A Bidding Strategy for Electrolytic Aluminum Enterprises Participating in the Demand Response Market Based on Electricity Cost Analysis

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Abstract—**The growing integration of renewable energy underscores the critical role of demand response (DR) in ensuring grid stability. As a flexible resource, electrolytic aluminum loads offer significant potential in DR markets. Based on Yunnan's 2024 DR mechanism, this paper proposes a capacity bidding strategy that incorporates thermal energy conversion costs and dynamic anode effect costs. A revenue model considering production safety constraints is developed, followed by a nonlinear optimization model aimed at maximizing net profit. Using sequential least squares programming, the optimal bidding capacity under varying market prices is derived, along with a cost-benefit analysis. Simulations confirm that this approach effectively supports electrolytic aluminum plants in balancing economic gains with operational safety in DR participation.**

Keywords—High energy electrolytic aluminum load;Demand response; Virtual power plant; Capacity declaration and price bidding.

I. INTRODUCTION

With the global consensus on addressing climate change and achieving carbon neutrality, the penetration of renewable energy in power systems has been rapidly increasing [1]. However, the inherent intermittency and volatility of renewable sources such as wind and solar pose significant challenges to the stability and flexibility of power grids [2]. In particular, the integration of large-scale renewables reduces system inertia and increases the need for fast-responding regulation resources [3]. Against this backdrop, high-energy-consuming industrial loads, especially electrolytic aluminum loads, have emerged as promising flexible resources due to their large capacity and adjustable characteristics [4]. Therefore, it is crucial to explore how electrolytic aluminum enterprises can participate in demand response (DR) through virtual power plants (VPPs) to enhance grid flexibility and support renewable energy integration.

Electrolytic aluminum loads, as typical energy-intensive industrial loads, possess significant regulation potential. Existing research has focused on their dynamic characteristics, cost modeling, and participation mechanisms in DR markets. In terms of load characteristics and cost analysis, studies have established external characteristic models of electrolytic aluminum loads and proposed power regulation methods via on-load tap changers (OLTC) and saturated reactors [5][6]. However, the impact of power adjustments on production safety—such as electrolyte temperature fluctuations and anode effects—has not been fully quantified. As for bidding strategies in DR markets, current research has developed optimization models for capacity declaration considering production process constraints and market rules [7][8]. Yet, most models lack integration of dynamic cost mechanisms such as electro-thermal conversion and anode effect penalties, leading to suboptimal bidding decisions.

To address these research gaps, this study makes the following key contributions:

1)A comprehensive control cost model for electrolytic aluminum loads is developed, integrating both dynamic anode effect costs and electro-thermal energy conversion costs. This model provides a more accurate basis for economic dispatch by capturing the real internal costs associated with power adjustments.

2)A demand response capacity declaration method is proposed, built upon the integrated cost model. The sequential least squares quadratic programming (SLSQP) algorithm is employed to solve the resulting optimization problem, enabling the determination of the optimal bidding strategy under both production safety constraints and market rules.

II. MARKET MECHANISMS AND PROBLEM FORMULATION

A. Analysis of Demand Response Market Mechanisms

Under Yunnan's 2024 Demand Response Plan, directly controllable industrial loads are now recognized as independent market entities. Load aggregators may represent users with voltages ≥380V and capacity ≥10kW. Key participation steps for electrolytic aluminum loads include market announcement, entity bidding, and market clearing:

1)The grid operator announces the demand response power shortfall information by 10:00 on the day before the bidding day:The market operator releases the demand response market information for the operating day, which includes specific requirements such as participant details,

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required capacity, demand periods, and upper/lower limits for bidding prices.

2)Market entities submit their capacity and price bids before 14:00 on the day preceding the bidding day:The main bidding information includes response capacity, response duration, and response price.

Demand Response Bidding Price Schedule		
Response Duration	***Price Standard***	***note***
0 minutes < Duration ≤ 60 minutes	0~3 CNY/kW per event	The maximum rate is 3 CNY/kWh
60minutes < Duration ≤ 120 minutes	0~8 CNY/kW per event	The maximum rate is 4 CNY/kWh
120minutes<Duration ≤ 180 minutes	0~15 CNY/kW per event	The maximum rate is 5 CNY/kWh

Market entities submit their bid response capacity (P_{bid}) and price, and the market is cleared using the marginal clearing method.The compensation revenue R_{comp} is calculated as follows:

$$R_{\text{comp}} = \lambda_{\text{clear}} \times R_{\text{eff}} \times T_{\text{resp}} \tag{1}$$

Here, λ_{clear} is the market clearing price, and T_{resp} is the response duration.The effective response capacity (R_{eff}) is determined in segments based on the ratio ($\alpha = R_{eff} / P_{bid}$) of the actual response capacity (R) to the awarded bid capacity (P_{bid}).

$$R_{\text{eff}} = \begin{cases} 0, & \alpha < 50\% \\ 0.6R, & 50\% \le \alpha < 80\% \\ R, & 80\% \le \alpha \le 120\% \\ 1.2P_{\text{bid}}, & \alpha > 120\% \end{cases} \tag{2}$$

The baseline load is calculated based on historical load data using the sliding window method to mitigate the impact of fluctuations.

B. Regulation Cost Model for Electrolytic Aluminum Loads

This process centers on alumina electrolysis. High-voltage power is stepped down and rectified into high-capacity direct current, which is then supplied to electrolytic cells to facilitate the reduction reaction. The electrical system structure is depicted in Figure 1.

The power characteristic of the electrolytic aluminum load can thus be expressed as:

$$P_{\text{AL}} = h(I_d) = I_{\text{d}}^2 R_{\text{AL}} + I_{\text{d}} E_{\text{AL}} \tag{3}$$

where P_{AL} is the active power of the electrolytic aluminum load, I_{d} is the DC-side current of the load, and E_{AL} and R_{AL} are the equivalent back electromotive force and equivalent resistance of the electrolytic cell, respectively.

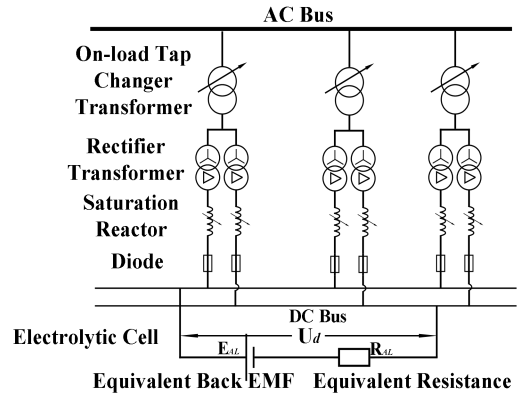

Fig.1 Schematic Diagram of the Electrolytic Aluminum Electrical System Structure

The net benefit for the electrolytic aluminum load participating in demand response is the market compensation revenue minus the internal costs incurred due to power adjustment ΔP, which primarily consists of two components:

1) Dynamic Anode Effect Control Cost

In the aluminum electrolysis process, the interpolar resistance mutation phenomenon, known as the anode effect, originates from electrochemical instability caused by imbalanced current distribution at the anode/molten salt interface.It is typically characterized by a stepwise surge in cell voltage.

Under normal conditions, the losses induced by the anode effect are primarily categorized into three aspects: power loss $C_{an\text{-}1}$, raw material loss $C_{an\text{-}2}$, and anode effect quenching cost $C_{an\text{-}3}$.

$$C_{\text{an-1}} = \Delta U_{\text{d}} I_{\text{d}} t_{\text{an}} \delta \tag{4}$$

$$C_{\text{an-2}} = c_1 m \tag{5}$$

$$C_{an-3} = \mu c_2 \tag{6}$$

where ΔU_{d} represents the DC-side voltage variation, tan denotes the anode effect duration, δ is the electricity price, m indicates the mass of aluminum fluoride lost per anode effect occurrence, c_1 stands for the unit price of aluminum fluoride, μ refers to the number of anode effect bars consumed to quench a single event, and c_2 represents the unit price of an anode effect bar.

Therefore, the anode effect loss of the electrolytic cell is calculated as:

$$C_{\text{an}} = (C_{\text{an}-1} + C_{\text{an}-2} + C_{\text{an}-3}) \tag{7}$$

This study developed a quadratic function-based mathematical model to characterize the dynamic relationship between the anode effect occurrence probability ε and the voltage adjustment of the magnetic control device：

$$\varepsilon = b_1 \left(\Delta U_{\text{SR}}\right)^2 + b_2 \left(\Delta U_{\text{SR}} + U_{\text{SR0}} - U_{\text{SRN}}\right)^2 \tag{8}$$

In the equation, b_1 and b_2 are correlation coefficients determined through statistical analysis; U_{SR0} is the initial voltage of the saturation reactor, and U_{SRN} is its rated voltage.

Consequently, the control cost incurred by the current stabilization system of the saturation reactor during the demand response process of the electrolytic aluminum load can be described as

$$C_{\text{SR}} = \varepsilon C_{\text{an}} \tag{9}$$

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The coupling relationship between the voltage adjustment of the saturation reactor and the active power adjustment is given by:

$$\Delta P_{AL} = \frac{1.35\Delta U_{\mathrm{SR}}(E_{\mathrm{AL}} - 2U_{\mathrm{d}}) + (1.35\Delta U_{\mathrm{SR}})^2}{R_{\mathrm{AL}}} \tag{10}$$

Given that $\Delta U_{\mathrm{d}} = -\Delta U_{\mathrm{SR}}, \Delta U_{\mathrm{SR}} << U_{\mathrm{d}}$, the coupling relationship between the power variation of the electrolytic aluminum load ΔP_{AL} and the voltage variation of the saturation reactor ΔU_{SR} can be approximated as:

$$\Delta P_{\mathrm{AL}} = 1.35\Delta U_{\mathrm{SR}}(E_{\mathrm{AL}} - 2U_{\mathrm{d}}) / R_{\mathrm{AL}} \tag{11}$$

The control cost of the electrolytic aluminum load considering the dynamic anode effect, C_{SR} , is formulated as

$$C_{\mathrm{SR}} = p_{\mathrm{SR}}(\Delta P_{\mathrm{AL}})^2 + q_{\mathrm{SR}}(\Delta P_{\mathrm{AL}}) + h_{\mathrm{SR}} \tag{12}$$

where p_{SR} , q_{SR} and h_{SR} are cost coefficients derived from the device parameters. The constant term h_{SR} represents the fixed operational cost of maintaining the saturation reactor regulation system in an active state, which includes baseline energy consumption and depreciation costs incurred regardless of the regulation magnitude ΔP_{AL} ：

$$p_{\mathrm{SR}} = C_{\mathrm{an}}(b_1 + b_2)\left(R_{\mathrm{AL}} / \left(1.35(E_{\mathrm{AL}} - 2U_{\mathrm{d}})\right)\right)^2 \tag{13}$$

$$q_{\mathrm{SR}} = 2b_2 C_{\mathrm{an}}(U_{\mathrm{SR}0} - U_{\mathrm{SRN}})\left(R_{\mathrm{AL}} / \left(1.35(E_{\mathrm{AL}} - 2U_{\mathrm{d}})\right)\right) \tag{14}$$

$$h_{\mathrm{SR}} = 2b_2 C_{\mathrm{an}}(U_{\mathrm{SR}0} - U_{\mathrm{SRN}})^2 \tag{15}$$

2) Electro-Thermal Energy Conversion Control Cost

Temperature variations in the aluminum electrolysis process exert multifaceted impacts on production, primarily manifested in altering electrochemical reaction kinetics, affecting current efficiency, and constraining equipment operational states.The standard operating temperature for the electrolysis process is set at 960℃, with an permissible fluctuation range of 950℃ to 960℃.

To quantitatively characterize the current regulation capability and production status of industrial loads, this paper defines a State of Temperature with Energy-intensive Equipment (SOE) model to normalize the electrolytic cell temperature:

$$\mathrm{SOE} = \frac{T_o - T_{\mathrm{N}}}{T_{\max} - T_{\min}} \tag{16}$$

where T_o is the current operating temperature of the industrial equipment; $T_{\min}$ and $T_{\max}$ are the lower and upper allowable temperature limits, and the temperature must be maintained within the interval $[T_{\min}, T_{\max}]$ to ensure production safety; T_{N} is the rated temperature of the equipment.

A power change causes the electrolytic cell temperature (T) to deviate from the optimal operating range $[T_{\min}, T_{\max}]$, resulting in three cost components:

1)Van 't Hoff effect loss C_v : Loss arising from the influence of temperature variation on the electrochemical reaction rate *v(T)*.

$$C_v = C_N - C_N \sigma^{(T - T_N)/10} \tag{17}$$

where σ is the Van 't Hoff coefficient typically ranging from 2 to 4, and C_N is the unit time revenue of the electrolytic load at the rated temperature.

2)Current efficiency loss C_η ： Loss due to the impact of temperature variation on current efficiency $\eta(T)$.

$$\eta(T) - \eta(T_{\mathrm{N}}) = \gamma(T - T_{\mathrm{N}}) \tag{18}$$

$$C_\eta = \gamma C_{\mathrm{N}}(T - T_{\mathrm{N}}) \tag{19}$$

where $\eta(T)$ is the current efficiency at T°C; $\eta(T_N)$ is the current efficiency at the rated temperature T_N°C; γ is the proportionality coefficient, typically ranging from -0.15% to -0.10% per °C.

3)Temperature deviation penalty loss C_{wdcut}: The degree of SOE deviation is positively correlated with the compensation cost.

$$C_{\mathrm{wdcut}} = \beta_{\mathrm{wdcut}} \mathrm{SOE}^2 \tag{20}$$

where β_{wdcut} is the penalty cost coefficient.

Therefore, the control cost incurred due to temperature variations during the demand response process of the electrolytic aluminum load can be described as:

$$C_{\mathrm{T}} = C_v + C_\eta + C_{\mathrm{wdcut}} \tag{21}$$

The coupling relationship between the control cost arising from temperature changes and the active power adjustment of the saturation reactor is given by:

$$C_{\mathrm{T}} = -c_{\mathrm{N}}\sigma^{a_{\mathrm{T}}(\Delta P_{\mathrm{AL}}\Delta t) + b_{\mathrm{T}}} + p_{\mathrm{T}}(\Delta P_{\mathrm{AL}}\Delta t)^2 + q_{\mathrm{T}}(\Delta P_{\mathrm{AL}}\Delta t) + h_{\mathrm{T}} \tag{22}$$

where a_T、b_T、p_T、q_T and h_T are the cost coefficients accounting for the regulatory effect of the saturation reactor，Similar to the previous model,h_T denotes the fixed thermal management costs and baseline efficiency losses associated with operating the cell in a flexible regulation mode：

$$a_{\mathrm{T}} = 1/(10cm); b_{\mathrm{T}} = (T_0 - T_{\mathrm{N}})/10 \tag{23}$$

$$p_{\mathrm{T}} = \beta_{\mathrm{wdcut}} / \left(cm(T_{\max} - T_{\min})\right)^2 \tag{24}$$

$$q_{\mathrm{T}} = \gamma C_{\mathrm{N}}/(cm) + 2\beta_{\mathrm{wdcut}}(T_0 - T_{\mathrm{N}})/(T_{\max} - T_{\min})^2) \tag{25}$$

$$h_{\mathrm{T}} = C_{\mathrm{N}} + \gamma C_{\mathrm{N}}(T_0 - T_{\mathrm{N}}) + \beta_{\mathrm{wdcut}}(T_0 - T_{\mathrm{N}})^2/(T_{\max} - T_{\min})^2 \tag{26}$$

Based on the standard physical characteristics described above, this section develops two refined operational cost assessment frameworks: a regulation cost calculation model incorporating dynamic anode effect characteristics and a regulation cost analysis model based on electro-thermal energy balance principles . These specific cost functions constitute the primary contribution of this modeling section, mapping physical variations directly to economic metrics.

C. *Quantity-Price Bidding Optimization Model*

Based on the production characteristics of electrolytic aluminum enterprises and the requirements of Yunnan Province's demand response mechanism, this section constructs a nonlinear programming model with multiple constraints to achieve the objective of net revenue maximization.Using the bidding capacity as the decision variable, the model comprehensively considers grid compensation revenue, dynamic anode effect control costs, and electro-thermal energy conversion control costs, while strictly adhering to voltage regulation safety margins and temperature regulation boundaries.

Taking the bidding capacity P_{bid} as the decision variable, a net revenue maximization model is established as follows:

Objective Function:

$$\max_{P_{\mathrm{bid}}} \mathrm{Profit} = R_{\mathrm{comp}}(P_{\mathrm{bid}}) - C_{SR}(P_{\mathrm{bid}}) - C_T(P_{\mathrm{bid}}) \tag{27}$$

Constraints:

Production Safety Boundary Constraints:

$$P_{bid} \in \left[\max\left(P_{\min^{SR}}, P_{\min^{T}}\right), \min\left(P_{\max^{SR}}, P_{\max^{T}}, B\right) \right] \tag{28}$$

The voltage regulation range is determined by the coordinated control of the saturation reactor and the on-load tap-changer transformer:

$$P_{\min SR} = \frac{(U_{dmin} - E_{AL})U_{dmin}}{R_{AL}}, \quad P_{\max SR} = \frac{(U_{dmax} - E_{AL})U_{dmax}}{R_{AL}} \tag{29}$$

where U_{dmin} and U_{dmax} are the minimum and maximum values of the DC-side voltage, respectively.

The temperature regulation range is derived based on the thermal balance equation of the electrolytic cell:

$$P_{\min}^{T} = P_{AL}(t) + \frac{(T_{\min} - T(t))cm}{\Delta t}, \quad P_{\max}^{T} = P_{AL}(t) + \frac{(T_{\max} - T(t))cm}{\Delta t} \tag{30}$$

Where T_{min}= 950°C, T_{max}= 970°C, c is the specific heat capacity, and m is the total mass of the molten electrolyte.

III. CASE STUDY

A. Case Study Setup

During the simulation, operational data from a 300 MW electrolytic aluminum plant in Yunnan was used to calculate the safety production boundary values.The necessary parameters for the case study are listed in the table below：

Basic Parameters of the Electrolytic Aluminum Enterprise			
Parameter Name	***Value***	***Parameter Name***	***Value***
Rated Temperature	950 °C	Daily Production per Cell	2280kg/day
Lower Temperature Limit	940°C	Specific Heat Capacity	1.2kJ/(kg·°C)
Upper Temperature Limit	960°C	Direct Current	302,000A
Number of Electrolytic Cells	248	Energy Efficiency	0.0625
Aluminum Unit Price	20.6CNY/kg	Equivalent Resistance	0.0016Ω
Back EMF	0.516kV	Duration	3600s

Anode Effect Parameters			
Parameter Name	***Value***	***Parameter Name***	***Value***
Electricity Price	0.6CNY/kWh	Mass Loss	15kg
Effect Coefficient 1	0.01	Effect Coefficient 2	0.02

Demand Response Parameters			
Parameter Name	***Value***	***Parameter Name***	***Value***
Van'tHoff Coefficient	2	Efficiency Coefficient	0.001/°C
Unit Time Revenue	58.98CNY/s	Temperature Penalty Coefficient	20000
SOE Penalty Coefficient		5	

Based on the aforementioned parameters, the calculation determines that the power adjustable range for the electrolytic aluminum enterprise is 262.83 MW to 301.25 MW, providing a fundamental constraint for the subsequent optimization analysis.

B. Sequential Least Squares Quadratic Programming

To solve the nonlinear optimization problem, the SLSQP algorithm is adopted. Although Equation (22) contains an exponential term that introduces non-linearity, the electrolytic aluminum process operates within a strictly bounded feasible region (Eq 28-30). Within these physical bounds, the cost function behaves predictably. To further mitigate the risk of local optima and ensure robust convergence, the optimization is performed from multiple starting points—specifically, the minimum, maximum, and midpoint of the allowable capacity range. The solution yielding the highest net profit is ultimately selected as the optimal bidding capacity.

C. Analysis of the Coupling Between Optimal Bidding Capacity and Clearing Price

In this study, a strong correlation is observed between the optimal bidding capacity and the clearing price. Figure 2 displays the optimal bidding capacities for the electrolytic aluminum enterprise under various clearing prices for 1-hour response durations:

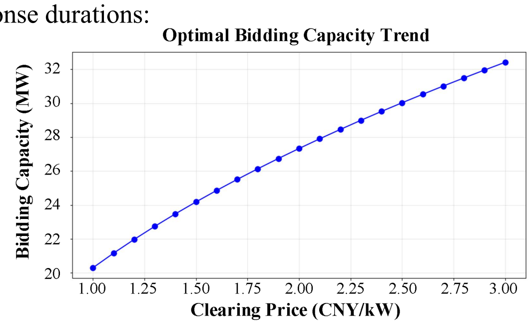

Fig.2 Optimal Capacity Trend Chart for Industrial Load Participation in Demand Response

The results indicate that as the price increases, the optimal capacity continues to rise, but its growth gradient gradually slows.When the grid clearing price is low, enterprises tend to declare a lower capacity to avoid high regulation costs;when the clearing price is high, the gradient of the optimal capacity increase slows due to the nonlinear growth in regulation costs.

D. Sensitivity Analysis of Net Profit to Clearing Price

A pronounced sensitivity relationship exists between net profit and the clearing price. Figure 3 shows the maximum net profit of the electrolytic aluminum enterprise under various clearing prices for both 1-hour durations:

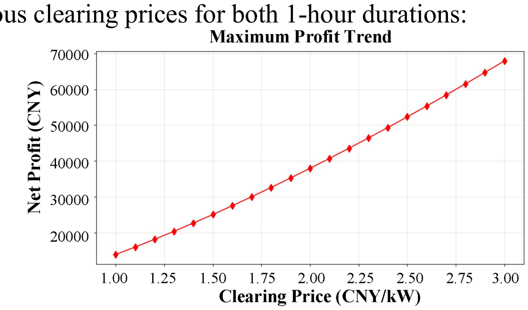

Fig.3 Maximum Profit Trend Chart for Industrial Load Participation in Demand Response

The data indicates that at a clearing price of 1.0 CNY/kW, the net profit was 13,910.68 CNY;when the clearing price increased to 3.0 CNY/kW, the net profit reached 67,941.41 CNY, representing an increase of approximately 3.9 times.This demonstrates that the clearing price exerts a critically important positive influence on net profit, which increases significantly in response to rising clearing prices.

E. Identification of Optimal Decision Regions via 3D Profit Surface

Based on the existing data of clearing prices, optimal bidding capacities, and net profits, a theoretical construction can be performed.Assuming the clearing price and optimal bidding capacity as the two coordinate axes, and net profit as the third axis, a three-dimensional space is constructed. The scenarios for 1-hour demand response are shown in Figure 4:

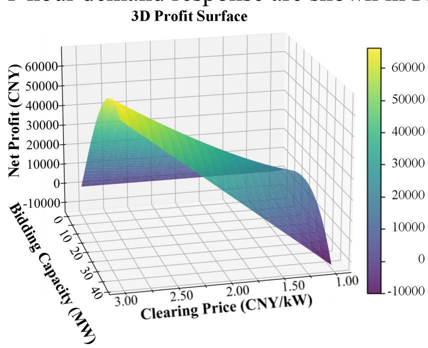

Fig.4 3D Bidding Quantity-Price-Profit Surface Plot for Enterprise Participation in Demand Response

This surface takes the clearing price and bidding capacity as independent variables and net profit as the dependent variable, with a color gradient applied to enhance readability.n the 1-hour demand response scenario, the surface exhibits a distinct ridge-like morphology, with high-profit regions concentrated within the price range of 3.0 CNY/kW and the capacity range of 20–35 MW.The dense contour lines at the top of the surface indicate that within this interval, minor capacity adjustments could lead to significant profit fluctuations, providing a reference for electrolytic aluminum enterprises in determining their demand response bidding quantities.

Finally, this study provides global bidding strategy guidance for enterprises by plotting a profit heatmap, as shown in Figure 5:

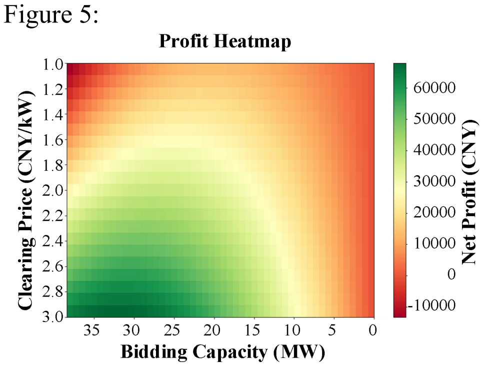

Fig.5 Profit Heatmap under Multi-segment Bidding Scenarios

The heatmap uses color intensity to represent profit levels, with green indicating high profits and red denoting low profits or losses. The horizontal axis represents bidding capacity, while the vertical axis represents clearing price. For the 1-hour scenario, high-profit areas (dark green) are concentrated in the upper-right corner, corresponding to prices of 2.5-3.0 CNY/kW and capacities of 270-275 MW. This region forms the "optimal decision window" that maximizes net profit while mitigating production risks.which can maximize net profit while mitigating production risks.

IV. CONCLUSION

This study developed refined models for capacity and price bidding of electrolytic aluminum loads in demand response markets. Key findings include:

1)The proposed regulation cost model, integrating thermal and dynamic anode effect costs, accurately captures the true internal costs of load adjustment.

2)The safety-constrained nonlinear optimization model, solved via SLSQP, effectively identifies optimal bidding strategies under complex constraints.

3)Case results show a positive but diminishing correlation between optimal bidding capacity and clearing price; longer durations require more conservative bids due to cost accumulation.

4)This work enhances the role of industrial loads in future power systems. Future research will explore multi-day response, price uncertainty, and coordination with distributed energy resources.

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