

Article

System Optimization Scheduling Considering the Full Process of Electrolytic Aluminum Production and the Integration of Thermal Power and Energy Storage

Yulong Yang, Han Yan *, Jiaqi Wang, Weiyang Liu and Zhongwen Yan

School of Electrical Engineering, Northeast Electric Power University, Jilin 132000, China; yangyulong@neepu.edu.cn (Y.Y.); 2202200180@neepu.edu.cn (J.W.); 2202300068@neepu.edu.cn (W.L.); 2202300130@neepu.edu.cn (Z.Y.)

* Correspondence: 2202200346@neepu.edu.cn

Abstract: To address the curtailment phenomenon caused by the high penetration of renewable energy in the system, an optimization scheduling strategy is proposed, considering the full process of electrolytic aluminum production and the integration of thermal power and energy storage. Firstly, to explore the differentiated response capabilities of various devices such as high-energy-consuming electrolytic aluminum units, thermal power units, and energy storage devices to effectively address uncertain variables in the power system, a Variational Mode Decomposition method is introduced to construct differentiated response methods for its low-frequency, medium-frequency, and high-frequency components. Secondly, based on the real production regulation characteristics of the high-energy-consuming electrolytic aluminum load, and considering various influencing factors such as current, temperature, and output, a scheduling model involving electrolytic aluminum load is established. Then, the power generation characteristics in other processes of electrolytic aluminum production are fully exploited to achieve energy storage conversion, replacing the energy storage batteries that respond to high-frequency components. Finally, by combining the deep peak-shaving model of thermal power units, an optimization scheduling model is established for the joint operation of the full electrolytic aluminum production load and thermal-power-storage systems, with the goal of minimizing system operating costs. The case study results show that the proposed model can significantly enhance the system's renewable energy absorption capacity, reduce energy storage installations, and enhance the economic efficiency of the system's peak-shaving operation.

Keywords: variational mode decomposition; wind power absorption; electrolytic aluminum load; optimal scheduling



Received: 31 December 2024

Revised: 22 January 2025

Accepted: 24 January 2025

Published: 27 January 2025

Citation: Yang, Y.; Yan, H.; Wang, J.; Liu, W.; Yan, Z. System Optimization Scheduling Considering the Full Process of Electrolytic Aluminum Production and the Integration of Thermal Power and Energy Storage. *Energies* **2025**, *18*, 598. <https://doi.org/10.3390/en18030598>

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1. Introduction

Energy crises, environmental pollution, and other issues have become increasingly prominent, attracting widespread attention from countries around the world [1]. New energy power generation, primarily based on wind and solar power, is showing rapid development, high operational quality, and strong industrial competitiveness [2]. The widespread adoption of renewable energy sources like wind and solar, which are clean and environmentally friendly, is seen as a crucial step in tackling the global energy shortage, mitigating environmental damage, and fostering a shift toward a more sustainable energy framework worldwide [3]. However, the integration of new energy sources such as wind power into the grid has raised higher demands for grid peak regulation. Due to

the inherent uncertainty, variability, and counter-peak regulation characteristics of wind power output [4], the grid's ability to reduce peak load is often insufficient, leading to severe wind curtailment [5,6], which may pose a threat to the safe and stable operation of the grid [7–9]. Therefore, there is an urgent need to explore reasonable multi-energy coordination operation models, considering the characteristics and methods of different energy sources in order to minimize the impact of wind and solar power generation on the grid, which is of great significance for improving new energy absorption and reducing carbon emissions [10,11].

Currently, many scholars have conducted research on different types of loads and response methods, achieving some notable results. Among the many flexible and dispatchable loads, large industrial loads represented by high-energy-consuming enterprises have the greatest potential for scheduling. High-energy-consuming loads, such as those in the aluminum electrolysis industry, account for a significant proportion in the country, and these loads are highly centralized with fast regulation speeds [12]. They have substantial peak-shaving potential, which can both promote wind power absorption and alleviate the peak regulation pressure of thermal power, thereby improving the economic efficiency of the system's peak-shaving operation.

Reference [13] takes the electrolysis copper industry load as an example and establishes a detailed power control model for the copper electrolysis production process. It proposes a high-energy load power control strategy aimed at market-oriented demand-side response transaction rules, providing a feasible solution for industrial loads to participate in demand response. References [14,15] both consider the production regulation characteristics of electric magnesium high-energy loads, establishing day-ahead and intraday optimization models and source-load coordination optimization models. However, neither considers the output constraint during the scheduling period. Reference [16] considers high-energy loads such as reduction iron and electric arc furnaces, constructs a low-carbon-integrated energy system model for steel industrial parks, and proposes a low-carbon scheduling method for integrated energy systems in the park, balancing multi-energy coupling and flexible process optimization.

These studies have effectively verified the feasibility of the rapid and continuous power regulation of high-energy loads, but few studies have considered the fine-tuned production safety regulation characteristics of electrolysis aluminum loads to tap into their peak-shaving potential and optimize the system's peak regulation operation and wind power absorption. Considering that China's northwest and southwest regions have abundant wind and hydroelectric resources as well as numerous high-energy enterprises, integrating high-energy electrolysis aluminum loads into the peak regulation system and guiding them to participate in new energy absorption could effectively alleviate the peak regulation pressure on the grid.

Reference [17] analyzes the regulation potential of high-energy industrial loads from a technical perspective based on the production process of high-energy industrial loads. Reference [18] studies and analyzes the production process of electrolysis aluminum enterprises and establishes detailed mathematical models for each production stage within the enterprise. Reference [19] establishes a detailed control model for the interaction between electrolysis aluminum loads and wind power, but the model is overly complex and difficult to compute. References [20,21] leverage the high energy consumption characteristics of electrolytic aluminum loads to perform peak shaving and valley filling, thereby reducing the peak-shaving pressure on thermal power units.

However, the above-mentioned studies only stimulate active participation in regulation from both the grid and load sides through mechanisms, without delving deeper into the operational features of various types of loads in relation to uncertain variables.

Reference [22] performs power distribution based on the state of charge of the energy storage battery, effectively preventing over-charging and over-discharging. Reference [23] studies the temperature–power operating characteristics of batteries, thereby extending their lifespan. However, the above studies are limited to examining the operational characteristics of energy storage devices themselves, without coupling the device’s response capabilities with the fluctuating characteristics of uncertain variables, which results in the failure to effectively explore the response capabilities of diverse devices.

In contrast, reference [24] uses Empirical Mode Decomposition to divide frequency regulation power into low-frequency and high-frequency components, with thermal power units and energy storage devices responding to the low-frequency and high-frequency components of load power, thereby achieving active power balance. Reference [25] establishes a multi-timescale scheduling model, using an improved Variational Mode Decomposition method to decompose wind power into low-frequency, medium-frequency, and high-frequency components with different frequencies and amplitudes based on the central frequency corresponding to the response speed of the devices. This allows the multi-source devices in the system to respond to different trends in wind power fluctuations according to their respective response capabilities, effectively enhancing the system’s ability to absorb new energy. Therefore, based on the response capabilities of multi-source devices, a scheduling method that decomposes uncertain variables into components with different frequencies and amplitudes can be introduced into the system optimization operation with high-energy loads.

Based on the above discussion, this paper proposes an optimized scheduling method for a high-proportion wind power system, considering the entire process of electrolysis aluminum production and the integration of thermal power and energy storage. The main contributions of this paper are listed as follows:

- (1) This study investigates the high-energy consumption load of electrolysis aluminum, analyzes its regulation characteristics throughout the entire production process, and establishes detailed regulation models for the electrolysis aluminum production process and other related processes. By incorporating the electrolysis aluminum production process into the scheduling, the wind power absorption capacity is enhanced, wind curtailment is reduced, the deep peak-shaving time for thermal power units is effectively shortened, their output range is narrowed, and the peak-shaving pressure is alleviated.
- (2) The VMD method is introduced to decompose and reconstruct uncertain variables such as wind power and conventional loads, obtaining low-frequency, medium-frequency, and high-frequency components with varying amplitudes and frequencies. Based on the different response features of various loads, targeted adjustments are made, smoothing the output curve of thermal power units, increasing the absorption rate of new energy, and improving the overall economic efficiency of the system.
- (3) In combination with the operational characteristics of other processes in electrolysis aluminum, a proposal is made to set up an energy storage system to replace the original energy storage devices responding to high-frequency components. By utilizing existing devices to equivalently replace the additional equipment functions, the construction costs of the system are significantly reduced, thereby enhancing the system’s economic efficiency.

The subsequent chapters of this paper are arranged as follows: Section 2 explains the principle of balancing the system’s energy supply and demand through the scheduling of high-energy consumption loads in electrolysis aluminum; Section 3 discusses the VMD method for processing loads; Sections 4 and 5 construct models for the entire process of electrolysis aluminum production; Section 6 develops a model for the deep peak-shaving of

thermal power units; Section 7 details the operating principles and processes of this paper; Sections 8 and 9 provide comparative analyses through scenario construction to verify the effectiveness and practicality of the model; Section 10 summarizes the research content and presents the conclusions.

2. Principle of Electrolytic Aluminum-Load-Absorbing Wind Power

The randomness and volatility of wind power output pose a significant challenge to the peak-shaving capabilities of thermal power plants. If the combined wind power and load demand exceeds the regulation capacity of the thermal power plant, introducing the electrolytic aluminum load into the dispatch can effectively narrow the regulation range of the thermal plant, thereby improving wind power absorption, reducing wind curtailment, and enhancing the operational stability of thermal power plants. Figure 1 shows the conventional wind power grid connection. In Figures 1 and 2, $P_{G,max}$ represents the maximum output of the thermal power unit, and $P_{G,min}$ represents the minimum output of the thermal power unit.

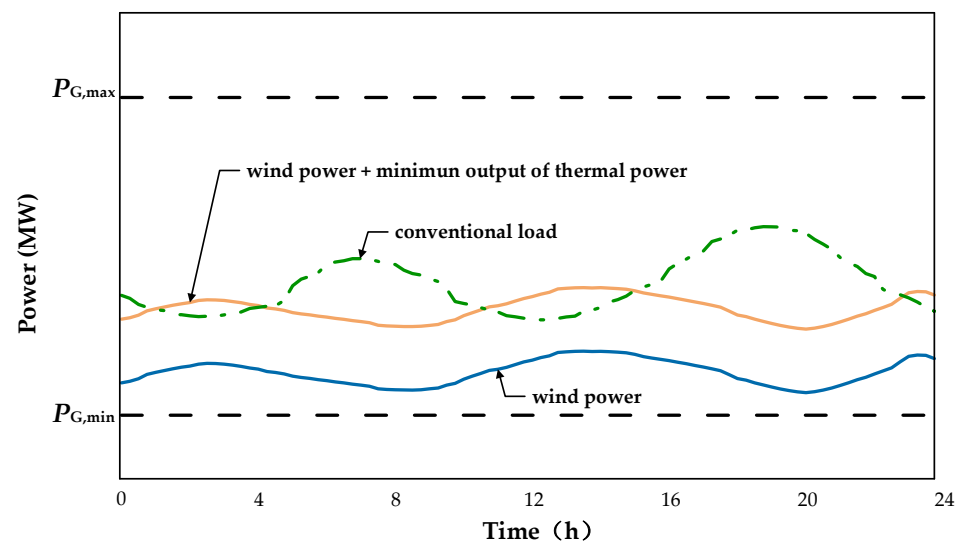


Figure 1. Conventional wind power grid connection.

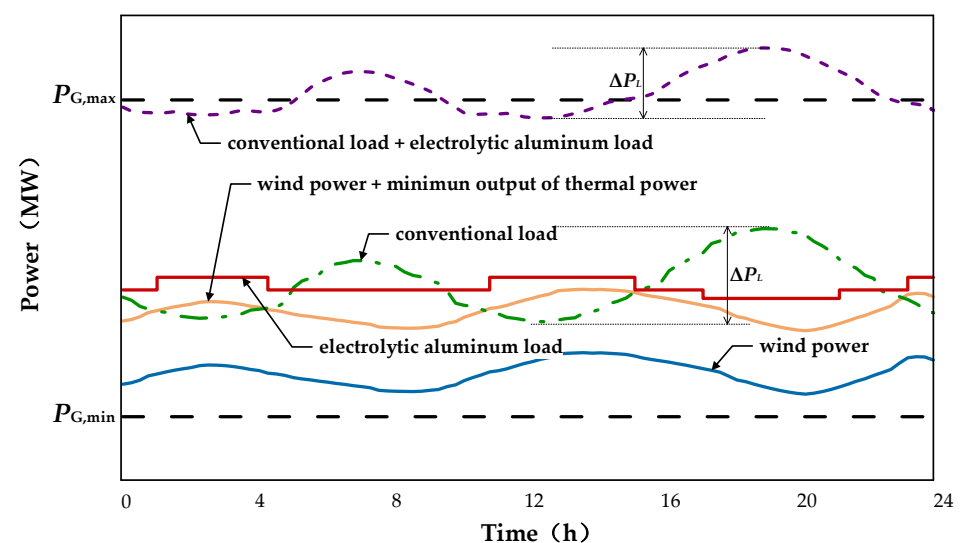


Figure 2. The impact of wind power grid integration on power grid peak shaving after the participation of aluminum electrolysis load in scheduling.

Under normal circumstances, the system load is relatively low during nighttime, and the grid can maintain power balance by shutting down units or reducing the output of units. However, after a huge number of wind turbines are merged into the power grid, their counter-peak regulation characteristics further reduce the system's equivalent load during the night. Since conventional grid units have a lower limit on peak regulation, balancing the source–load power solely through the adjustment of conventional unit output is insufficient. To ensure the safety and economic operation of the system, wind curtailment is implemented to maintain the power balance, resulting in a significant waste of wind power resources.

As shown in Figure 2, after the scheduling of high-energy consumption loads in electrolysis aluminum, the electricity loss caused by wind power being unable to meet the load demand on its own, and the thermal power units participating in scheduling at their minimum output, is significantly reduced. This greatly enhances the overall system's economic efficiency and electricity reliability. At the same time, by involving high-energy consumption loads in electrolysis aluminum in the scheduling, the difference between the maximum and minimum values of the original net load is reduced. Reducing the peak–valley difference allows the system units to adjust more effectively. It also prevents the deep regulation of thermal power units, which could otherwise cause wear on the units. This has significant benefits for the maintenance and service life of thermal power units and reduces regulation losses.

3. Variational Mode Decomposition

Due to the influence of weather and other environmental factors, wind power exhibits significant randomness. When a high proportion of wind power is integrated into the system, the uncertainty of wind power output poses a significant challenge to the load regulation of thermal power units. Although the trend of wind power output can be roughly predicted, the frequent fluctuations over short periods still pose a substantial threat to the stability and safety of the system. Therefore, we introduce Variational Mode Decomposition (VMD) to handle these fluctuations.

Empirical Mode Decomposition (EMD) is a new adaptive non-stationary signal decomposition method that may encounter modal aliasing problems. In contrast, VMD is a novel adaptive non-stationary signal decomposition method that avoids modal aliasing [26]. During VMD decomposition, modal aliasing is avoided by controlling the frequency and bandwidth of each Intrinsic Mode Function (IMF). Additionally, VMD imposes constraints on the singular values of the modal functions to ensure that the decomposed modal function curves are as smooth as possible, thereby reducing endpoint effects [27].

The original data are decomposed by VMD into multiple modes u_k and their corresponding central frequencies ω_k , and the decomposition process can be represented as follows:

$$\min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \times u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}, \text{ s.t. } \sum_k u_k = f \quad (1)$$

In the formula, f is the load curve, and $\delta(t)$ is the impulse function. The process is as follows: initialize the modes $\{u_k^1\}$ and $\{\omega_k^1\}$ and the Lagrange multipliers λ , and set the initial state $n = 0$; determine the number of modes K to be decomposed and establish the Lagrange function:

$$\mathcal{L}(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \times u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \sum_k \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \langle \lambda(t), f(t) - \sum_k u_k(t) \rangle \quad (2)$$

When the Lagrange function reaches its minimum value, the initial values for the next iteration step are obtained:

$$\begin{cases} u_k^{n+1} \leftarrow \underset{u_k}{\operatorname{argmin}} \mathcal{L}(\{u_{i < k}^{n+1}\}, \{u_{i \geq k}^n\}, \{\omega_i^n\}, \lambda^n) \\ \omega_k^{n+1} \leftarrow \underset{\omega_k}{\operatorname{argmin}} \mathcal{L}(\{u_i^{n+1}\}, \{\omega_{i < k}^{n+1}\}, \{\omega_{i \geq k}^n\}, \lambda^n) \\ \lambda^{n+1} \leftarrow \lambda^n + \tau(f - \sum_k u_k^{n+1}) \end{cases} \quad (3)$$

Once the iterative results meet the error tolerance, the decomposed modes and their center frequencies can be obtained.

$$\frac{\sum_k \|u_k^{n+1} - u_k^n\|_2^2}{\|u_k^n\|_2^2} < \epsilon \quad (4)$$

The complete solving process can be simplified as follows:

$$\begin{cases} u_k^{n+1}(\omega) = \frac{f(\omega) - \sum_{i \neq k} u_i(\omega) + \frac{\lambda^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \\ \omega_k^{n+1} = \frac{\int_0^\infty \omega |u_k^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |u_k^{n+1}(\omega)|^2 d\omega} \end{cases} \quad (5)$$

Through the decomposition, we can obtain K sets of modes $\{u_k\} = \{u_1, \dots, u_k\}$ and their corresponding central frequencies $\{\omega_k\} = \{\omega_1, \dots, \omega_k\}$ from the original data f.

As shown in Figure 3, the modes after the decomposition of the original data are clearly observed. Compared to the original data, different modes' fluctuations are separated according to the differences in their center frequencies. The amplitude of fluctuations for each mode varies, and as the center frequency increases, the amplitude of fluctuations gradually decreases. Through mode decomposition, the original net load curve can be broken down into a mode that reflects the trend of the original signal and a few modes of fluctuation. Therefore, after performing mode decomposition and recombination on the wind power forecast curve and load forecast curve, the low-frequency, mid-frequency, and high-frequency component curves of the net load can be obtained. This decomposition process facilitates the subsequent development of targeted scheduling strategies based on the different operational characteristics of the equipment.

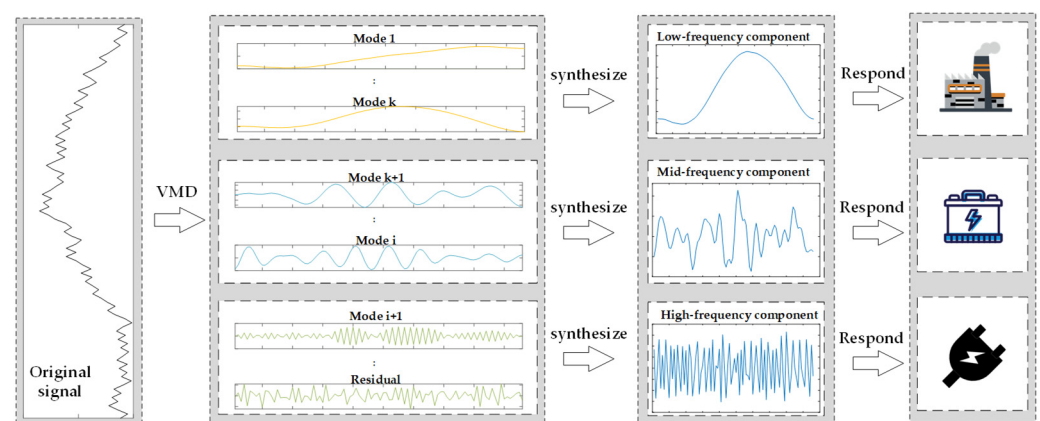


Figure 3. Flowchart of the load response based on VMD.

4. Electrolytic Aluminum Load

This paper references [28], providing a detailed model of factors such as power, temperature, current, and production output for electrolytic aluminum.

4.1. Power Constraint

In the study of high energy-consuming aluminum electrolysis loads, we usually focus more on the magnitude and variation of current and temperature. These two indicators directly affect the power, production, and quality of the aluminum produced by the high-energy-consuming electrolysis load. According to the commonly used equivalent circuit diagram of aluminum electrolysis loads, the power and current at each moment have an approximately quadratic relationship. The detailed constraints are as follows:

$$P_{Al,min} \leq P_{Al}(t) \leq P_{Al,max} \quad (6)$$

$$I_{Al,min} \leq I_{Al}(t) \leq I_{Al,max} \quad (7)$$

$$P_{Al} = I_{Al}^2(t)R_m + I_{Al}(t)E_m \quad (8)$$

In the formula, $P_{Al}(t)$ and $I_{Al}(t)$ represent the power and current of electrolysis aluminum load j at time t ; $P_{Al,max}$ and $P_{Al,min}$ are the inherent upper and lower limits of the power of the electrolysis aluminum load; $I_{Al,max}$ and $I_{Al,min}$ are the inherent upper and lower limits of the current of the electrolysis aluminum load; R_m and E_m are the equivalent resistance and the equivalent back electromotive force, and they are usually known and fixed.

$$T_{Al,min} \leq T_{Al}(t) \leq T_{Al,max} \quad (9)$$

$$(P_{Al}(t) - P_{Al}(t-1))\Delta t = \zeta_{Al}(T_{Al}(t) - T_{Al}(t-1)) \quad (10)$$

In the formula, ζ_{Al} represents the coefficient that describes the impact of a unit temperature change on power; $T_{Al}(t)$ is the production temperature of the electrolysis aluminum load; $T_{Al,max}$ and $T_{Al,min}$ are the upper and lower temperature limits of electrolysis aluminum load, generally taken as 970 °C and 950 °C.

$$\begin{cases} P_{Al}(t) - P_{Al}(t-1) \leq \lambda_{Al,up}(t)R_{Al,up} \\ P_{Al}(t) - P_{Al}(t-1) \leq \lambda_{Al,down}(t)R_{Al,down} \end{cases} \quad (11)$$

In the formula, $R_{Al,up}$ and $R_{Al,down}$ represent the upper and lower adjustment speeds of the electrolysis aluminum load for each time step.

4.2. Operating Status Constraints

$$\lambda_{Al,up}(t) + \lambda_{Al,down}(t) \leq 1 \quad (12)$$

In the formula, $\lambda_{Al,up}(t)$ and $\lambda_{Al,down}(t)$ represent whether the electrolysis aluminum load is in the power-up adjustment state or the power-down adjustment state at time t , with 1 meaning “yes” and 0 meaning “no”.

$$\lambda_{Al,up}(t) + \lambda_{Al,up}(t+1) + \dots + \lambda_{Al,up}(t+k) + \lambda_{Al,down}(t) + \lambda_{Al,down}(t+1) + \dots + \lambda_{Al,down}(t+k) \leq 1 \quad (13)$$

Continuous adjustments of electrolysis aluminum load can lead to frequent fluctuations in the electrolysis cell temperature. To maintain production stability to the greatest extent, no continuous adjustments can be made within k time steps, which includes continuous up-regulation, continuous down-regulation, or both up and down-regulation.

After a unit starts up-regulation or down-regulation at time t , no further up-regulation or down-regulation is allowed in the time period from t to $t + k$.

4.3. Output Constraints

To avoid economic losses caused by the participation of the electrolytic aluminum loads in the scheduling, it is required that the aluminum production meets the minimum production requirement within the scheduling period. The output calculation formula and the output invariance constraint are as follows:

$$M_{Al}(t) = n_{Al}K_{Al}I_{Al}(t)\Delta t \quad (14)$$

$$\sum_t^T M_{Al}(t) \geq M_{Al,min} \quad (15)$$

In the formula, $M_{Al}(t)$ is the output, and $M_{Al,min}$ is the minimum production requirement that the electrolytic aluminum load must reach within the scheduling period T ; n_{Al} is the number of electrolysis cells for the electrolysis aluminum load; K_{Al} is the proportional relationship representing the amount of aluminum produced per unit current per unit time.

5. The Other Processes in Electrolytic Aluminum Production

5.1. Delivering Raw Materials

$$P_{Al_2O_3,del}(t) = E_{Al_2O_3,del}Z_{Al_2O_3}(t)\Delta t \quad (16)$$

$$0 \leq \sum_{t=1}^{96} Z_{Al_2O_3}(t) \leq m_{Al_2O_3,max} + \sum_{t=1}^{96} \rho M_{Al}(t) \quad (17)$$

In the formula, $P_{Al_2O_3,del}(t)$ is the electricity consumption for delivering Al_2O_3 at time t , $Z_{Al_2O_3}(t)$ is the mass of the delivered material at time t , $E_{Al_2O_3,del}$ is the electricity consumption per ton of Al_2O_3 delivered, $m_{Al_2O_3,rest}$ is the remaining Al_2O_3 inventory in the cell from the previous day, and ρ is the amount of Al_2O_3 required to produce one unit of aluminum.

$$\sum_{t=1}^{96} \rho M_{Al}(t) \leq \sum_{t=1}^{96} Z_{Al_2O_3}(t) \leq \delta(m_{Al_2O_3,max} + \sum_{t=1}^{96} \rho M_{Al}(t)) \quad (18)$$

This paper takes into account that the remaining Al_2O_3 inventory in the cell from the previous day may be zero. To ensure the continuation of electrolysis aluminum production, the lower limit for the delivery of alumina is raised to the amount of alumina required for the day's schedule. In subsequent work, different production factors can be considered to expand the range.

5.2. Siphoning Aluminum

$$P_{Al,del}(t) = E_{Al,del}Z_{Al}(t)\Delta t \quad (19)$$

$$0 \leq \sum_{t=1}^{96} Z_{Al}(t) \leq m_{Al,rest} + \sum_{t=1}^{96} M_{Al}(t) \quad (20)$$

In the formula, $P_{Al,del}(t)$ is the electricity consumption for aluminum siphoning at time t , $Z_{Al}(t)$ is the amount of aluminum siphoned at time t , $E_{Al,del}$ is the electricity consumption

per ton of aluminum siphoned, and $m_{Al,rest}$ is the remaining aluminum liquid inventory in the cell from the previous day.

$$\sum_{t=1}^{96} M_{Al}(t) \leq \sum_{t=1}^{96} Z_{Al}(t) \leq m_{Al,rest} + \sum_{t=1}^{96} M_{Al}(t) \quad (21)$$

This paper takes into account that if the remaining aluminum liquid inventory in the cell from the previous day is too large, it may prevent the load from responding to demand by producing aluminum early, or if the remaining aluminum liquid is too small, it may prevent the load from responding by producing aluminum later. Thus, the lower limit for siphoning aluminum is raised to the amount of aluminum liquid produced on the scheduling day, creating a dynamic balance between scheduling cycles. In subsequent work, different production factors can be considered to expand the range.

5.3. Simulated Energy Storage Device

As shown in Figure 4, in the conventional aluminum production process, the delivery of raw materials for electrolysis aluminum and the aluminum extraction process are both carried out in batches at scheduled times, and both operate at a constant rated power P_e , with the total energy consumed being $P_e t$.

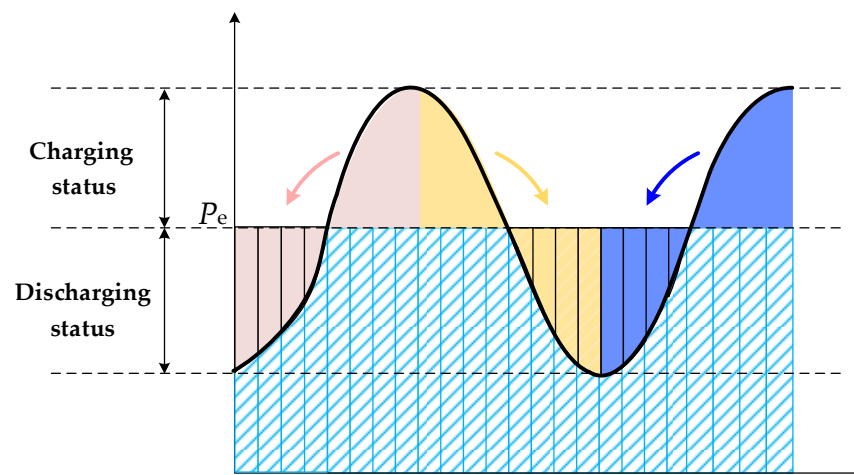


Figure 4. Schematic diagram of transforming the loads of other electrolytic aluminum production processes to be energy-storable.

Since the electrolysis cell has storage capacity, it can store the amount of Al_2O_3 required for one day's production as well as the aluminum produced in one day. Therefore, through reasonable coordination, the raw material delivery schedule and aluminum extraction schedule can be adjusted to respond to demand.

As shown in the figure, P_e is considered as an energy storage device in a no-storage state. When the power consumed by other processes at a given moment is greater than P_e , the electrolysis aluminum processes consume more electricity, and this can be viewed as the "electrolysis aluminum process" energy storage device being in charging mode at that moment. Similarly, when the power consumed by other processes at a given moment is less than P_e , the electrolysis aluminum processes consume less electricity, and this can be viewed as the "electrolysis aluminum process" energy storage device being in discharging mode at that moment.

6. Deep Peak-Shaving of Thermal Power Units

This paper references [29,30] and models the deep peak-shaving of thermal power units.

6.1. Fuel Cost

$$E_1 = \sum_{i=1}^n \sum_{t=1}^T C_1 (a_i P_{i,t}^2 + b_i P_{i,t} + c_i) \quad (22)$$

In the formula, n is the number of thermal power units, T is the total operating time of the scheduling period, C_1 is the coal price, a_i , b_i , and c_i are the coal consumption coefficients of thermal power unit i , and $P_{i,t}$ is the output of thermal power unit i at time t .

6.2. Deep Peak-Shaving Mechanical Loss Cost

According to the Manson–Coffin formula, the mechanical loss cost of the deep peak-shaving period for peak-shaving units is defined as follows:

$$E_2 = \sum_{t=1}^T \frac{\beta S_{th}}{2N_f(P_{i,t})} \quad (23)$$

$$N_f = 0.005778 P_{i,t}^3 - 2.682 P_{i,t}^2 + 484.8 P_{i,t} - 8411 \quad (24)$$

In the formula, β is the operating impact coefficient of the thermal power unit, S_{th} is the purchase price of the thermal power unit, and $N_f(P_{i,t})$ is the number of rotor fracture cycles.

6.3. Other Additional Costs

$$E_3 = \sum_{t=1}^T C_2 S_{oil,t} \quad (25)$$

$$E_4 = C_S K_S \mu_S + C_N K_N \mu_N \quad (26)$$

In the formula, C_2 is the fuel price, $S_{oil,t}$ is the oil consumption of the peak-shaving unit at time t , C_S and C_N are the penalties for sulfur oxide and nitrogen oxide emissions per unit volume, K_S and K_N are the emission standards for sulfur oxides and nitrogen oxides, and μ_S and μ_N are the sulfur oxide and nitrogen oxide emission excess rates during the deep peak-shaving phase.

6.4. Total Cost

The various stages of deep peak-shaving for thermal power units are shown in Figure 5.

$$F_G = \begin{cases} E_1, P_{\min} \leq P \leq P_{\max} \\ E_1 + E_2, P_{\text{deep-a}} \leq P \leq P_{\min} \\ E_1 + E_2 + E_3 + E_4, P_{\text{deep-b}} \leq P \leq P_{\text{deep-a}} \end{cases} \quad (27)$$

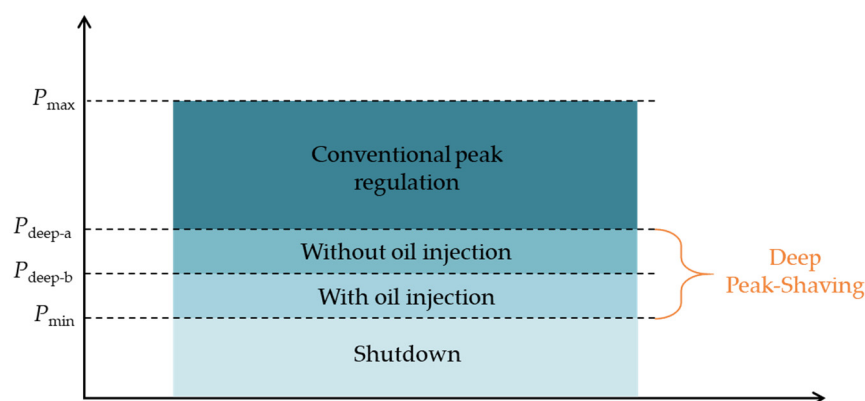


Figure 5. Schematic diagram of deep peak-shaving of thermal power units.

7. Economic Optimization Scheduling Model

The system in this paper consists of thermal power plants, wind power plants, battery energy storage devices, high-energy consumption aluminum electrolysis loads, and general conventional loads, without considering the grid structure and constraints.

In general, the coordinated scheduling of energy storage devices, thermal power units, and electrolytic aluminum units essentially treats the thermal power units, battery storage devices, and electrolytic aluminum units as distinct variables within the same objective function, thus enabling joint optimization. However, due to constraints such as capacity limits of the battery storage devices, their output characteristics differ significantly from those of thermal power units. This leads to the overall scheduling model evolving into a complex mixed nonlinear programming problem, which increases the difficulty of solving it. If the wind power and load curves are decomposed and then recombined into corresponding low-frequency, mid-frequency, and high-frequency component curves of the net load, and control strategies are implemented for each decomposed frequency band, the model's solving process can be simplified, and the feasibility of scheduling operations can be improved.

In this paper, to better understand wind power curtailment, the wind power forecast curve and conventional load forecast curve are first decomposed separately using VMD. The wind power forecast curve and conventional load forecast curve are decomposed into modes with different central frequencies. Then, the net load curve for each central frequency mode is calculated separately. The net load curves are divided into low, mid, and high-frequency components, and the low-frequency, mid-frequency, and high-frequency components of the net load curve are synthesized. The low-frequency component of the net load curve is smooth with small fluctuations and high energy consumption and is regulated by thermal power units and high-energy consumption aluminum electrolysis units. The mid-frequency component has large fluctuations with a slower fluctuation frequency and is regulated by batteries. The high-frequency component has small fluctuations with very fast fluctuation frequencies and is regulated by the energy-efficient aluminum production stages.

Based on the unit operation conditions shown in Figure 6, the wind power operation cost, wind curtailment penalty cost, thermal power unit coal consumption cost, and battery regulation cost can be calculated. The optimization result is derived by minimizing the system operation cost, with the system operation cost as the objective function.

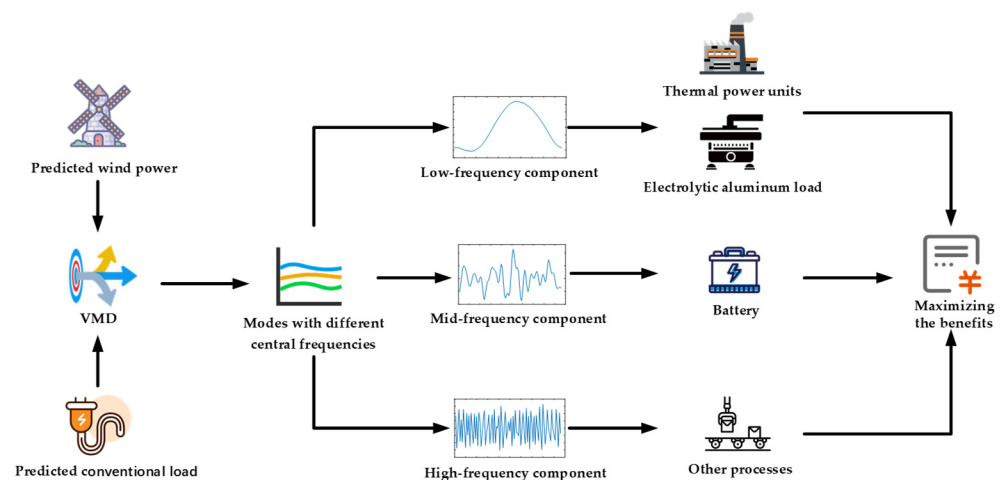


Figure 6. Process flow diagram of the Economic Optimization Scheduling Model.

8. Objective Function

This paper comprehensively considers the operational costs of thermal power units, wind power operation costs, wind curtailment penalty costs, and the battery storage operating cost, with the goal of minimizing the total operational cost of the system. The objective function is as follows:

$$\begin{cases} \min F = \min \{F_G + F_w + F_{wc} + F_{bat}\} \\ F_G = \begin{cases} E_1, P_{\min} \leq P \leq P_{\max} \\ E_1 + E_2, P_{\text{deepa}} \leq P \leq P_{\min} \\ E_1 + E_2 + E_3 + E_4, P_{\text{deepb}} \leq P \leq P_{\text{deepa}} \end{cases} \\ F_w = \sum_{t=1}^T (\lambda_w P_w(t)) \\ F_{wc} = \sum_{t=1}^T [\lambda_{wc} (P_w^{\text{pre}}(t) - P_w(t))] \\ F_{bat} = \lambda_{ch} P_{bat}^{\text{ch}}(t) - \lambda_{dis}(t) P_{bat}^{\text{dis}}(t) \end{cases} \quad (28)$$

In the formula, F , F_G , F_w , F_{wc} , and F_{bat} represent the system operating cost, thermal power unit operating cost, wind power operating cost, wind curtailment penalty cost, and battery storage operating cost, respectively. λ_w is the wind power unit operating cost; λ_{wc} is the unit wind curtailment penalty cost; λ_{ch} is the wind power grid connection price; $\lambda_{dis}(t)$ is the real-time electricity price at time t .

8.1. System Power Balance Constraint

8.1.1. Low-Frequency Component Constraint

The low-frequency components decomposed by VMD are jointly responded to by the thermal power units and the electrolytic aluminum production process. Power balance must be maintained, and the balance equation is as follows:

$$P_{w,1}(t) + P_G(t) = P_{\text{load,low}}(t) + P_{Al}(t) \quad (29)$$

In the formula, $P_G(t)$ is the total output of thermal power units in the region; $P_{\text{load,low}}(t)$ is the low-frequency component of the conventional load forecast decomposition; $P_{w,1}(t)$ is the wind power absorbed by the low-frequency component.

8.1.2. Mid-Frequency Component Constraint

The mid-frequency components decomposed by VMD are responded to by the energy storage batteries. Power balance must be maintained, and the balance equation is as follows:

$$P_{w,2}(t) = P_{\text{load,mid}}(t) + P_{bat,m}(t) \quad (30)$$

$$P_{bat,m}(t) = S_{bat}(t) P_{bat,m}^{\text{ch}}(t) - (1 - S_{bat}(t)) P_{bat,m}^{\text{dis}}(t) \quad (31)$$

In the formula, $P_{bat,m}(t)$ represents the power of the battery storage device at that moment; $S_{bat}(t)$ is the charge/discharge flag at time t , with 1 for charging and 0 for discharging; $P_{w,2}(t)$ is the wind power absorbed by the mid-frequency component.

8.1.3. High-Frequency Component Constraint

The high-frequency components decomposed by VMD are responded to by the variations in other electrolytic aluminum production processes. Power balance must be maintained, and the balance equation is as follows:

$$P_{w,3}(t) = P_{\text{load,high}}(t) + \Delta P_{Al_2O_3}(t) + \Delta P_{Al}(t) \quad (32)$$

In the formula, $P_{w,3}(t)$ is the wind power absorbed by the high-frequency component; $\Delta P_{Al_2O_3}(t)$ and $\Delta P_{Al}(t)$ are the differences between the actual operating process and the constant values.

8.1.4. Wind Power Constraint

The wind power absorbed by the system at low, medium, and high frequencies during operation must be balanced with the forecasted wind power and the curtailed wind power. The balance equation is as follows:

$$P_{w,1}(t) + P_{w,2}(t) + P_{w,3}(t) = P_{w,pre}(t) - P_{w,waste}(t) \quad (33)$$

In the formula, $P_{w,pre}(t)$ is the predicted wind power, and $P_{w,waste}(t)$ is the wind power curtailment.

8.2. System Residual Constraint

8.2.1. Wind Power

The wind power uses known forecast data, and its output range is as follows:

$$0 \leq P_w(t) \leq P_{w,pre}(t) \quad (34)$$

8.2.2. Thermal Power Unit

$$\begin{cases} P_{G,min} \leq P_{G,i}(t) \leq P_{G,max} \\ P_{G,i}(t) - P_{G,i}(t-1) \leq R_{G,up} \\ P_{G,i}(t-1) - P_{G,i}(t) \leq R_{G,down} \end{cases} \quad (35)$$

In the formula, $P_{G,max}$ and $P_{G,min}$ are the upper and lower limits of the total thermal power output; $R_{G,up}$ and $R_{G,down}$ are the up-ramping and down-ramping rates of the total thermal power unit output.

8.2.3. Energy Storage Device

The energy storage batteries must meet their own charge/discharge constraints during operation:

$$\begin{cases} 0 \leq P_{bat,m}^{ch}(t) \leq P_{bat,me} \times S_{bat}(t) / \psi_{ch} \\ 0 \leq P_{bat,m}^{dis}(t) \leq P_{bat,me} \times (1 - S_{bat}(t)) \times \psi_{dis} \\ -(1 - \theta)W_{bat,m} \leq \sum_{t=1}^T P_{bat,m}(t)\Delta T \leq \theta W_{bat,m} \end{cases} \quad (36)$$

In the formula, $P_{bat,m}^{ch}(t)$ and $P_{bat,m}^{dis}(t)$ represent the charging and discharging power of the battery storage device; $P_{bat,me}$ is the rated charging and discharging power of the storage device; $S_{bat}(t)$ is the charge and discharge flag at time t ; ψ_{ch} and ψ_{dis} are the charging and discharging efficiencies of the storage device; θ represents the percentage of the allowed maximum discharge depth; $W_{bat,m}$ represents the capacity of the battery storage device; ΔT is the time interval.

The electricity prices at different time periods are shown in Figure 7.

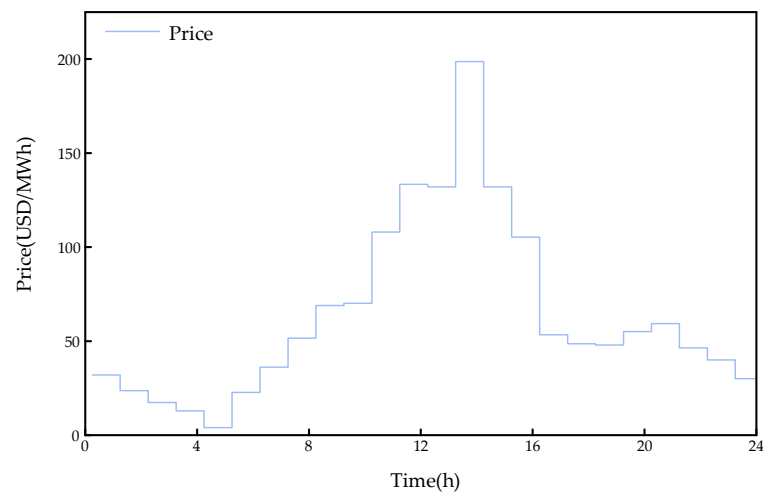


Figure 7. Real-time electricity price.

9. Case Study Analysis

9.1. Example Calculation Overview

This section will use case studies to validate the effectiveness and rationality of the proposed optimization scheduling method for a high-proportion wind power system that integrates the full-process electrolytic aluminum production with thermal power and battery storage. For Equations (8) and (22) in the paper, we applied a piecewise linearization approach. For the handling of Equations (23) and (24), we referred to the linear fitting model of loss rate from Reference [30] for the solution.

The simulation is based on Matlab R2022a, using the YALMIP plugin and the Gurobi solver for optimization. By leveraging YALMIP's integration capabilities with different solvers and its convenient modeling environment, along with Gurobi's powerful solving performance for mixed-integer programming and other problems, we were able to successfully solve the results presented in this paper.

The system in this study consists of thermal power plants, wind power plants, battery storage devices, high-energy consumption electrolytic aluminum loads, and general conventional loads. The network structure and constraints are not considered, and the effects of power line losses are neglected.

The operational parameters of the electrolytic aluminum section are provided in Table 1. The operational parameters of the thermal power units are provided in Table 2. The power regulation of the high-energy consumption electrolytic aluminum load is controlled by the series current and follows the thermal balance principle. The production temperature must be strictly controlled between 950 °C and 970 °C, with 960 °C as the rated temperature.

Table 1. Parameters for load regulation of electrolytic aluminum.

Load Category	Rated Power (MW)	Current/kA	Number of Electrolytic Cells	E_m/V	$R_m/m\Omega$
Electrolytic Aluminum	520	400	325	496	2.01

Table 2. Parameters of thermal power units.

Unit Number	Rated Power (MW)	Maximum Output (%)	Minimum Output (%)	Ramping Power (MW/h)	$a/(USD/MW^2 \cdot h)$	$b/(USD/MW \cdot h)$	$c/(USD/h)$
1, 2, 3	400	100	50	100	0.0450	21.62	192.0

9.2. Case Overview

To verify the effectiveness and rationality of the proposed optimization scheduling method for a high-proportion wind power system, which integrates full-process electrolytic aluminum production with thermal power and battery storage, the following schemes are proposed for result analysis.

Case 1: The entire electrolytic aluminum production process does not participate in the scheduling and maintains a constant rated power output, with regulation solely carried out by the thermal power plants in coordination with the battery storage.

Case 2: The entire electrolytic aluminum production process does not participate in the scheduling. VMD is used to decompose the load, with thermal power units and battery storage working together to schedule the different modal components derived from the VMD decomposition.

Case 3: VMD is used to decompose the load, with the electrolytic aluminum production and other aluminum production processes participating in the scheduling. This scheme involves coordination between thermal power units and battery storage, with the scheduling of different modal components derived from VMD decomposition.

9.3. Analysis of Optimization Results

9.3.1. Comparison of Optimization Results Under Different Scenarios

(1) The Optimization Results of Case 1

Figure 8 illustrates the supply–demand balance of the electrical load under the scheduling of Case 1. During the period from 0:00 to 7:30, the wind power generation is relatively high. However, during this period, the total output of thermal power plants' regular peak shaving and wind power far exceeds the amount of electricity that can be absorbed by the conventional load and the full-process electrolytic aluminum production, forcing thermal power plants into deep peak shaving mode. At the same time, in order to minimize system operating costs, it is necessary to balance the additional costs of deep peak shaving by thermal power plants and the losses incurred from wind curtailment. As a result, some degree of wind curtailment occurs during this period. To mitigate this issue, the battery storage device continuously absorbs surplus power from 0:00 to 0:30, reducing the amount of wind curtailment.

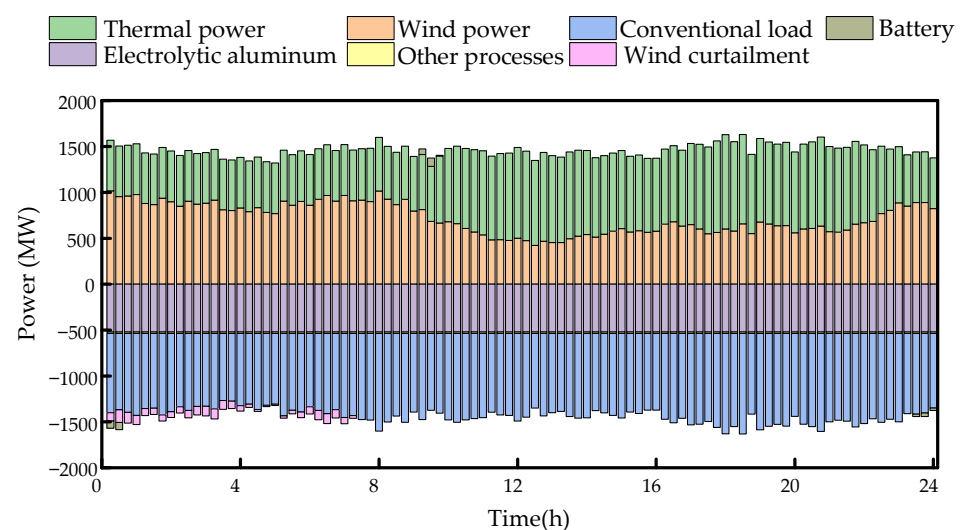


Figure 8. Power supply and demand balance relationship diagram of Case 1.

From 7:30 to 23:00, as wind power generation significantly decreases and conventional load gradually increases, the total output of thermal power units' regular peak shaving

and wind power is sufficient to meet the electrical demand of the conventional load and full-process electrolytic aluminum production. Thermal power plants recover from the deep peak shaving mode to regular peak shaving, alleviating the pressure of deep peak shaving and reducing costs. Additionally, to improve the system's economic efficiency, after thermal power plants return to regular peak shaving, the battery storage releases the previously stored energy between 9:15 and 9:45, further assisting the thermal power plants in reducing peak shaving costs.

During the period from 23:00 to 24:00, wind power generation rises again, causing thermal power plants to re-enter deep peak shaving mode, accompanied by a certain degree of wind curtailment. Therefore, the installed battery storage devices continue charging from 23:00 to 23:30 to further reduce the occurrence of wind curtailment.

(2) The Optimization Results of Case 2

Figure 9 presents the supply–demand balance of the electrical load after the optimization scheduling of Case 2. The operational conditions of Case 2 are similar to those of Case 1. After introducing VMD, the smoother low-frequency components are responded to by thermal power plants, while the mid-frequency and high-frequency components with periodic oscillatory characteristics are continuously managed by the battery storage throughout the day. This makes the output of thermal power plants smoother, ensuring the stability and security of the system.

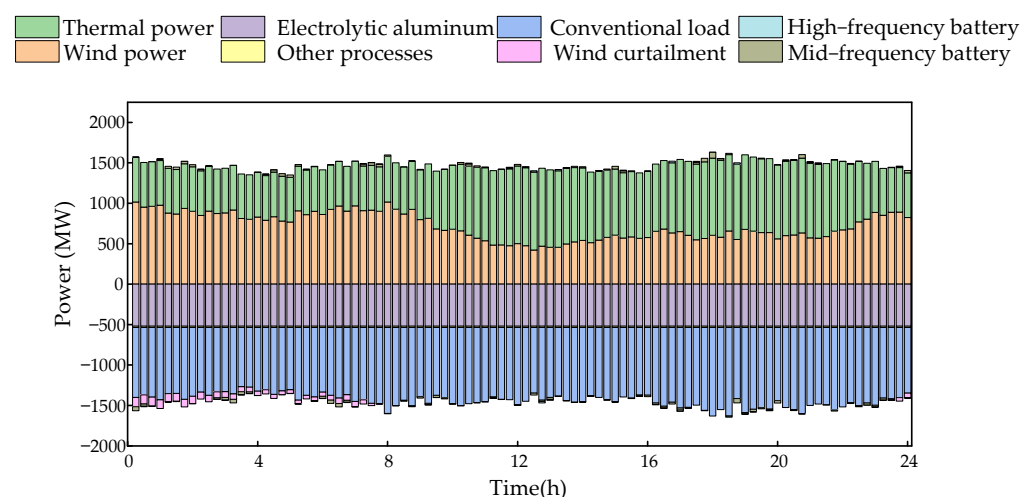


Figure 9. Power supply and demand balance relationship diagram of Case 2.

(3) The Optimization Results of Case 3

Figure 10 shows the supply–demand balance of the electrical load after the optimization scheduling of Case 3. During the period from 0:00 to 7:30, wind power generation remains at a high level. To promote wind power consumption, the thermal power plants maintain a low output level. At this time, the electrolytic aluminum production process appropriately increases its output, actively responding to load demand, reducing the additional costs caused by deep peak shaving of thermal power plants, and effectively decreasing wind curtailment. At the same time, the battery storage device actively collaborates with the mid-frequency components, continuously performing charge and discharge operations.

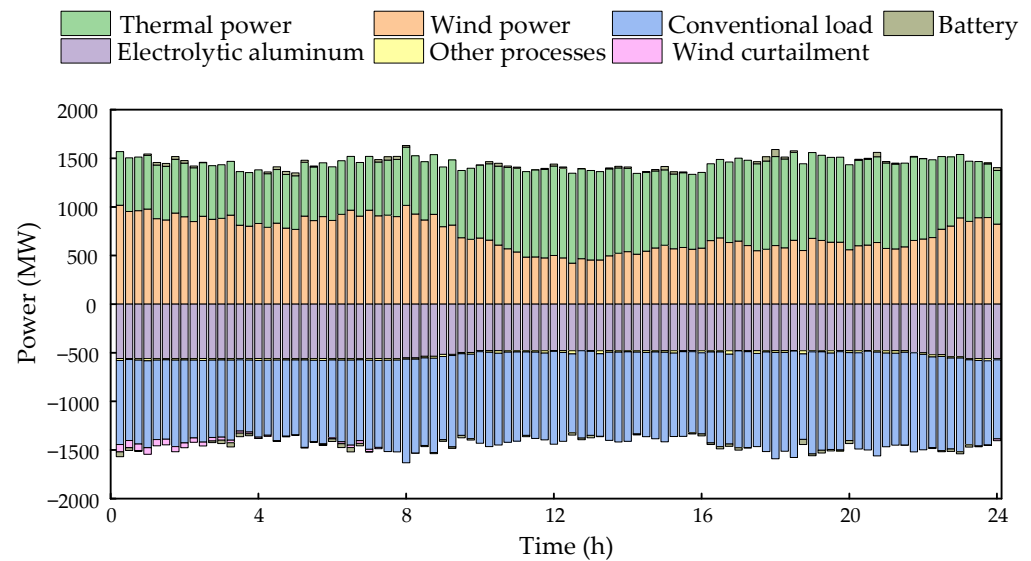


Figure 10. Power supply and demand balance relationship diagram of Case 3.

From 7:30 to 23:00, due to the decline in wind power output, the thermal power plants return to the regular peak shaving mode. To reduce the overall system cost, the electrolytic aluminum production process decreases its output to the minimum, thus reducing the costs of thermal power plants during regular peak shaving and easing the output pressure on thermal power plants during peak load periods. During this period, the battery storage device continues to balance load fluctuations through charge and discharge operations, reducing the volatility of thermal power plants' output.

During the period from 23:00 to 24:00, as wind power output rises again, the electrolytic aluminum production process increases its output to avoid the high additional costs, large unit losses, and system pressure caused by deep peak shaving by thermal power plants. The electrolytic aluminum production process works in coordination with the battery storage, reducing wind curtailment and smoothing the fluctuations in the thermal power plant output.

By adopting the above scheduling strategies, this case effectively combines the complementary roles of battery storage, electrolytic aluminum loads, and traditional thermal power plants. It flexibly adjusts the operating mode according to the specific conditions at different times, achieving a coordinated use of wind and thermal power resources, thereby improving the operational efficiency and economic benefits of the entire power grid system.

9.3.2. Impact of Different Scenarios on the System

As shown in Figures 11 and 12, the wind power consumption under different cases is illustrated. From the chart, it can be seen that the wind curtailment mainly occurs in two periods: 0:00–7:30 and 23:00–24:00. As shown in Table 3, Compared to other cases, Case 3 significantly reduces wind curtailment, decreasing the wind curtailment rate by 1.86% and improving the curtailment volume by 45.07%.

Table 3. Comparison of power system operation data under different cases.

Case	Operating Cost/USD	Thermal Power Unit Operating Cost/USD	Wind Curtailment Penalty Cost/USD	Wind Curtailment Rate
Case 1	1,583,853.617	1,300,635.468	63,235.006	3.22%
Case 2	1,561,755.877	1,296,616.543	62,577.791	3.02%
Case 3	1,494,492.725	1,218,062.437	49,930.232	1.36%

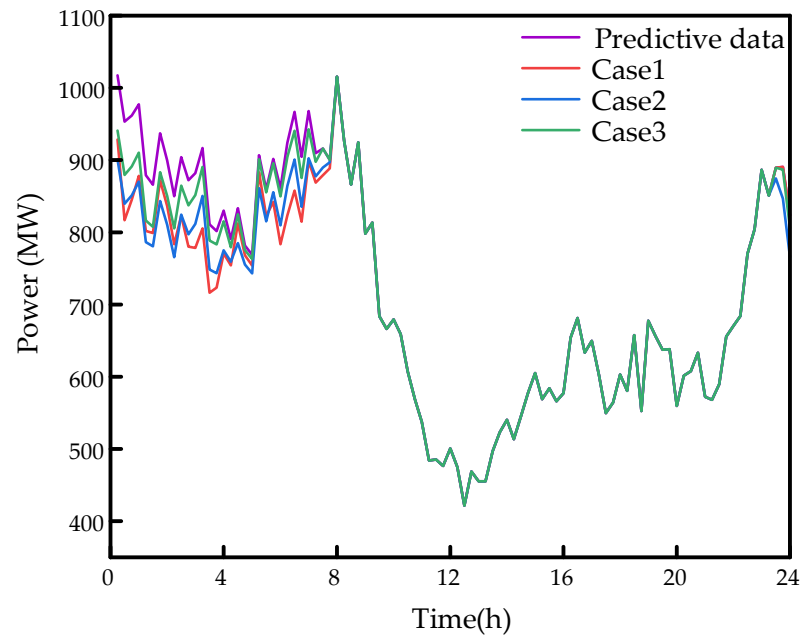


Figure 11. Wind power consumption under different cases.

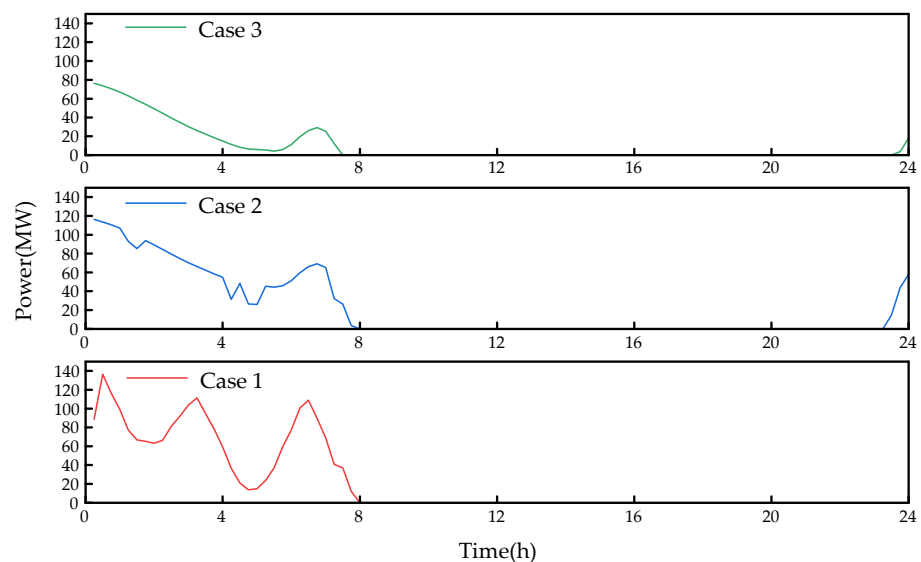


Figure 12. The wind power curtailment under different cases.

9.3.3. Analysis of Thermal Power Unit Operation Results

As shown in Figure 13, compared to Case 1, Case 2 results in significantly smoother thermal power plant output, with a clear improvement in the output peak of the thermal power plants. The system operating cost is reduced by 1.40%. This indicates that Case 2 can effectively alleviate the output pressure of thermal power plants and enhance their operational stability.

Compared to Case 2, in Case 3, the difference between the maximum and minimum output of the thermal power plants is further reduced. Due to the temperature stability requirements in the electrolytic aluminum production process, the consumed power cannot decrease rapidly between 7:30 and 9:00, which allows the thermal power plants to exit the deep peak shaving mode more quickly, improving both stability and economic efficiency. Compared to Case 1, the system operating cost is reduced by 5.64%, and, compared to Case 2, it is reduced by 4.31%.

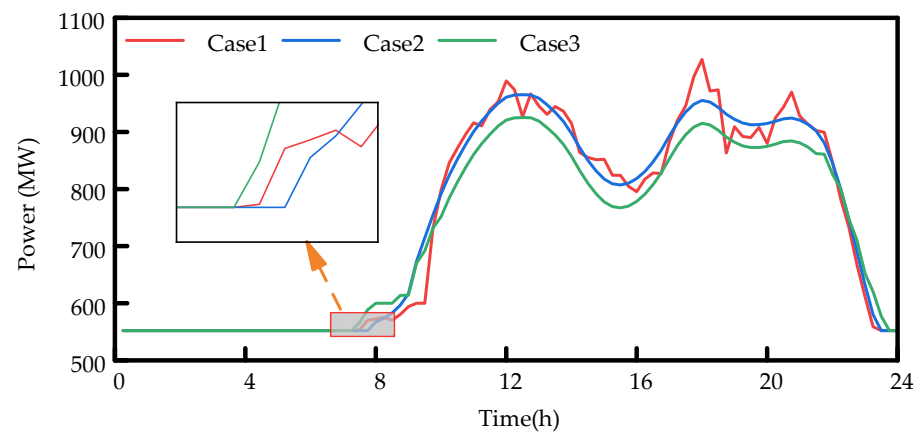


Figure 13. Output conditions of thermal power units under different cases.

The smoothness of thermal power plant output not only helps to reduce disturbances to the grid and enhances grid stability but also alleviates the pressure caused by frequent and large-scale peak shaving, thereby improving system operational safety and electricity reliability. Additionally, stable output results in more uniform combustion in the thermal power plants, reducing pollutant emissions and contributing to the achievement of environmental goals. Moreover, stable output from thermal power plants reduces the need for reserve capacity, thereby minimizing resource waste and operational costs.

9.3.4. Analysis of Operational Results in the Full Process of Electrolytic Aluminum Production

(1) Analysis of the Operational Results of the Electrolytic Aluminum Production Process

As shown in Figure 14, after the electrolytic aluminum production process participates in demand response, when the wind power output is high and the thermal power plants face deep peak shaving pressure, the electrolytic aluminum production process maintains maximum output, alleviating the peak shaving pressure on thermal power plants and reducing wind curtailment. As wind power gradually decreases, the output of thermal power plants increases. Due to the operational constraints of the electrolytic aluminum production process, its output cannot be adjusted frequently or significantly, allowing thermal power plants to exit the deep peak shaving mode more quickly. Additionally, thermal power plants will not experience extreme output variations due to frequent and large fluctuations in electrolytic aluminum production, ensuring output stability. When wind power output is low and thermal power units return to regular peak shaving, the output is appropriately reduced, thereby effectively lowering the overall system operating cost. Finally, due to the output constraints of the electrolytic aluminum production process, it acts in advance before thermal power units enter the deep peak shaving mode, shortening the deep peak shaving time and reducing wind curtailment. By participating in demand response, the electrolytic aluminum production process not only lowers the overall system operating cost but also enhances the system's operational stability, improving electricity reliability.

(2) Analysis of the Operational Results of the other Processes in Electrolytic Aluminum

As shown in Figures 15 and 16, in Case 2, the high-frequency components derived from VMD decomposition are responded to by the battery storage device. In Case 3, after the participation of other electrolytic aluminum processes in the optimization scheduling, the high-frequency components derived from VMD decomposition are responded to by these processes. The number of devices involved in the electrolytic aluminum production process is large, and the output of each device is relatively small. This characteristic is well suited to the high-frequency fluctuations, which have a high frequency but small amplitude.

Therefore, other electrolytic aluminum processes can effectively handle the fluctuations of the high-frequency components and mitigate the output changes of low-frequency components, making the output of thermal power plants more stable. By integrating storage into other electrolytic aluminum processes, these processes can be equivalent to a battery storage device with a capacity of 16 MW·h, effectively reducing the need for additional battery storage devices to handle high-frequency components post-VMD decomposition, thereby reducing the system's construction costs.

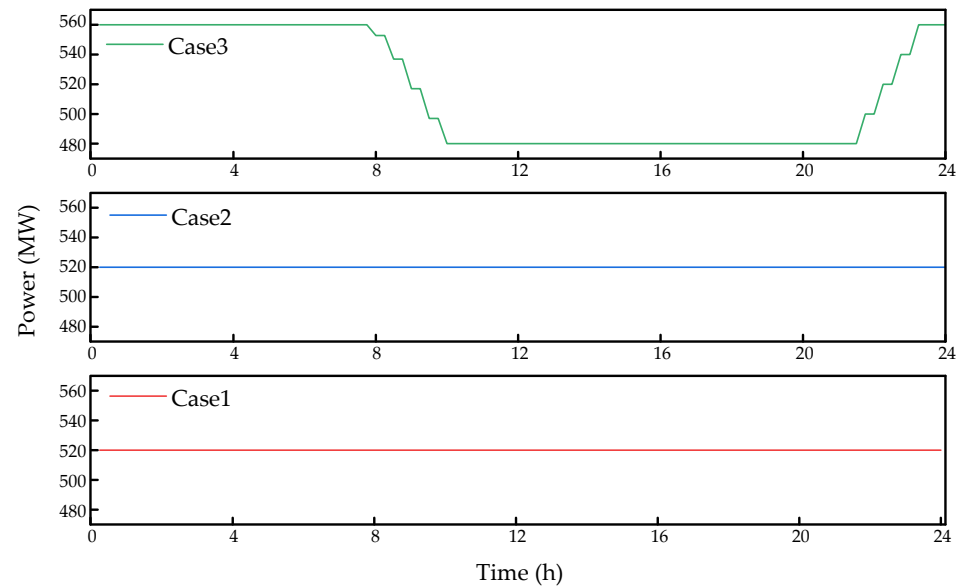


Figure 14. Output performance of electrolytic aluminum production process under different cases.

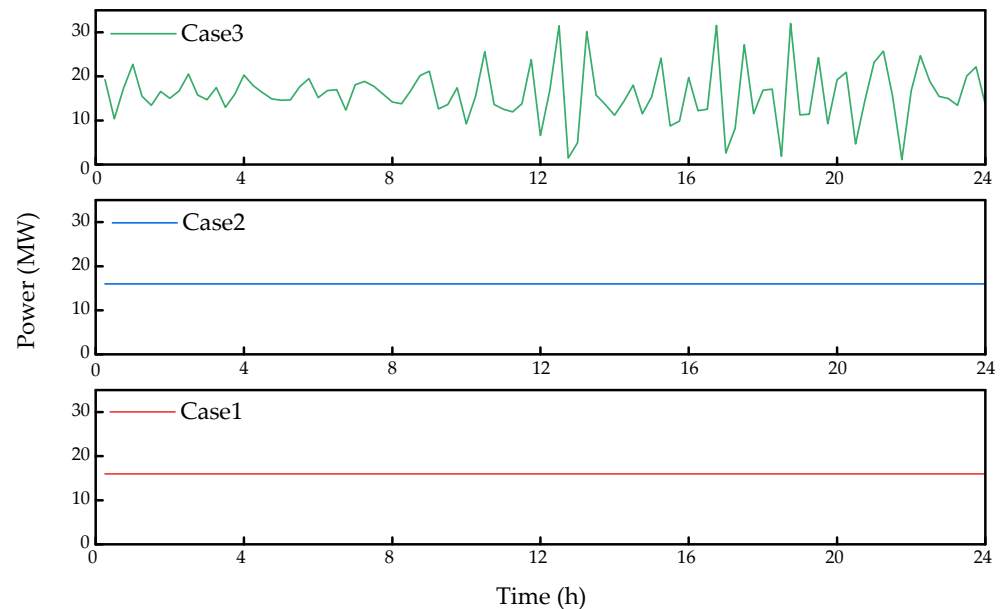


Figure 15. Output performance of other processes in electrolytic aluminum under different cases.

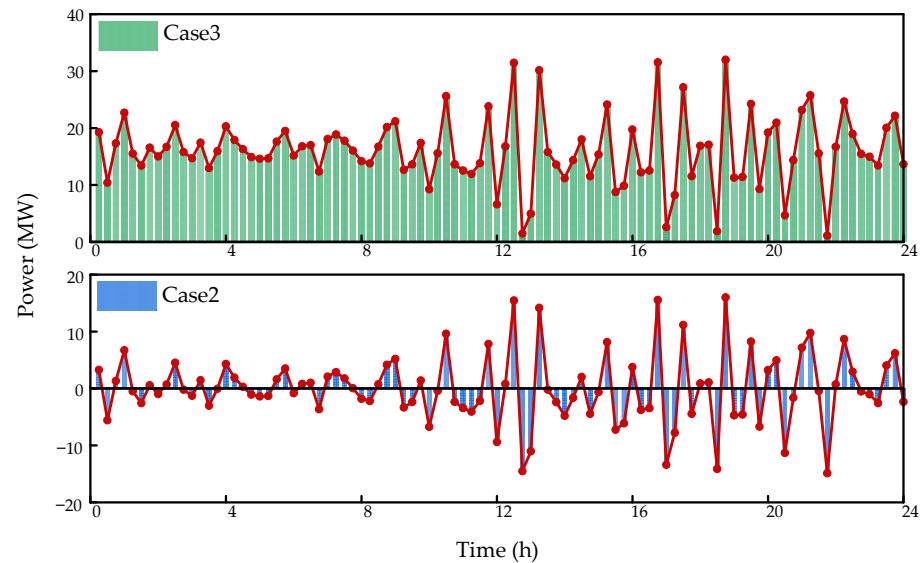


Figure 16. Response of different cases to high-frequency components.

9.3.5. Analysis of Energy Storage Operation Results

Comparing the battery storage output in each scheme, as shown in Figure 17, in Case 1, the battery storage device independently participates in the optimization scheduling. During the wind curtailment phase, the battery storage continuously charges until fully charged and then enters standby mode without further operation. When thermal power plants return to regular peak shaving, the battery storage begins discharging, but after discharging ends, the battery storage returns to standby mode until the next deep peak shaving phase of the thermal power plants when it resumes charging.

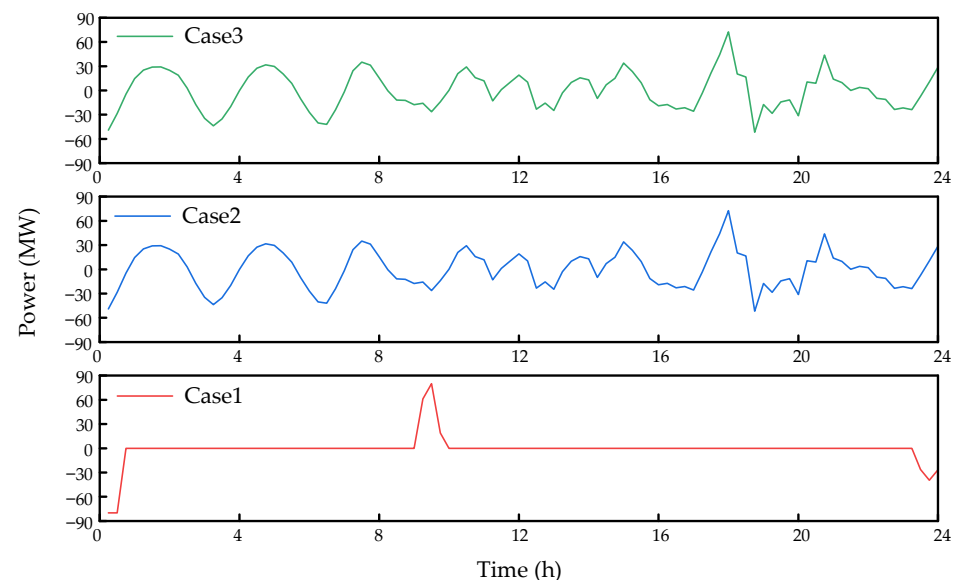


Figure 17. Output conditions of battery storage devices under different cases.

In Case 2 and Case 3, after introducing VMD, the battery storage device operates according to the mid-frequency components derived from the VMD decomposition. It participates in the scheduling process throughout, without entering standby mode. The battery storage device continuously responds to the net load fluctuations, effectively smoothing the output curve of the thermal power plants, thus improving their operational performance. This scheduling approach not only improves the system's operational efficiency but also reduces the operational pressure on thermal power plants.

10. Conclusions

This paper considers incorporating the high-energy consumption load of electrolytic aluminum into the grid's optimization scheduling, jointly participating in system peak shaving with thermal power plants through deep peak shaving. It integrates the VMD method to decompose different frequency modes, analyzes the characteristics of these modes, and utilizes the distinct characteristics of different units to handle mode curves with varying output characteristics. An optimization model is established to minimize the system's operational cost, and the economic impacts on the system's units are analyzed in depth. The following conclusions were reached:

- (1) The proposed approach effectively improves the system's overall peak-shaving performance, reducing the system's operational cost by 5.64%. Moreover, the coordination between electrolytic aluminum load regulation and deep peak-shaving of thermal power plants promotes wind power absorption, leading to a 1.86% reduction in the wind curtailment rate and a 45.07% relative decrease in the wind curtailment volume. During periods of high peak-shaving pressure, the demand response from the high-energy consumption load of the electrolytic aluminum process plays a crucial role.
- (2) Under the proposed approach, both the economic and technical performances of thermal power plants participating in grid peak-shaving are improved. After the high-energy consumption load of the electrolytic aluminum process participates in grid regulation, the output of the aluminum load is increased when the wind power generation is high and decreased when the wind power generation is low and the load demand is high. This not only enhances wind power absorption and reduces wind curtailment but also significantly narrows the output range of thermal power plants, easing the peak-shaving pressure on thermal units. Additionally, the constraints of not frequently adjusting the electrolytic aluminum production process and ensuring the minimum production volume are beneficial for the system to move away from deep peak-shaving with thermal power units, shortening the duration of deep peak-shaving, optimizing the operation of deep peak-shaving in thermal power plants, and improving both the economic efficiency of the system and the operational stability of thermal power plants.
- (3) The proposed scheme in this paper utilizes VMD to decompose the net load into corresponding components with different center frequencies, which are then classified into high, mid, and low-frequency components for separate regulation. Compared to traditional control methods, the results show that this approach increases the utilization rate of renewable energy while reducing operational costs and ensuring a smoother operation of thermal power plants. In addition, we decomposed the different stages of aluminum electrolysis production and modelled the other aluminum production processes as energy storage units. By utilizing the operational characteristics of each stage to address different frequency components, this approach not only optimizes the output of thermal power units but also facilitates further power absorption, thereby reducing system construction costs while enhancing operational efficiency and supply reliability.

Author Contributions: Conceptualization, Y.Y. and H.Y.; methodology, Y.Y. and H.Y.; software, Y.Y. and H.Y.; validation, Y.Y., H.Y. and J.W.; formal analysis, Y.Y. and H.Y.; investigation, Z.Y. and W.L.; resources, Y.Y.; data curation, H.Y. and J.W.; writing—original draft preparation, H.Y.; writing—review and editing, Y.Y. and H.Y.; supervision, H.Y.; project administration, Y.Y.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Research and Development Program Project of Xinjiang Uyghur Autonomous Region (2022B01020-1).

Data Availability Statement: All data are referenced in the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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