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Research on Multi-Timescale Coordinated Source-Load Forecasting and Control for Multiple Distributed Resources

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Abstract

Socioeconomic development continues to increase urban electricity demand. At the same time, the global greenhouse effect has made extreme heat events more frequent and prolonged in recent years, substantially affecting urban power loads. Cities are major load centers but are often far from large power-generation bases, resulting in an inverse geographical distribution of sources and loads. During extreme-heat peak-load periods, remote power supplies may be insufficient because of various constraints. It is therefore necessary to coordinate distributed generation, energy storage, adjustable loads, and other resources in or near cities with remote power supplies across regions to support urban demand and ensure a reliable electricity supply. This paper develops a three-stage, multi-timescale coordinated forecasting and control method for multiple distributed resources. The day-ahead analysis and forecasting, intraday rolling optimization, and real-time coordinated optimization stages are solved sequentially to coordinate multi-resource output. Case-study simulations in a typical grid scenario with an inverse source-load distribution verify the method's feasibility.

Keywords

distributed generation, adjustable load, multi-timescale forecasting, power shortfall, optimal control

1. Introduction

Climate-related pressures are changing the way electricity is produced and consumed, making the transition toward low-carbon energy increasingly urgent. Wind and solar capacity has expanded rapidly in the power sector, and their growing penetration is reshaping the generation mix. Meanwhile, extreme heat is pushing up electricity demand in cities. Because many large generation bases are geographically separated from major load centers, both long-distance transmission and system regulation become more difficult. One practical way to ease this pressure is to make fuller use of flexible resources within load-center cities. The regulation capability of distributed generation, energy storage, and adjustable loads can be pooled [1-5] and coordinated with remote supplies. Such coordination is especially important when extreme weather strains the available supply. This situation motivates the study of joint source-load forecasting and control for multiple distributed resources.

Short-term output from distributed resources has been forecast using grey models, neural networks, data-driven fitting, and other machine-learning methods [6-9]. Zhang [6] combines grey relational information with

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an STGCN to predict distributed photovoltaic output across counties and weather regimes. Although the method improves prediction accuracy, the network structure adds training and inference overhead. Liu [7] instead focuses on data quality: U-Net segmentation, the quartile rule, and k-means++ are combined in a zonal cleaning procedure intended to preserve valid renewable-energy records. Qi et al. [8] build an AdaRNN forecasting model within a horizontal federated-learning framework, allowing local stations to analyze a large dataset without pooling all raw data. Lai [9] partitions the study area by weather type and uses the spatial and temporal dependence between subregions to improve forecasts for representative stations.

Research on coordinated generation control has followed a somewhat different route. Existing studies employ hierarchical control, neural networks, artificial-intelligence techniques, and fits to historical operating data [10-13]. Fu et al. [10], for example, train controllers in a distributed manner and apply centralized coordination through an interconnected multi-agent architecture. Li et al. [11] use reinforcement learning for source-load coordination in a microgrid, with an emphasis on reducing the computational burden. Lv et al. [12] survey evolutionary algorithms and discuss where individual approaches perform well or poorly. Fan et al. [13] modify a neural-network-based control algorithm, but the wider class of intelligent optimizers still faces a familiar problem: the search may settle at a local rather than a global optimum, which can degrade the final control result.

The present work therefore formulates cross-regional source-load coordination over three linked horizons. A day-ahead forecast and schedule is obtained first; intraday rolling optimization then corrects forecast-driven deviations; finally, a real-time stage refines the dispatch. The stages are solved in sequence, and the output of one stage provides the reference for the next. The complete procedure is examined on a representative power-system test case.

2. Day-Ahead Control Optimization Model

The first stage is the day-ahead analysis and forecasting model, which simultaneously forecasts renewable-energy output (including centralized and distributed generation) and electricity demand. The system-wide operating cost of the bulk power grid with multiple distributed resources (energy storage, photovoltaics, wind power, and adjustable loads) serves as the objective function and is minimized subject to operating constraints. The electricity purchase cost is also included in the objective function to reduce total electricity costs and obtain the economically optimal coordinated control solution. The resulting integrated optimization model is shown in (1).

$$\min C_{all}=C_{sy}+C_{ge}+C_{ne}+C_{st}+C_{lo} \tag{1}$$

where C_{sy} denotes the operation and maintenance cost of the transmission and distribution network; C_{all} denotes the total system operating cost; C_{ge} denotes the cost of conventional power plants; C_{ne} denotes the cost of centralized and distributed renewable-energy generation; C_{st} denotes the operating cost of grid energy storage; C_{lo} denotes the load-adjustment cost. Because this study concerns coordinated regulation and control of distributed resources during extreme-temperature peak-load periods when remote power supplies are insufficient, centralized renewable-energy output limits, network constraints, and loss-related costs are not considered.

The operation and maintenance cost of the transmission and distribution network, C_{sy}, is provided by the relevant grid utility. The cost of each generating unit is calculated using the relationship between its power output capability and the cost data provided by the generator manufacturer. Energy-storage charging and discharging costs are calculated using cost data from the energy-storage station. The load-adjustment cost is determined in accordance with the compensation rules for electricity consumers participating in regulation. Detailed calculations are as follows:

$$C_{ge}=\sum_{1}^{24}\sum_{i=1}^{n} C_{gei} \times P_{gei} \tag{2}$$

$$C_{ne}=\sum_{1}^{24}\sum_{i=1}^{m}(C_{neci} \times P_{neci}+C_{nedi} \times P_{nedi}) \tag{3}$$

$$C_{st}=\sum_{1}^{24}\sum_{i=1}^{j}(C_{stci} \times P_{stci} + C_{stgi} \times P_{stgi}) \tag{4}$$

$$C_{lo}=\sum_{1}^{24}\sum_{i=1}^{k} C_{loi} \times P_{loi} \tag{5}$$

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where $P_{gei,}C_{gei}$ denote the output and unit-power cost coefficient of conventional generating units, respectively; n is the total number of units in the system; $P_{neci,}C_{neci}, P_{nedi,}C_{nedi}$ denote the outputs and corresponding unit-power cost coefficients of centralized and distributed renewable-energy generating units, respectively; $P_{stci}, C_{stci}, P_{stgi}, C_{stgi}$ denote the charging and discharging powers of the energy-storage system and their corresponding unit-power cost coefficients, respectively. P_{loi}, C_{loi} denote the adjustable-load power and its corresponding regulated unit-power cost coefficient, respectively.

Unit and energy-storage operating constraints are considered simultaneously. The unit operating constraints are as follows:

$$maxP_{gei} \geq P_{gei} \geq \min P_{gei}$$

$$maxP_{neci} \geq P_{neci} \geq \min P_{neci}$$

$$maxP_{nedi} \geq P_{nedi} \geq \min P_{nedi}$$

The energy-storage system operating constraints are as follows:

$$maxP_{stci} \geq P_{stci} \geq \min P_{stci}$$

$$maxP_{stgi} \geq P_{stgi} \geq \min P_{stgi}$$

Solving the minimum-cost model yields the recommended generation schedules for each period (including peak periods), charging and discharging power levels and durations, and load-adjustment quantities for day-ahead control optimization. These parameters provide the basis for intraday rolling optimization.

3. Intraday Rolling Control Optimization Model

Based on the day-ahead control optimization results, the intraday rolling control stage uses rolling-horizon optimization to correct power deviations in the day-ahead schedule caused by forecasting errors. Intraday rolling control compensates for ultra-short-term source-load fluctuations at minimum cost while maintaining the stability of the day-ahead results. Based on (1), an intraday correction penalty function is introduced, and unit operating costs and load-adjustment costs are updated iteratively, as shown in (6).

$$\min C_{allo}=C_{geo}+C_{neo}+C_{loo}+C_{pun} \quad (6)$$

where C_{geo} is the total iteratively updated operating cost of conventional generating units and represents the cost change caused by the deviation between intraday control and the day-ahead schedule during a given period; C_{neo} is the total iteratively updated operating cost of renewable-energy units and represents the cost change caused by the deviation between intraday control and the day-ahead schedule during a given period; C_{loo} is the iteratively updated load-adjustment cost and represents the cost change caused by the deviation between intraday control and the day-ahead schedule during a given period; and C_{pun} is the minimum-cost compensation penalty function, in which the deviation distance determines the penalty value.

$$C_{geo}=\sum_{t1}^{t2}\sum_{i=1}^{n} C_{gei} \times P_{gei} \times \Delta T \quad (7)$$

$$C_{neo}=\sum_{t1}^{t2}\sum_{i=1}^{m} (C_{neci} \times P_{neci}+C_{nedi} \times P_{nedi}) \times \Delta T \quad (8)$$

$$C_{loo}=\sum_{t1}^{t2}\sum_{i=1}^{k} C_{loi} \times P_{loi} \times \Delta T \quad (9)$$

$$C_{pun}=\sum_{t1}^{t2}\sum_{i=1}^{n} C_{puni} \times (P_{rgei} - P_{gei} \text{ or } P_{neci} \text{ or } P_{nedi}) \times \Delta T \quad (10)$$

where ΔT is the 15 min time step; P_{rgei}, C_{puni} are the intraday forecast outputs of conventional units and centralized and distributed renewable-energy units, respectively; their deviations from the day-ahead output forecasts are used to calculate the penalty cost.

The equations above optimize and adjust system variables over local time intervals according to actual variations. At the same time, the penalty function in (10) keeps the results as close as possible to the day-ahead schedule.

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4. Real-Time Coordinated Control Model

Real-time coordination operates on the shortest timescale and is the most precise of the three stages, with a 5-min time step. This stage accounts for normal instantaneous load fluctuations to fine-tune the intraday schedule while satisfying physical constraints such as unit ramping. Real-time coordination minimizes deviations between the intraday rolling-optimization schedule and real-time operations. It also accounts for uncertainty in unit ramping and introduces a power-shortfall penalty function to bring the results closer to actual operation, as shown in (11).

$$\text{in}C_{real}=C_{gereal}+C_{preal} \quad 11)$$

where C_{gereal} is the cost associated with generation-output deviations over 5 min, and C_{preal} is the penalty function for output shortfalls caused by insufficient unit regulation over 5 min.

$$_{\text{gereal}}= \sum_{0}^{5min} \sum_{i=1}^{n} C_{reali} \times (P_{realgei} - P_{rgei}) \quad 12)$$

where C_{reali} is the cost coefficient for unit output deviation over 5 min; $P_{realgei}$ is the actual output of each unit.

The unit ramp-rate constraints are as follows:

$$-\Delta P_{rgei} \geq P_{rgei}' - P_{rgei} \geq \Delta P_{rgei}$$

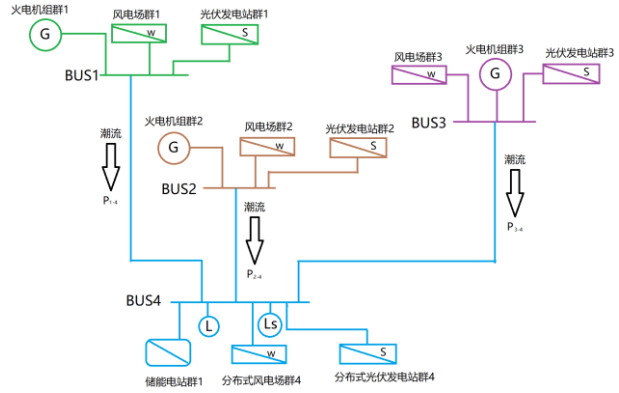
where P_{rgei}' is the unit's actual output 5 min later; $\pm\Delta P_{rgei}$ denotes the upper and lower ramping-power limits.

5. Case Study

5.1 Parameter Settings and Step-by-Step Calculation

An IEEE-standard large-system test case is used as a reference, and a system comprising three interconnected regional power grids is configured to verify the multi-timescale control model. The generation mix is dominated by thermal power and includes large-scale centralized wind and solar, as well as distributed solar and wind. The test system is shown in Fig. 1 and comprises regions A, B, and C, which differ in transmission capacity, line-loss rate, and unit transmission price. The specific parameters are as follows:

Figure Schematic Diagram of the Case-Study Power System



The first-stage model uses 96 data points at 15-min intervals over 24 h to forecast system load and renewable-energy generation. The second-stage model performs forecasting and calculations at 15-min intervals, and the third-stage model uses 5-min data for forecasting and calculations. The rated energy-storage capacity of the system containing the load center is 1 MWp, the maximum charging and discharging power is 0.1 MW, and the efficiency is 92%.

Table 2: Ramping Parameters of Various Unit Types in the Four Systems

Category	Ramp Rate	Output Ratio
Thermal Power	1.5	10
Wind Power	0.5	0

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Photovoltaics	0.6	0

Table 3: Total Generation Capacity by Unit Type (MW)

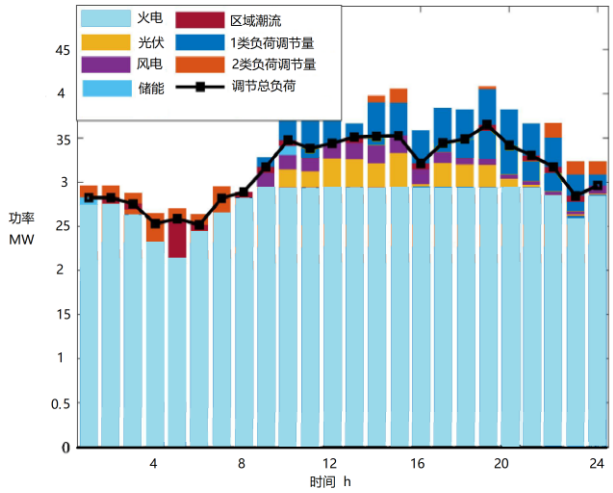
Thermal Power	Wind Power	Photovoltaics
30	5	12

Table 4: Generation Capacity of Units Participating in Regulation (MW)

System	Thermal Power	Wind Power	Photovoltaics
1	1	0.5	1
2	2	1.5	0.2
3	1	1.5	0.5

Analysis of simulation results: The day-ahead model minimizes system operating cost. The simulation results show that around 20:00, when the BUS4 system is at its evening peak load, distributed renewable energy output in the load center (BUS4) is insufficient, resulting in a supply shortfall. The multi-timescale control then proceeds to the second-stage optimization, which increases load adjustment; external systems supply the remaining shortfall. Activating adjustable loads reduces pressure on the external transmission. During the third-stage real-time calculation, some adjustable loads and their response rates are insufficient, leaving a 0.09 MW output shortfall in System 4. The 5-min calculation further optimizes and adjusts the output of thermal generating units in external regions to restore power balance. The simulation results demonstrate that the method is feasible and produces results close to actual operating conditions.

Figure 2: Simulated Output Results of Coordinated Control by the Three-Stage Model



5.2 Performance Analysis of Three-Stage Coordinated Control

Across multiple timescales, this paper employs an optimized three-stage approach to coordinate the forecasting and control of distributed resources and to ensure a reliable electricity supply during peak-load periods. It proposes a coordinated output-control model for multiple resources, along with a corresponding three-stage algorithm.

The proposed model is compared with other models, and the coefficient of determination (R2) is calculated using regression analysis. The results show that the optimized three-stage model decomposes a complex real-time simulation into three steps that successively approach the optimal solution. Error interpolation indicates gains of 7.26% relative to the conventional calculation and 8.35% relative to the initial model forecast.

6. Conclusions

The case considered here represents a city with several flexible resources but limited support from remote generation during peak demand. Distributed generation, storage, and adjustable loads close to the load center are scheduled together with cross-regional power supply. For this setting, the study links forecasting and dispatch through a day-ahead stage, an intraday rolling stage, and a real-time correction stage. The test-case

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results indicate that this sequence can coordinate the available resources and cover the peak-period imbalance. The main observations are summarized below.

Splitting the calculation by timescale reduces the burden that would arise if all decisions were handled in one optimization. In the implementation, each stage has its own immediate objective, while the schedule passed forward from the preceding stage keeps the three calculations connected. This arrangement also allows distributed generation, storage, and adjustable loads to be represented in the same scheduling process; the benefit is most apparent when load flexibility is available. The numerical study, however, uses representative load days and concentrates on peak-load intervals. Transmission congestion, planned equipment outages, and several other operating details are simplified. These effects should be introduced in a subsequent version of the model and tested over a broader range of system conditions.

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Conflicts of Interest

The authors declare no conflict of interest.

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