New Business Entity Participation Models in Electricity Market Transactions

Songtai Yu[1, a], Nan Zhang[1, b], Shuo Liu[1, c], Hui Huang[2, d], Meng Song[2*]

[1]Beijing Electric Power Trading Center Co., Ltd, Beijing, China
[2]North China Electric Power University, Beijing, China

[a]yu-songtai@sgcc.com.cn, [b]zhangnan@sgcc.com.cn
[c]liushuo@sgcc.com.cn, [d]hh@ncepu.edu.cn
*18246252726@163.com

Abstract. With the deepening of power market reforms, the participation of new market entities such as virtual power plants and load aggregators in multi-market transactions has become a significant trend. This paper establishes a bidding model for aggregators based on multi-market coordination, coordinating and optimizing bidding strategies across the electricity energy market, frequency regulation market, and peak shaving market. It further incorporates the conditional value at risk (CVaR) measurement method to develop a two-level optimization dispatch model that incorporates risk aversion, achieving an effective balance between expected returns and risks. Case study analysis demonstrates that the multi-market coordinated strategy yields higher returns compared to participation in a single market, validating the model's effectiveness and economic benefits.

Keywords: New types of business entities, Aggregation-based models, Conditioned risk value

1 Introduction

1.1 Research Background

With the ongoing advancement of China's "dual carbon" goals, the nation faces formidable challenges in transitioning its energy and power systems toward clean and low-carbon operations, while witnessing rapid growth in renewable energy installations. In December 2024, the National Energy Administration issued the "Guiding Opinions on Supporting the Innovative Development of New Business Entities in the Power Sector," explicitly defining Virtual Power Plants (VPPs) and Load Aggregators (LA) as resource-aggregating entities. These entities are encouraged to consolidate distributed resources with limited regulation capacity into a unified entity with enhanced regulatory capabilities to participate in electricity markets and achieve coordinated dispatch. The deepening of power market reforms has created favorable conditions for such aggregating entities to engage in market

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transactions. The "Basic Rules for Power Market Operations" now classify VPPs and LA as market participants, enabling them to participate in various trading activities including energy trading, ancillary service transactions, and capacity trading.

1.2 Current Research Status Domestically and Internationally

In addressing the bidding decision-making of aggregators in electricity markets, Liu Jinpeng[1] considered the adjustable potential of residential users and developed an optimization model for load aggregators 'day-ahead bidding decisions based on non-cooperative game theory, effectively supporting optimal bidding strategies. Luan Wenpeng[2] proposed a distributed transaction decision-making approach utilizing a master-side blockchain architecture to address internal trading decision optimization in virtual power plants, achieving information tamper-proofing and privacy protection. Xu Xiangchu[3] established a robust optimization model for electric vehicle aggregators participating in energy-frequency regulation markets by comprehensively accounting for multiple uncertainties including EV users' response willingness, frequency regulation signals, and market electricity prices.

Regarding aggregators 'participation in multi-market collaborative transactions, Zhu Lan[4] comprehensively examined the multi-stage interactive effects of EV charging and discharging behaviors within energy-frequency regulation markets, proposing a multi-stage operational strategy to maximize aggregators' returns. Chang[5] investigated a low-carbon collaborative energy management framework for virtual power plants integrated across multiple microgrids, incorporating carbon emission quantification throughout the dispatch process and employing a peer-to-peer (P2P) electricity trading pricing mechanism. Wen Yilin[6], utilizing a distributed robust chance constraint approach, investigated bidding strategies for charging operators participating in peak shaving markets, effectively addressing the uncertainty inherent in renewable energy generation.

In the field of dispatch optimization for electric vehicle aggregators, Wan Lingling[7] investigated the energy spatiotemporal transfer characteristics of large-scale shared electric vehicles in urban environments and proposed a deep reinforcement learning-based charging-discharging optimization method. Research on EV clusters participating in grid peak shaving under the aggregator model demonstrates that aggregators can effectively integrate dispersed EV resources and accomplish system peak-shaving tasks through optimized control strategies [8].

In the field of demand response aggregation modeling, Nojavan[9] conducted a comparative analysis of optimal approaches for demand response aggregation in wholesale power markets, evaluating polyhedral, ellipsoidal, and box-based uncertainty modeling methods, thereby providing theoretical support for aggregator uncertainty modeling. Liu[10] investigated a combinatorial auction approach for virtual power plants participating in demand-side ancillary service markets with interconnected microgrids, proposing a two-stage optimization model to maximize virtual power plant economic benefits. Tran[11] reviewed the transformation challenges faced by demand response aggregators in power markets, examining how they can support climate objectives and address key operational challenges.

An analysis of current domestic and international research reveals several shortcomings in existing studies: (1) Research on multi-market linkage trading strategies remains insufficient, particularly regarding aggregators' coordinated bidding strategies across spot, frequency regulation, and peak shaving markets; (2) Risk decision optimization models require refinement, as aggregators face multiple uncertainties such as price volatility and load forecasting deviations, while risk measurement methods like conditional value at risk (CVaR) are underutilized in their decision-making processes; (3) The two-tier game-theoretic relationship between aggregators and aggregated resources needs further exploration, with profit distribution and coordination mechanisms requiring additional investigation.

2 A Bid Model for Aggregators Based on Multi-Market Interconnection

2.1 Problem Description and Basic Assumptions

This chapter investigates the multi-market coordinated bidding strategy of Load Aggregators (LA), which participate simultaneously in the electricity energy market, frequency regulation ancillary service market, and peak shaving market. By integrating distributed resources such as photovoltaic systems, energy storage systems, controllable loads, and electric vehicles, the aggregators form virtual power plants with certain regulation capabilities and generate revenue through participation in electricity market transactions.

To establish a mathematical model, the following basic assumptions are proposed: (1) The aggregation operator possesses the ability to forecast intraday market electricity prices, frequency regulation capacity prices and peak-shaving compensation prices, and the forecast errors follow a normal distribution. This assumption of a normal distribution has been verified using actual operational data: the Kolmogorov-Smirnov (K-S) test was applied to a sample of historical prediction errors for the aggregator over the past 90 days, with normality tests conducted at a 5% significance level. The test results show that the K-S statistic for the day-ahead market electricity price prediction error is 0.062, with a p-value of 0.713 (greater than 0.05), so the null hypothesis of a normal distribution cannot be rejected; simultaneously, the Jarque-Bera test statistic is 2.347, with a p-value of 0.309, further validating the validity of the normal distribution assumption. The mean of the forecast error is 0, and the standard deviation is set at 5%–15% based on the accuracy of the forecasting method. (2) The operational characteristics of each distributed resource are known, including upper and lower output limits, ramping rates, and energy storage charge/discharge efficiency; (3) Market clearing employs a unified marginal pricing mechanism, with aggregators acting as price takers; (4) There are coupling relationships between markets, and the same resource cannot simultaneously participate in market segments subject to mutually exclusive constraints.

2.2 Polymerization Polymerizer Decision-Making Framework

The multi-market coordinated decision-making framework for aggregators is illustrated in Figure 1. This framework comprises three decision-making levels: day-ahead market bidding decisions, intraday rolling optimization, and real-time scheduling execution.

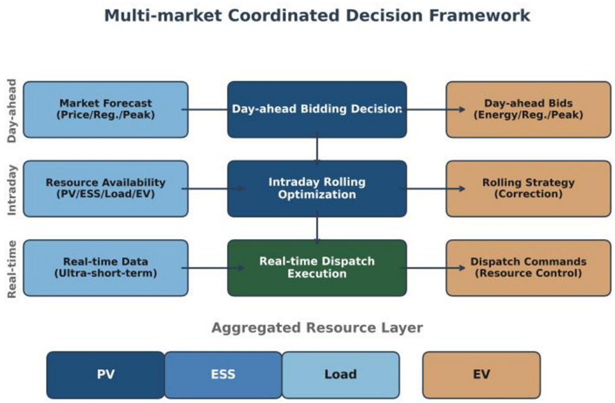

Fig. 1. Multi-market Coordinated Decision-Making Framework for Polymerizers

In the initial phase, aggregators determine bid volumes for each market based on market forecasts and resource availability; during the intra-day phase, they dynamically optimize bidding strategies using the latest forecast data; and in the real-time phase, they execute scheduling instructions and address deviations.

2.3 Bid Model for Multi-Market Integrated Aggregator

With the goal of maximizing the daily operating revenue for aggregators, the objective function is formulated as follows:

$$\max F = F_E + F_R + F_P - C_O - C_D \tag{1}$$

In the F,F_E,F_R,F_P,C_O,$C_D$formula: represents the total revenue of the aggregator (in yuan); represents the revenue from the electricity energy market (in yuan); represents the revenue from the frequency regulation ancillary service market (in yuan); represents the revenue from the peak shaving market (in yuan); represents the operating cost (in yuan); and represents the deviation penalty cost (in yuan).

The revenue of the electricity energy market is determined jointly by the day-ahead market and the decomposition curve of medium-to-long-term contracts.

$$F_E = \ _{t=1}^{T} [\lambda_t^{DA} \cdot P_t^{DA} + \lambda_t^{CT} \cdot P_t^{CT}] \cdot \Delta t \tag{2}$$

In the formula $\lambda_t^{DA}, P_t^{DA}, \lambda_t^{CT}, P_t^{CT}, \Delta t, T$: is the day-ahead market clearing price per MWh; is the day-ahead market bid volume in MW; is the decomposed price per MWh for the medium-to-long-term contract; is the decomposed volume for the medium-to-long-term contract in MW; is the duration of the period in hours; and is the total number of periods.

In particular, the electricity volume P_t^{CT} for medium- and long-term contracts is determined using the standard load curve decomposition method. Specifically, based on the historical electricity load characteristics of the aggregator, a typical daily load curve is selected as the decomposition benchmark, and the total electricity volume under medium- and long-term contracts is allocated proportionally across the various time periods:

$$P_t^{CT} = P^{CT,total} \cdot \frac{L_t^{typical}}{\sum_{t=1}^{T} L_t^{typical}} \tag{3}$$

In the formula: $P^{CT,total}$ represents the total electricity volume under medium- and long-term contracts, in MWh; $L_t^{typical}$ represents the typical load per unit for time period t. This decomposition method reflects the aggregator's actual electricity consumption patterns and avoids bidding discrepancies in the day-ahead market caused by an unreasonable allocation of contract volumes.

The revenue from the frequency modulation ancillary service market includes revenue from increased capacity and revenue from decreased capacity:

$$F_R = \sum_{t=1}^{T} [\lambda_t^{RU} \cdot R_t^{UP} + \lambda_t^{RD} \cdot R_t^{DN}] \tag{4}$$

In the formula $\lambda_t^{RU}, R_t^{UP}, \lambda_t^{RD}, R_t^{DN}$: is the price for increased frequency regulation capacity during the period, in yuan/MW; is the bid volume for increased frequency regulation capacity during the period, in MW; is the price for decreased frequency regulation capacity during the period, in yuan/MW; is the bid volume for decreased frequency regulation capacity during the period, in MW.

The revenue from the peak shaving market is calculated separately based on peak shaving and valley filling services:

$$F_P = \sum_{t=1}^{T} [\lambda_t^{PS} \cdot P_t^{PS} + \lambda_t^{VF} \cdot P_t^{VF}] \tag{5}$$

In the formula $\lambda_t^{PS}, P_t^{PS}, \lambda_t^{VF}, P_t^{VF}$: is the peak shaving compensation price per hour (RMB/MWh); is the peak shaving capacity in MW; is the valley filling compensation price per hour (RMB/MWh); is the valley filling capacity in MW.

2.4 Polymer Polymerizer Bid Constraints

1) Aggregating resource constraints.

a) Distributed photovoltaic power output constraints.

$$0 \le P_{i,t}^{PV} \le P_{i,t}^{PV,forecast} \tag{6}$$

In the formula $P_{i,t}^{PV}, P_{i,t}^{PV,forecast}$: represents the actual output of the photovoltaic unit during the period, in MW; represents the predicted output of the photovoltaic unit during the period, in MW.

b) Operational constraints of the energy storage system.

$$SOC_{j,t} = SOC_{j,t-1} + \eta_j^{ch} \cdot P_{i,t}^{ch} \cdot \Delta t - P_{j,t}^{dis} \cdot \Delta t / \eta_j^{dis} \tag{7}$$

$$SOC_j^{min} \leq SOC_{j.t} \leq SOC_j^{max} \tag{8}$$

$$0 \leq P_{i,t}^{PV} \leq u_{j,t} \cdot P_j^{ch,max} \tag{9}$$

$$0 \leq P_{j,t}^{dis} \leq (1 - u_{j,t}) \cdot P_j^{dis,max} \tag{10}$$

In the formula $SOC_{j,t}, \eta_j^{ch}, \eta_j^{dis}, P_j^{ch}, P_j^{dis}, SOC_j^{min}, SOC_j^{max}, u_{j,t}$: represents the energy storage's state of charge during the time period; and denote the charging and discharging efficiencies of the energy storage, respectively; and indicate the charging and discharging powers of the energy storage during the period; and define the upper and lower limits of the energy storage's state of charge; represents the energy storage's state variable for charging and discharging during the period, with a value of 1 for charging and 0 for discharging.

c) Controllable load regulation constraints.

$$P_{k,t}^{DR} = P_{k,t}^{base} + P_{k,t}^{UP} - P_{k,t}^{dn} \tag{11}$$

$$0 \leq P_{k,t}^{UP} \leq P_{k,t}^{UP,max} \tag{12}$$

$$0 \leq P_{k,t}^{dn} \leq P_{k,t}^{dn,max} \tag{13}$$

In the formula $P_{k,t}^{DR}, P_{k,t}^{base}, P_{k,t}^{UP}, P_{k,t}^{UP,max}, P_{k,t}^{dn,max}$: is the actual power of the controllable load during the period, in MW; is the reference power of the controllable load during the period, in MW; and are the upward and downward adjustment powers of the controllable load during the period, in MW; and are the upper limits for the upward and downward adjustment powers of the controllable load during the period, in MW.

2) Constraints imposed by market rules.

a) Energy balance constraint.

$$P_t^{DA} + P_t^{CT} = {}_{i} P_{i,t}^{PV} + {}_{j} (P_{j,t}^{dis} - P_{j,t}^{ch}) + {}_{k} P_{k,t}^{DR} + {}_{m} P_{m,t}^{EV} \tag{14}$$

In the formula $P_{m,t}^{EV}$: represents the charging and discharging power of the electric vehicle during the time period, measured in MW (positive for discharge, negative for charging).

b) Frequency modulation capacity mutual exclusion constraint.

$$R_t^{UP} + R_t^{DN} \leq R^{max} \tag{15}$$

In the formula R^{max} : represents the maximum frequency modulation capacity available from the aggregator, measured in MW.

c) Peak shaving period constraints.

$$P_t^{PS} \cdot P_t^{VF} = 0 \tag{16}$$

Equation (15) indicates that peak shaving and valley filling cannot be performed simultaneously within the same time period.

2.5 Model Solving Method

The aforementioned model is a Mixed Integer Linear Programming (MILP) problem, which can be solved using commercial solvers such as CPLEX or Gurobi. The solution process is as follows:

(1) Enter the previous day's market forecast data, resource parameters, and constraint conditions;

(2) Formulate the mathematical expressions for the objective function and constraints;

(3) Call the solver to perform optimization and obtain the optimal bidding quantities for each market;

(4) Output the solution results and perform a sensitivity analysis.

The time complexity of model solving primarily depends on the number of resources and market periods. For a typical scenario (100 resource units and 24 periods), the solution time typically falls within the second range.

3 An Optimized Scheduling Model for Aggregators Considering Risk Aversion

3.1 Selection of Risk Measurement Methods

Aggregators participating in the electricity market face various uncertainties, primarily including market price volatility risk, renewable energy output forecasting deviation risk, and load forecasting error risk. To CVaR effectively measure and manage these risks, this paper employs Conditional Value at Risk (CVR) as the risk measurement indicator.

CVaR compared with traditional risk measurement methods (such as variance), it offers the following advantages: (1) It satisfies the axioms of consistent risk measurement; (2) It reflects tail risks and is sensitive to extreme events; (3) It facilitates linearization and is suitable for integration into optimization models.

3.2 Conditioned Risk ($CVaR$)Value Model

The revenue function of the aggregator $f(x, \xi)$, x, ξ, $\beta \in (0,1)$, VaR is defined as follows, where is the decision variable and are random variables (e.g., market price, photovoltaic output, etc.). For a given confidence level, it is defined as:

$$VaR_{\beta}(X) = \max\{\alpha: P(F(x, \xi) \geq \alpha) \geq \beta\} \tag{17}$$

$CVaR$ defined as the conditional expectation when the return is below a certain level:

$$CVaR_{\beta}(X) = E[F(x, \xi)|F(x, \xi) \leq VaR_{\beta}(X)] \tag{18}$$

According to the research by Rockafellar $CVaR$and Uryasev, the calculation can be performed using the following auxiliary function:

$$CVaR_{\beta}(X) = \max_{\alpha}\{\alpha - \frac{1}{1-\beta}\cdot E[\alpha - F(x, \xi)]_{+}\} \tag{19}$$

In the formula αVaR: is an auxiliary variable that automatically converges to its optimal value during the optimization process.

For discrete scenario $\{s = 1,2..., S\}$,$CVaR$ sets, it can be linearized as:

$$CVaR_{\beta}(X) = \alpha - \frac{1}{1-\beta}\cdot \quad {}_{s} p_s \cdot \eta_s \tag{20}$$

$$\eta_s \geq \alpha - F_s(X), \eta_s \geq 0, \forall s \tag{21}$$

In the formula p_s, η_s, $F_s(X)$: is the probability of the scenario occurring; is the auxiliary variable of the scenario; is the profit function under the scenario.

3.3 Dual-layer Optimization Model

To address the interest coordination between aggregators and aggregated resources, a two-tier optimization model based on principal $CVaR$ -agent game theory is constructed. The upper tier represents the aggregator's decision-making layer, aiming to maximize expected returns and minimize risks; the lower tier constitutes the resource scheduling layer, with the objective of minimizing operational costs.

1) Upper-level Model (Aggregator Decision Layer).

The upper-level model aims to maximize the aggregate provider's expected return and comprehensive risk indicators.

$$\max_{x}\emptyset = E[F(x, y^{*}(x))] + \omega\cdot CVaR_{\beta}(X) \tag{22}$$

In the formula x, $y^{*}(x)$, $E[F]$, ω, $\omega > 0$, $\omega < 0$: is the decision variable of the aggregator, i.e., the bidding volume of the aggregator in each market; is the optimal solution of the underlying model; is the expected return; is the risk aversion coefficient, indicating risk aversion; is the risk preference; and is the risk neutrality.

The upper-level constraints include market bidding constraints and resource availability constraints:

$$0 \le x_t \le X_t^{max}, \forall t \tag{23}$$

2) Lower-level model (Resource Scheduling Layer).

The lower-level model optimizes x resource scheduling schemes given the upper-level decisions.

$$\min_y C(y) = \sum_t \left[\sum_j C_j^{ESS}(y_{j,t}) + \sum_k C_k^{DR}(y_{k,t}) + \sum_m C_m^{EV}(y_{m,t}) \right] \tag{24}$$

In the formula $C_j^{ESS}(y_{j,t})$,$C_k^{DR}(y_{k,t})$,$C_m^{EV}(y_{m,t})$:,represent the operating cost functions for energy storage, controllable loads, and electric vehicles, respectively.

The lower-level constraints include operational constraints for various resources (as defined in Equation 5-12) and power balance constraints:

$$\sum_j y_{j,t}^{ESS} + \sum_k y_{k,t}^{DR} + \sum_m y_{m,t}^{EV} = x_t, \forall t \tag{25}$$

3.4 Model Transformation and Solving

The dual-layer optimization KKT model can be transformed into a single-layer optimization problem through conditional constraints. The conditions for the lower-layer model include:

$$\nabla_y L(y^*, \lambda^*, \mu^*) = 0 \tag{26}$$

$$0 \le \lambda^* \perp g(y^*) \tag{27}$$

$$h(y^*) = 0 \tag{28}$$

In the formula L, λ, μ, g, h: is the Lagrange function; are the multipliers for the inequality constraint and the equality constraint, respectively; are the functions for the inequality constraint and the equality constraint, respectively.

Embed KKT the conditions into the upper-level model to obtain a single-layer optimization problem:

$$\max_{x,y,\lambda\mu} \phi = E[F(x, y)] + \omega \cdot CVaR_\beta(X) \tag{29}$$

Due to the nonlinear nature of the complementary constraints (26), the large M method is employed for linearization.

$$0 \le g(y) \le M \cdot z \tag{30}$$

$$0 \le \lambda \le M \cdot (1 - z) \tag{31}$$

In the formula:z $\in(0,1)$ is a variable; m is a sufficiently large positive number.

When selecting the value of M in the Big M method, it is necessary to balance the accuracy of the model solution with computational efficiency. If M is too small, the complementary relaxation condition may not be fully relaxed, resulting in a suboptimal solution; conversely, if M is too large, it may lead to numerical instability and increase the computational burden on the solver. This paper employs a hierarchical determination method based on problem characteristics: firstly, the initial value of M is set to $M_0 = 10^6$ based on the upper bound of the right-hand side of the lower-level model constraints; secondly, the value of M is gradually reduced using a binary search method, with a convergence criterion of a relaxation error of the complementary constraints less than 10^{-6}; In the final example, the value of M was determined to be $M = 10^5$. At this value, the model solution time was reduced by 23% compared to $M = 10^8$, whilst the deviation in the objective function value was less than 0.01%, thereby validating the appropriateness of the selected value of M.

The transformed single-layer model constitutes a mixed integer linear programming problem, which can be solved using either the branch-and-bound method or the cutting-plane method.

4 Case Study Analysis

4.1 Example Setting

To validate the proposed model's effectiveness, this chapter conducts simulation analysis using a typical case study. The scenario configuration includes: an aggregator integrating 10 MW of distributed photovoltaic capacity, a 20 MWh energy storage system with 10 MW power output, 20 MW controllable loads, and15MW electric vehicle aggregation capacity.

The market parameters are based on actual operational data from a provincial electricity market: the day-ahead market employs a 24-hour time-of-use pricing mechanism; the frequency regulation market comprises two types—upward and downward adjustments; and the peak shaving market features two periods—peak shaving and valley filling.

4.2 Parameter configuration

The main parameter configurations are shown in Table 1:

Table 1. Aggregator Resource Configuration

Resource Type	Capacity/Power	parameter	numeric value
Distributed Photovoltaic	10 MW	Prediction Error	15%
Energy Storage System	20 MWh/10 MW	Charging and discharging efficiency	90%

Resource Type	Capacity/Power	parameter	numeric value
Controllable Burden	20 MW	Adjustment depth	30%
Electric Vehicle	15 MW	Available time slot	00:00-07:00

The market parameters are set as follows: The day-ahead market electricity price forecast employs the weighted average method based on historical data; the frequency regulation capacity price is determined by market clearing results; and the peak shaving compensation price follows government-approved standards.

4.3 Interpretation of result

Based on the aforementioned parameter configuration, the CPLEX solver was employed to solve the model. The resource capacity composition of aggregator is shown in Figure 2.

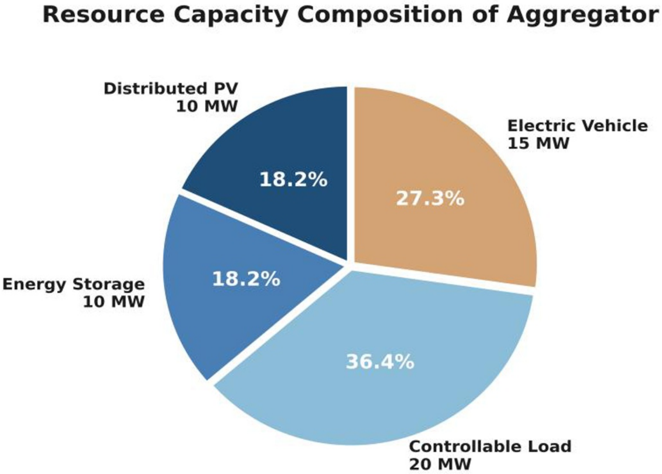

Fig. 2. Composition of Aggregator Resources

The numerical capacity configurations for the various types of resources aggregated by the aggregator are shown in Table 2:

Table 2. Detailed Allocation of Aggregator Resource Capacity

Resource Type	Capacity/Power	Percentage of total capacity	Primary regulatory capacity
Distributed Photovoltaic	10 MW	18.2	Power Output Control

Resource Type	Capacity/Power	Percentage of total capacity	Primary regulatory capacity
Energy Storage System	10 MW	18.2	Bidirectional charging and discharging control
Controllable Burden	20 MW	36.4	Demand Response Regulation
Electric Vehicle	15 MW	27.3	Controlled charging and discharging

The recent market electricity price forecast curve is shown in Figure 3. The price exhibits a distinct bimodal pattern, with peak hours (10:00–16:00) seeing prices exceed 500 yuan/MWh, while off-peak hours (1:00–6:00) average around200yuan/MWh.

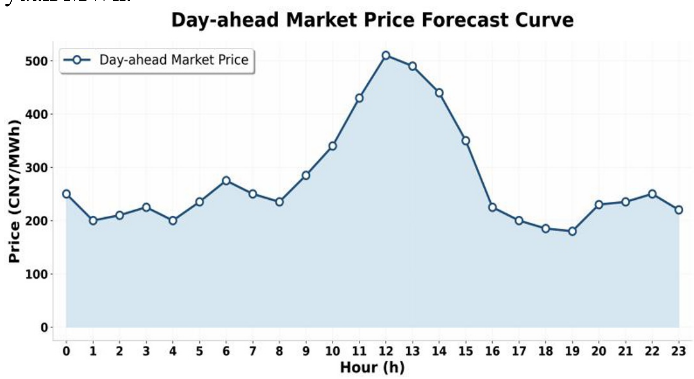

Fig. 3. Recent Market Electricity Price Forecast Curve

The multi-market coordinated bidding strategy adopted by aggregators is illustrated in Figure 4. Bidding volumes in the electricity energy market generally align with electricity price trends, with increased output during peak hours to maximize profits; bidding in the frequency regulation market is concentrated during morning and evening peak periods; peak shaving capacity in the peak shaving market is primarily provided during midday peak hours, while valley filling capacity is supplied during the early morning off-peak hours.

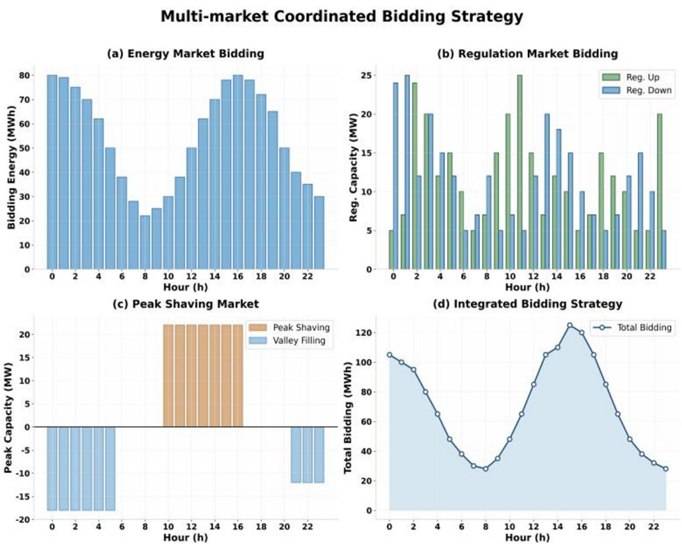

Fig. 4. Polymer Business Multi-market Joint Bidding Strategy

4.4 Comparison validation

To verify the advantages of the multi-market linkage strategy, four comparative scenarios were established: (1) participation solely in the electricity energy market; (2) electricity energy + frequency regulation market; (3) electricity energy + peak shaving market; (4) participation in multiple markets simultaneously. The daily return comparisons for each scenario are shown in Figure 5.

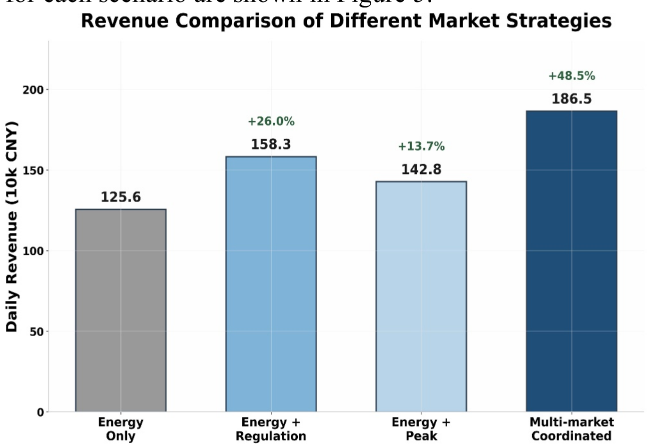

Fig. 5. Comparison of returns under different market participation strategies

As shown in Figure 5, the daily return of the multi-market coordinated participation strategy reached 1.865 million yuan, representing a 48.5% increase compared to participation in the electricity energy market alone, demonstrating the economic benefits of multi-market collaborative optimization.

The iterative convergence process of the dual-layer optimization model is illustrated in Figure 6. The model converged after 15 iterations, with both the upper-level objective function value (aggregated revenue) and the lower-level objective function value (system cost) stabilizing.

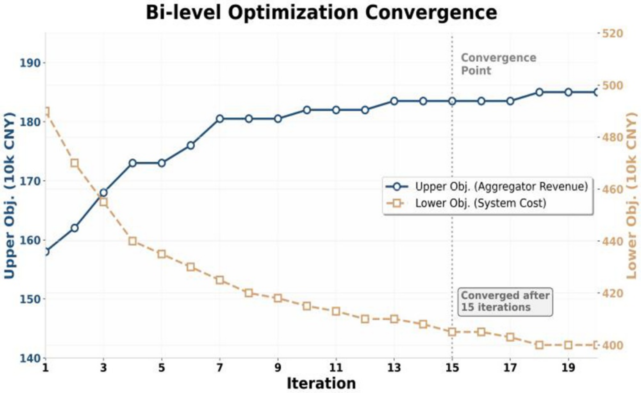

Fig. 6. Iteration convergence process of the dual-layer optimization model

4.5 Sensibility analysis

To analyze the impact of key parameters on the optimization results, a sensitivity analysis was conducted. Figure 7 illustrates the trade-off relationship between expected returns and CVaR risk values under different confidence levels of β.

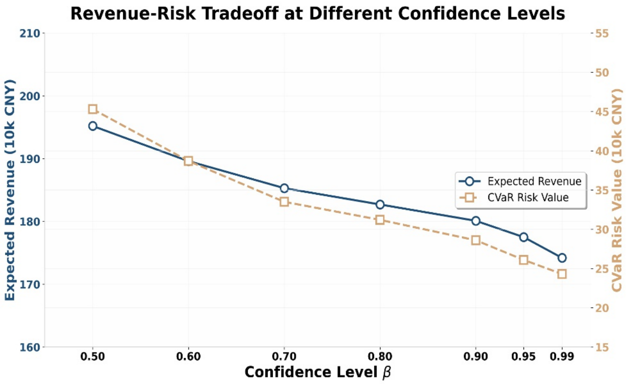

Fig. 7. The trade-off relationship between return and risk at different confidence levels

As shown in Figure 7, as the confidence level β increases, the CVaR risk value gradually decreases, but the expected return also decreases accordingly. When β increases from 0.5 to 0.99, the CVaR risk value decreases from 453,000 yuan to 243,000 yuan, and the expected return decreases from 1,952,000 yuan to 1,742,000 yuan. Further sensitivity analysis was conducted using additional discrete confidence levels. When β is set to 0.7, 0.8, 0.85, 0.9, and 0.95, the expected returns are 1.896 million, 1.853 million, 1.827 million, 1.801 million, and 1.775 million yuan, respectively, with corresponding CVaR risk values of 387,000, 335,000, 312,000, 286,000, and 261,000 yuan. It can be seen that when β falls within the range of 0.8 to 0.9, the slope of the risk-return trade-off curve changes most significantly, making this the critical range for aggregators' risk preference decisions. Aggregators can select an appropriate confidence level based on their own risk preferences.

Figures 8 illustrate the impact of electricity price forecasting errors, load forecasting errors, and energy storage capacity on expected returns.

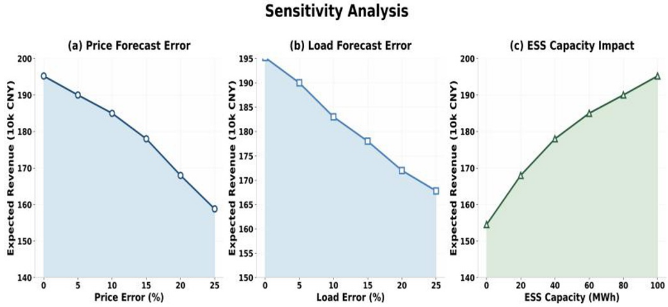

Fig. 8. Sensitivity Analysis

As shown in Figure 8: (1) The electricity price forecasting error significantly impacts revenue; when the error increases from 0% to 25%, revenue decreases by 18.6%; (2) The load forecasting error has a relatively smaller effect, with revenue dropping by 14.1% at an error level of 25%; (3) Increasing energy storage capacity substantially enhances revenue—when capacity rises from 0% to 100 MWh, revenue increases by 26.4%.

5 Conclusion

This study addresses the participation of new types of market entities in electricity market transactions by developing a multi-market coordinated aggregator bidding model and an optimized dispatch model incorporating risk aversion considerations. The key findings are as follows: (1) The proposed multi-market coordinated bidding model effectively aligns aggregators 'bidding strategies across the electricity energy market, frequency regulation market, and peak shaving market, achieving a 48.5% increase in daily revenue compared to single-market participation strategies, demonstrating the economic benefits of multi-market synergy. (2) By employing the CVaR risk measurement approach, a two-tier optimization model incorporating risk aversion is established, enabling an effective balance between expected returns and risk. Sensitivity analysis reveals that the choice of confidence level significantly impacts optimization outcomes. (3) Case studies validate the model's effectiveness and the convergence of the solution algorithm. Sensitivity analysis further elucidates how electricity price forecasting accuracy, load forecasting precision, and energy storage configuration influence aggregator profitability, providing actionable insights for practical operations.

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