. Therefore, the research objects and the multi-timescale coordinated framework are explained in this section.

With increasing wind farm connected into power system, the uncertainty of wind power brings a new challenge for the power system scheduling. The prediction accuracy of wind power is related with timescales, namely the precision of prediction is higher when timescale is shorter, and the prediction time is closer to the actual time. DR resources also have multi-timescale characteristics, namely the scheduling time is different for various types of loads and each type has different response characteristics, response rapid and response lasting time, etc. Therefore, the uncertainty of wind power forecasting and the diversity of DR resources should be coordinated on the aspect of timescales. This paper includes three kinds of scheduling resources:

(1) Generator: only considering the generating cost of generators, and the generators with automatic generation control (AGC) could be adjusted in the process of real-time scheduling.

(2) Wind farm: the forecasting error of a single wind farm is diverse under different timescales. The forecasting error is less when the prediction time is closer to the actual time. In general, the forecasting error is 25–40% in day-ahead, 10–20% within 4 h, less than 10% within 1 h, and ignorable in real-time [28].

(3) Load resources: this paper studies the electrical load for residents. According to the RELOAD database [29], the smart appliances of consumers include cooling air conditioner (AC), heater, water heater (WH), dryer, induction cooker, refrigerator, lighting, etc. These loads have different dynamic operating characteristics, response ability, and response time, for instance, WH and AC could respond to the scheduling signal immediately, washer, dryer, and some other motor loads could respond to the scheduling signal lingeringly, and EVs and energy storage systems [30,31], which have high requirements, should be informed before a long time. In this paper, the responsive loads are divided into three types: A load, which should be informed before 1 day, B load, which should be informed before 1 h, and C load, which could be scheduled in real-time. Therefore, A type load could consist of EVs and energy storage systems, B type load could consist of washer, dryer, and some other motor loads, and C type load could consist of ACs and WHs.

Based on the timescale characteristics of DR and dispatching, the scheduling process consists of day-ahead scheduling (24 h), intraday scheduling (1 h), and real-time scheduling (1 min). Figure 1 shows the technological framework. There is an input layer, scheduling control layer, agent coordination layer, and local response layer for each timescale. For input layer, the prediction power of wind farm and load, except responsive load, are set as input parameters to be deployed, in which, \( P_{\text{wfa}} \) and \( P_{\text{lfa}} \), \( P_{\text{wfn}} \) and \( P_{\text{lfn}} \), and \( P_{\text{wfr}} \) and \( P_{\text{lfr}} \) are the prediction power of wind farm and load, except responsive load, in day-ahead scheduling, intraday scheduling, and real-time scheduling, respectively. Scheduling control layer takes charge of formulating and implementing the scheduling plan. The day-ahead scheduling is executed every 24 h and the time interval is 1 h, whose mission is to determine the generator output power and the responsive amount of load A. The intraday scheduling is executed every 15 min and the time interval is 15 min, whose mission is to determine the variable quantity of generator power and the responsive amount of load B. The real-time scheduling is executed every 1 min and the time interval is 1 min, whose mission is to determine the variable quantity of generator power and the responsive amount of load C. The day-ahead scheduling plan is formulated at 24:00, during which the intraday...
scheduling plan is formulated every 15 min, during which the real-time scheduling plan is formulated every 1 min. \( P_{G,i,t} \) and \( P_{Lr,t} \), \( P_{Gr} \) and \( P_{Lr} \) are the output results of generator and load for day-ahead scheduling, intraday scheduling, and real-time scheduling, respectively. Agent coordination layer coordinates the scheduling information and load resources, makes the optimal decision for a given optimization object, and issues a control signal to the responsive load. During real-time scheduling, each load aggregator of the agent coordination layer uploads aggregated DR potential, \( D_{Lt} \), to the scheduling control layer in real-time. Local response layer uploads power utilization of responsive load to each load aggregator.

\[
\text{min} \sum_{t=1}^{N_t} \left( \sum_{j=1}^{N_G} C_{G,i,j} P_{G,i,j,t} + \sum_{j=1}^{N_G} \left( C_{LA,j,t}^+ S_{LA,j,t}^+ + C_{LA,j,t}^- S_{LA,j,t}^- \right) P_{LA,j,t} + \sum_{k=1}^{N_r} C_{W,k,t} \left( P_{W,head,k,t} - P_{W,k,t} \right) \right)
\]  

(1)

where \( S_{LA,j,t}^+ = 1 \) means that jth load A responds to the increment signal at t time interval, \( S_{LA,j,t}^- = 0 \) means that jth load A does not respond to the increment signal at t time interval, \( S_{LA,j,t}^- = 1 \) means that jth load A responds to the decreased signal at t time interval, and \( S_{LA,j,t}^- = 0 \) means that jth load A does not respond to the decreased signal at t time interval.

The day-ahead independent variables are \( P_{G,i,j,t} \), \( P_{LA,j,t} \), and \( P_{W,k,t} \), and the decision variables are \( S_{LA,j,t}^+ \), \( S_{LA,j,t}^- \), \( P_{m,n,t} \), and \( \theta_t \). These variables are defined through minimizing Equation (1) by considering the following constraints.

**Figure 1.** The technological framework of the proposed method.

3. Multi-Timescale Scheduling Model Considering DR

3.1. Day-Ahead Scheduling Model Considering DR

3.1.1. Objective Function

Day-ahead scheduling is defined as formulating generation dispatching before one day, in which the time interval is 1 h. Based on the prediction power of wind farm and load in day-ahead, the output power of conventional generator units and wind farm and the response quantity are scheduled by 24 time-intervals for 1 day in the future. The objective is to minimize the total cost consisting of generator cost, wind curtailment cost, and load A responsive cost. The objective function is shown as follows:

\[
\text{min} \sum_{t=1}^{N_t} \left( \sum_{j=1}^{N_G} C_{G,i,j} P_{G,i,j,t} + \sum_{j=1}^{N_G} \left( C_{LA,j,t}^+ S_{LA,j,t}^+ + C_{LA,j,t}^- S_{LA,j,t}^- \right) P_{LA,j,t} + \sum_{k=1}^{N_r} C_{W,k,t} \left( P_{W,head,k,t} - P_{W,k,t} \right) \right)
\]  

(1)
3.1.2. Constraints

1. Active power balance constraint:

\[ \sum_{i=1}^{N_G} P_{G,i,t} + \sum_{k=1}^{N_W} P_{W,k,t} = \sum_{i=1}^{N_i} P_{i,t} + \sum_{j=1}^{N_{LA}} S_{LA,j,t}^+ P_{LA,j} - \sum_{j=1}^{N_{LA}} S_{LA,j,t}^- P_{LA,j} \] (2)

2. Response balance constraint of load A:

\[ \sum_{i=1}^{N_L} \sum_{j=1}^{N_{LA}} (S_{LA,j,t}^+ - S_{LA,j,t}^-) P_{LA,j} = 0 \] (3)

3. Line power flow constraint:

\[ P_{mn,t} = B_{mn}(\theta_{n,t} - \theta_{m,t}) \] (4)

4. Generator output power constraint:

\[ P_{G,i,min} \leq P_{G,i,t} \leq P_{G,i,max} \] (5)

5. Generator ramp constraint:

\[ -R_{d,i} \Delta T \leq P_{G,i,t} - P_{G,i,t-1} \leq R_{u,i} \Delta T \] (6)

6. Security constraint:

\[ |P_{mn,t}| \leq P_{mn,\text{lim}} \]

\[ -\pi \leq \theta_t \leq \pi \] (8)

7. Wind output power constraint:

\[ 0 \leq P_{W,k,t} \leq P_{W,\text{ahead},k,t} \] (9)

8. Load A response constraint:

\[ \sum_{j=1}^{N_{LA}} S_{LA,j,t}^+ P_{LA,j} \leq DRP_{\text{ahead},u} \] (10)

\[ \sum_{j=1}^{N_{LA}} S_{LA,j,t}^- P_{LA,j} \leq DRP_{\text{ahead},d} \] (11)

3.1.3. Optimal Results

The independent variables of the day-ahead scheduling model include the output power of each generator, wind power, and adjustment quantity of load A. The generator output power and adjustment quantity of load A are determined to benefit intraday scheduling as a reference value.

3.2. Intraday Scheduling Model Considering DR

For intraday scheduling, the generator output power and load B power are scheduled to minimize the total cost according to the prediction error of the wind farm. The intraday scheduling objective function is shown as follows.

3.2.1. Objective Function

\[ \min \left( \sum_{i=1}^{N_G} C_{G,i} \left( P_{Nei} - P_{G,i} \right) + \sum_{j=1}^{N_B} \left( C_{LB,j}^+ S_{LB,j}^+ + C_{LB,j}^- S_{LB,j}^- \right) P_{LB,j} + \sum_{k=1}^{N_W} C_{W,k} \left( P_{W,Nei,k} - P_{W,k} \right) \right) \] (12)
where \( S_{LB,j}^+ = 1 \) means that \( j \)th load \( B \) responds to the increment signal, \( S_{LB,j}^- = 0 \) means that \( j \)th load \( B \) does not respond to the increment signal, \( S_{LB,j}^- = 1 \) means that \( j \)th load \( B \) responds to the decreased signal, and \( S_{LB,j}^- = 0 \) means that \( j \)th load \( B \) does not respond to the decreased signal.

The intraday independent variables are \( P_{G,i} \), \( P_{LB,j} \), and \( P_{Nei,W,k} \), and the decision variables are \( S_{LB,j}^+ \), \( S_{LB,j}^- \), \( P_{mn} \), and \( \theta_t \). These variables are defined through minimizing Equation (12) by considering the following constraints.

### 3.2.2. Constraints

1. **Active power balance constraint:**
   \[
   \sum_{i=1}^{N_G} P_{Neli,G,i} + \sum_{k=1}^{N_W} P_{Neli,W,k} = \sum_{i=1}^{N_G} P_i + \sum_{j=1}^{N_{LB}} S_{LB,j}^+ P_{LB,j} - \sum_{j=1}^{N_{LB}} S_{LB,j}^- P_{LB,j} + \sum_{j=1}^{N_{LB}} \delta_{Bj} P_{LB,j}
   \]  
   (13)

   where \( \delta_{Bj} = 1 \) means that the \( j \)th load \( B \) is working, and \( \delta_{Bj} = 0 \) means that the \( j \)th load \( B \) stopped working.

2. **Line power flow constraint:**
   \[
   P_{mn} = B_{mn}(\theta_n - \theta_m)
   \]  
   (14)

3. **Generator output power constraint:**
   \[
   P_{G,j,\text{min}} \leq P_{Neli,G,j} \leq P_{G,j,\text{max}}
   \]  
   (15)

4. **Generator ramp constraint:**
   \[
   -R_{d,i} \Delta T \leq P_{Neli,G,j} - P_{Neli,G,j-1} \leq R_{u,i} \Delta T
   \]  
   (16)

5. **Security constraint:**
   \[
   |P_{mn}| \leq P_{\text{mn,lim}}
   \]  
   (17)

   \[
   -\pi \leq \theta_t \leq \pi
   \]  
   (18)

6. **Wind output power constraint:**
   \[
   0 \leq P_{Neli,W,k} \leq P_{W,Neli,k}
   \]  
   (19)

7. **Load B response constraint:**
   \[
   \sum_{j=1}^{N_{LB}} S_{LB,j}^+ P_{LB,j} \leq DRP_{Nei,u}
   \]  
   (20)

   \[
   \sum_{j=1}^{N_{LB}} S_{LB,j}^- P_{LB,j} \leq DRP_{Nei,d}
   \]  
   (21)

### 3.2.3. Optimal Results

The independent variables of the intraday scheduling model include the output power of each generator, wind power, and adjustment quantity of load \( B \). The generator output power and adjustment quantity of load \( B \) are determined to benefit real-time scheduling as a reference value.

### 3.3. Real-Time Scheduling Model Considering DR

The time interval of real-time scheduling is 1 min. The real-time scheduling is performed by coordinating AGC units, wind farm, and DR. The output power of AGC units is controlled by two signals, which contains of area control error updated by seconds and...
The base value which is determined by day-ahead scheduling and intraday scheduling. The objective of real-time scheduling is to minimize the total cost.

### 3.3.1. Objective Function

\[
\min \left( \sum_{i=1}^{N_G} C_{G,i} \left( P_{G,i}^{real} - P_{G,i}^{Net} \right) + \sum_{j=1}^{N_LC} \left( C_{LC,j}^+ S_{LC,j}^+ + C_{LC,j}^- S_{LC,j}^- \right) P_{LC,j} + \sum_{k=1}^{N_W} C_{W,k} \left( P_{W,k}^{real} - P_{W,k}^{real} \right) \right) 
\]

(22)

where \( S_{LC,j}^+ = 1 \) means that \( j \)th load \( C \) responds to the increment signal, \( S_{LC,j}^- = 0 \) means that \( j \)th load \( C \) does not respond to the increment signal, \( S_{LC,j}^- = 1 \) means that \( j \)th load \( C \) responds to the decreased signal, and \( S_{LC,j}^- = 0 \) means that \( j \)th load \( C \) does not respond to the decreased signal.

The real-time independent variables are \( P_{G,i}^{real}, P_{LC,j} \), and \( P_{realW,k} \), and the decision variables are \( S_{LC,j}^+, S_{LC,j}^-, P_{mn}, \) and \( \theta_t \). These variables are defined through minimizing Equation (22) by considering the following constraints.

### 3.3.2. Constraints

1. **Active power balance constraint:**

\[
\sum_{i=1}^{N_G} P_{G,i}^{real} + \sum_{k=1}^{N_W} P_{W,k}^{real} = \sum_{i=1}^{N_{G2}} P_i + \sum_{j=1}^{N_{LC}} S_{LC,j}^+ P_{LC,j} + \sum_{j=1}^{N_{LC}} S_{LC,j}^- P_{LC,j} + \sum_{j=1}^{N_{LC}} \delta_{Cj} P_{LC,j} 
\]

(23)

where \( \delta_{Cj} = 1 \) means that the \( j \)th C load is working, and \( \delta_{Cj} = 0 \) means that the \( j \)th C load stopped working.

2. **Line power flow constraint:**

\[
P_{mn} = B_{mn}(\theta_n - \theta_m) 
\]

(24)

3. **Generator output power constraint:**

\[
P_{mn} = B_{mn}(\theta_n - \theta_m) 
\]

(25)

4. **Generator ramp constraint:**

\[
-R_{d,j} \Delta T \leq p_{G,j,l}^{\text{real}} - p_{G,j,l-1}^{\text{real}} \leq R_{u,j} \Delta T 
\]

(26)

5. **Security constraint:**

\[
-R_{d,j} \Delta T \leq p_{G,j,l}^{\text{real}} - p_{G,j,l-1}^{\text{real}} \leq R_{u,j} \Delta T 
\]

\[-\pi \leq \theta_t \leq \pi 
\]

(27)

(28)

6. **Wind output power constraint:**

\[
0 \leq P_{W,k}^{real} \leq P_{W,real,k} 
\]

(29)

7. **Load C response constraint:**

\[
\sum_{j=1}^{N_{LC}} S_{LC,j}^+ P_{LC,j} \leq DRP_{real,u} 
\]

(30)

\[
\sum_{j=1}^{N_{LC}} S_{LC,j}^- P_{LC,j} \leq DRP_{real,d} 
\]

(31)

where
\[ DRP_{real,u}(t+1) = \left( \sum_{i=1}^{N_1} P_{i,AC} \cdot D_{i,AC}(t) + \sum_{j=1}^{N_2} P_{j,WH} \cdot D_{j,WH}(t) + \sum_{k=1}^{N_3} P_{k,EV} \cdot D_{k,EV}(t) \right) \left( 1 - Re(t) \right) \] (32)

\[ DRP_{real,u}(t+1) = \left( \sum_{i=1}^{N_1} P_{i,AC} \cdot D_{i,AC}(t) + \sum_{j=1}^{N_2} P_{j,WH} \cdot D_{j,WH}(t) + \sum_{k=1}^{N_3} P_{k,EV} \cdot D_{k,EV}(t) \right) \left( 1 - Re(t) \right) \] (33)

3.3.3. Optimal Results

The optimal results of the real-time scheduling model include the output power of each generator, wind power, and adjustment quantity of load C.

4. Solution Method of Multi-Timescale Scheduling Considering DR

The flowchart of the solution method is shown in Figure 2. The optimal results of prior timescale scheduling are treated as input parameters of posterior timescale scheduling. For real-time scheduling, the operation status of C loads such as ACs and WHs at t time interval is related to the operation power at t-1 time interval, which means the DR potential should be updated in real-time. When the response instructions are issued, the smart appliances that agree to participate in the DR program in advance may fail to respond in time due to personal reasons of the consumers. When the required response quantity is large and the regret probability is high, it may lead to wind curtailment or load shedding, and even cause the power system instability. Therefore, in case DR resources may not respond to scheduling instructions in time, this section proposes a DR control strategy considering user regret in the real-time scheduling process. Figure 3 is the flow chart of the DR control strategy.

![Figure 2. Flow chart of solution method.](image-url)
5. Case Study

The proposed scheduling model is verified based on the IEEE 24-node system, which is shown in Figure 4. The test system consists of 12 generators and 17 load nodes, in which the parameters of generator and load are described in Reference [32]. In the case study, the line resistance is not considered, namely the line active power loss is ignored. The wind farm is located at bus 19. It is assumed that there are 10 load aggregators located at nodes 3, 4, 5, 6, 8, 9, 10, 14, 19, and 20. Each aggregator consists of load A, load B, and load C. The node location and cost of generators are shown in Table 1. The cost of wind curtailment is $21/MWh and the response costs of load A, load B, and load C are $9.87/MWh, $12/MWh, and $14/MWh, respectively.

It is assumed that the scheduled capacity of load A and load B are both not more than five percent of the total load. The dispatched capacity of load C varies with time and its total rated power is not more than twenty-five percent of the total load. The total load power is shown in Table 2. In order to indicate the applicable effect of influence factors, the transmission power limit of each line is reduced to 50% of the permitted power. The simulations were conducted in Matlab. Figure 5 shows the wind prediction power with different timescales, including day-ahead 24 h, intraday 15 min, and real-time [33].
Figure 4. Modified IEEE 24-node system.

Table 1. 24-node system: the node location and cost of generator ($/MWh).

| No. | Node Location | Generation Cost ($/MWh) |
|-----|---------------|------------------------|
| 1   | 1             | 11.46                  |
| 2   | 2             | 11.46                  |
| 3   | 7             | 18.60                  |
| 4   | 13            | 19.20                  |
| 5   | 15            | 23.41                  |
| 6   | 15            | 9.92                   |
| 7   | 16            | 9.92                   |
| 8   | 18            | 5.31                   |
| 9   | 21            | 5.31                   |
| 10  | 22            | 0.00                   |
| 11  | 23            | 9.92                   |
| 12  | 23            | 10.08                  |

Table 2. Total load power within different timeframes.

| Timeframe      | Power (MW) | Timeframe      | Power (MW) |
|----------------|------------|----------------|------------|
| 00:00–01:00    | 1775.835   | 12:00–13:00    | 2517.975   |
| 01:00–02:00    | 1669.815   | 13:00–14:00    | 2517.975   |
| 02:00–03:00    | 1590.300   | 14:00–15:00    | 2464.965   |
| 03:00–04:00    | 1563.795   | 15:00–16:00    | 2464.965   |
| 04:00–05:00    | 1563.795   | 16:00–17:00    | 2623.995   |
| 05:00–06:00    | 1590.300   | 17:00–18:00    | 2650.500   |
| 06:00–07:00    | 1961.370   | 18:00–19:00    | 2650.500   |
| 07:00–08:00    | 2279.430   | 19:00–20:00    | 2544.480   |
| 08:00–09:00    | 2517.975   | 20:00–21:00    | 2411.955   |
| 09:00–10:00    | 2544.480   | 21:00–22:00    | 2199.915   |
| 10:00–11:00    | 2544.480   | 22:00–23:00    | 1934.865   |
| 11:00–12:00    | 2517.975   | 23:00–24:00    | 1669.815   |
Table 2. Total load power within different timeframes.

| Timeframe       | Power (MW) |
|-----------------|------------|
| 00:00–01:00     | 1775.835   |
| 01:00–02:00     | 1669.815   |
| 02:00–03:00     | 1590.300   |
| 03:00–04:00     | 1563.795   |
| 04:00–05:00     | 1563.795   |
| 05:00–06:00     | 1590.300   |
| 06:00–07:00     | 1961.370   |
| 07:00–08:00     | 2279.430   |
| 08:00–09:00     | 2517.975   |
| 09:00–10:00     | 2544.480   |
| 10:00–11:00     | 2544.480   |
| 11:00–12:00     | 2517.975   |
| 12:00–13:00     | 2517.975   |
| 13:00–14:00     | 2464.965   |
| 14:00–15:00     | 2464.965   |
| 15:00–16:00     | 2623.995   |
| 16:00–17:00     | 2650.500   |
| 17:00–18:00     | 2650.500   |
| 18:00–19:00     | 2544.480   |
| 19:00–20:00     | 2411.955   |
| 20:00–21:00     | 2199.915   |
| 21:00–22:00     | 1934.865   |
| 22:00–23:00     | 1669.815   |
| 23:00–24:00     | 1669.815   |

Figure 5. Wind prediction power in different timescales.

To showcase the scheduling results of all resources, four distinct case studies were conducted as follows, in which the day-ahead scheduling is executed firstly, whose decision variables are determined to benefit intraday scheduling as given parameters and the decision variables of intraday scheduling are determined to benefit real-time scheduling as given parameters. For the day-ahead scheduling, different amounts of scheduled load A and transmission power limit of line could affect the optimal results. Table 3 shows the results with different response potentials of load A and transmission power limits.

Table 3. Results with different response potentials of load A and transmission power limits for day-ahead scheduling.

| Response Potential of Load A (MW) | Transmission Power Limit | Total Cost ($) | Wind Power Accommodation | Response Quantity of Load A (MWh) |
|----------------------------------|--------------------------|----------------|--------------------------|----------------------------------|
| [−1000,1000]                    | 50%                      | 430,823.46     | 100%                     | 723.59                           |
| [−1000,1000]                    | 55%                      | 415,265.08     | 100%                     | 723.16                           |
| [−350,350]                      | 50%                      | 431,731.55     | 100%                     | 612.81                           |
| [−350,350]                      | 55%                      | 416,485.21     | 100%                     | 467.33                           |
| [−150,150]                      | 50%                      | 433,363.71     | 99.71%                   | 548.97                           |
| [−150,150]                      | 55%                      | 417,595.20     | 100%                     | 210.00                           |
| [0,0]                            | 50%                      | 435,269.68     | 99.27%                   | 0                                 |
| [0,0]                            | 55%                      | 418,651.69     | 100%                     | 0                                 |

It can be seen from Table 3 that the scheduling total cost is highest, and the wind accommodation rate is lowest at 99.27% when load A does not take part in the DR program and the line transmission limit is 50%. With the scheduled capacity of load A increasing, the total cost reduces, wind accommodation rate increases, and the response capacity increases. With the scheduled capacity of load A constant and the line transmission limit increasing, the total cost decreases, wind accommodation rate increases, and the response capacity decreases.

In order to execute the intraday scheduling and real-time scheduling, the optimal results of day-ahead scheduling are obtained on the premise that the scheduled capacity of A load is [−150 MW, 150 MW] and the line transmission limit is 50%.

Figure 6 shows the power of generator, wind, and load in day-ahead scheduling.
It can be seen from Table 3 that the scheduling total cost is highest, and the wind accommodation rate is lowest at 99.27% when load A does not take part in the DR program and the line transmission limit is 50%. With the scheduled capacity of load A increasing, the total cost reduces, wind accommodation rate increases, and the response capacity increases. With the scheduled capacity of load A constant and the line transmission limit increasing, the total cost decreases, wind accommodation rate increases, and the response capacity decreases.

In order to execute the intraday scheduling and real-time scheduling, the optimal results of day-ahead scheduling are obtained on the premise that the scheduled capacity of load A is $[-150, 150]$ MW and the line transmission limit is 50%. Figure 6 shows the power of generator, wind, and load in day-ahead scheduling.

The generator power of day-ahead scheduling serves as a reference value of generator power for intraday scheduling and the optimal load serves as the initial load of intraday scheduling. The intraday scheduling is executed every 15 min and the time interval is 15 min. The response action of load B is to transfer usage time so that the electricity consumption remains unchanged. Therefore, the model of intraday scheduling could be optimized for every 15 min in one day and the total cost of one day may not be the minimum. Table 4 shows the results of intraday scheduling.

| Response Potential of Load B (MW) | Total Cost ($) | Wind Power Accommodation | Response Quantity of Load B (MWh) |
|----------------------------------|---------------|--------------------------|----------------------------------|
| $[-1000,1000]$                   | 4586.04       | 100%                     | 86.08                            |
| $[-350,350]$                     | 4582.88       | 100%                     | 86.01                            |
| $[-150,150]$                     | 4609.40       | 100%                     | 88.23                            |
| $[0,0]$                          | 6058.49       | 99.89%                   | 0                                |

It can be seen from Table 4 that the participation of load B could reduce the cost and increase wind accommodation rate compared with no DR. However, there is no negative correlation between the scheduled capacity of load B and total cost or response capacity. The total cost and response capacity of load B in the case where the scheduled capacity range of load B is $[-1000$ $MW, 1000$ $MW]$ is more than the case where the scheduled capacity range of load B is $[-350$ $MW, 350$ $MW]$, which is on account of the optimization for each time interval, not for one day. Figure 7 shows the power of generator, wind, and load in intraday scheduling.

Figure 7 shows that the optimized wind power is less than the wind power before optimization most of the time, which brings out the power imbalance combined with the load variation. The response cost of load B is high so the power imbalance is mainly smoothed by adjusting AGC units’ power, and the response capacity of load B is less. Table 5 shows the scheduling results with different load C ratios.
range of load B is \([-1000 \text{ MW}, 1000 \text{ MW}\)] is more than the case where the scheduled capacity range of load B is \([-350 \text{ MW}, 350 \text{ MW}\)], which is on account of the optimization for each time interval, not for one day. Figure 7 shows the power of generator, wind, and load in intraday scheduling.

Figure 7. Optimal results for intraday scheduling.

Table 5. Results with different load C ratios for real-time scheduling.

| Load C Ratio | Total Cost ($) | Wind Power Accommodation | Response Quantity of Load C (MWh) |
|--------------|---------------|---------------------------|----------------------------------|
| 25%          | 1895.72       | 100%                      | 44.88                            |
| 20%          | 1921.69       | 100%                      | 43.69                            |
| 15%          | 1948.92       | 100%                      | 44.39                            |
| 10%          | 2179.42       | 100%                      | 56.54                            |
| 5%           | 2118.80       | 100%                      | 52.68                            |
| 0            | 1929.51       | 99.74%                    | 0                                |

It can be seen from Table 5 that the wind accommodation rate increases from 99.74% to 100% with the assistance of load C. With the proportion of load C increasing, there is a decreasing trend for total cost. However, there is no negative correlation between them. The optimization of real-time scheduling is for every 1 min. Therefore, the total cost of one day may not be the minimum.

In order to further analyze the function of DR in real-time scheduling, the phenomenon of ‘duck curve’ is simulated. The generator is limited by its own ramp and could not provide much power within a short time. Therefore, the DR program is utilized to smooth the power imbalance by controlling load C. It is assumed that there is a high power imbalance during 6:00 p.m.–9:00 p.m., and the results are analyzed considering different proportion of load C combined with AGC units. Table 6 shows the response capacity of load C and load shedding with different load C proportions.

Table 6. Results with different load C ratios for real-time scheduling under duck curve conditions.

| Load C Ratio | Response Quantity of Load C (MWh) | Load Shedding (MWh) |
|--------------|-----------------------------------|---------------------|
| 25%          | 311.76                            | 76.09               |
| 20%          | 246.29                            | 89.25               |
| 15%          | 181.22                            | 101.17              |
| 10%          | 118.04                            | 113.88              |
| 5%           | 56.53                             | 126.51              |
| 0            | 0                                 | 139.25              |
It can be seen from Table 6 that the adjustment ability of the generator could not keep the power balance in the case of a high power imbalance and the increment of load C proportion could reduce the amount of load shedding, which verifies the important function of DR.

Figure 8 shows the results of real-time scheduling when the proportion of load C is 25%.

Figure 8. Optimal results for real-time scheduling.

It can be seen from Figure 8 that the power imbalance is smoothed by AGC units and DR. The difference of load C curve between no scheduling and after real-time scheduling indicates that the response potential of load C is time-varying. In the process of real-time scheduling, the consumers may refuse to respond to the DR signal even if they consented to join the DR program before. Therefore, this paper proposes a DR strategy considering consumers’ regret to realize the power balance. It is assumed that the response cost of load C is $4/MWh and the regret rate of smart appliances is 30%. Figure 9 shows the comparison of two conditions, in which the upper figure is in the condition of not considering consumers’ regret and the lower figure is in the condition of considering consumers’ regret.

Figure 9. Result comparisons of considering and not considering regret.
It can be seen from Figure 9 that the response potential of load C is time-varying and response capacity is always within the maximum potential. The actual response capacity is lower than the required one in the upper figure and the required response capacity could be satisfied as shown in lower figure, which considers the consumers’ regret. Table 7 shows the response capacity of load C and cost with different regret rates. With the regret rate increasing, the response capacity of load C increases and the cost decreases.

| Regret Rate | Response Quantity of Load C (MWh) | Cost ($) |
|------------|----------------------------------|----------|
| 10%        | 1239.5                           | 5058.6   |
| 20%        | 1251.5                           | 5108.6   |
| 30%        | 1265.1                           | 5165.8   |

In order to verify the proposed multi-timescale model, there are two simulation scenarios. Scenario I is that the timescales include day-ahead, intraday, and real-time, as presented in this paper. Scenario II is that the timescales include day-ahead and real-time. The corresponding results are shown in Table 8.

| Simulation Scenario | Total Cost ($) | Wind Accommodation (%) | Response Quantity (MW) |
|---------------------|----------------|------------------------|------------------------|
| I                   | 439,353.15     | 100%                   | 680.89                 |
| II                  | 465,280.56     | 100%                   | 1819.86                |

It can be seen from Table 8 that both scheduling methods could realize the wind accommodation at 100%. The cost and the load response quantities in scenario I are lower than the ones in scenario II.

6. Conclusions

In this paper, a multi-timescale source-grid-load coordinated scheduling model was proposed, including day-ahead scheduling, intraday scheduling, and real-time scheduling. It considered the uncertainty of wind power output, network constraints, and DR users’ regret and realized the improvement of wind accommodation and the economy. Simulation results demonstrate that (1) the amounts of load participating in DR and transmission constraints of power grid lines have a significant impact on the cost optimization of source-grid-load coordinated scheduling, and (2) the regret rate of load participating in DR has an impact on the coordinated scheduling results of source-grid-load. In order to improve the DR accuracy and the economy, it is necessary to consider the consumers’ regret in DR programs. (3) Compared with the scheduling models in two timescales, including day-ahead and real-time, the proposed multi-timescale scheduling models could reduce the scheduling cost by formulating more precise DR quantities and increase the wind accommodation.

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Abbreviations

Set & Indices

\( t \) Index of time
\( i \) Set of generators
\( j \) Set of loads
\( k \) Set of wind farms

Parameters

\( N_T \) The amount of time interval
\( C_{G,i,t} \) Cost of \( i \)th generator at \( t \) time interval ($)
\( C_{min}^{\text{Nei}}, C_{max}^{\text{real}} \) Cost of \( i \)th generator output power variation in intraday scheduling and real-time scheduling ($)
\( P_{G,i,t} \) Output power of \( i \)th generator at \( t \) time interval (kW)
\( P_{G,i} \) Output power of \( i \)th generator for day-ahead scheduling (kW)
\( P_{G,i}, P_{W,ahead,k} \) Prediction power of \( k \)th wind farm at \( t \) time interval in day-ahead (kW)
\( P_{G,i}, P_{W,real,k} \) Wind prediction power of intraday, 1 h (kW)
\( P_{W,k} \) Real time output power of \( k \)th wind farm (kW)
\( N_G, N_W \) The amount of generators, wind farms
\( N_{L1}, N_{L2} \) The amount of load except load A, load B, load C
\( P_{l,t}, P_{l} \) Rated power of \( l \)th load (kW)
\( \delta_{Bj}, \delta_{Cj} \) Operating status of \( j \)th load B, C, which does not take part in the DR program
\( P_{mn,t}, P_{mn} \) Transmission power of line \( mn \) (kW)
\( B_{mn} \) Susceptance of line \( mn \)
\( \theta_{m,t}, \theta_{n,t} \) Phase angle of node \( m \) and node \( n \) in line \( mn \) at \( t \) time interval
\( \theta_m, \theta_n \) Phase angle of node \( m \) and node \( n \) in line \( mn \)
\( P_{G,i}, P_{G,i,min}, P_{G,i,max} \) Minimum and maximum output power of \( i \)th generator (kW)
\( R_{d,i}, R_{u,i} \) Re-scending and ascending ramp
\( \Delta T \) Time interval
\[ P_{nn,lim} \]
\[ \theta_l \]
\[ DRP_{\text{ahead},u}, DRP_{\text{ahead},d} \]
\[ DRP_{\text{net},u}, DRP_{\text{net},d} \]
\[ DRP_{\text{real},u}, DRP_{\text{real},d} \]
\[ N_1, N_2, N_3 \]
\[ P^i_{\text{AC}}, P^i_{\text{WH}}, P^i_{\text{EV}} \]
\[ D_{\text{DP}}^i(t), D_{\text{DRP}}^i(t), D_{\text{DP}}^k(t), D_{\text{DRP}}^k(t), \]
\[ P(t), P_{\text{Re}}(t) \]
Maximum transmission limit at line \( mn \) (kW)
Phase angle of each node
Maximum responsive power of load \( A \) to increment signal and decreased signal in day-ahead scheduling (kW)
Maximum responsive power of load \( B \) to increment signal and decreased signal in intraday scheduling (kW)
Maximum DR potential of load \( C \) to response increment signal and decreased signal (kW)
The amount of ACs, WHs, EVs
DR potential status of \( i \)-th AC, \( j \)-th WH, \( k \)-th EV (kW)
Regret probability of smart appliances at \( t \) time interval based on the historical data

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