Method For Medium- to Long-Term Time-of-day Trading Decision in Agent-Based Power Purchase of Grid Enterprises Considering Cvar

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Abstract. To further promote fair participation of grid enterprise agent power purchasers in electricity spot trading, it is necessary to strengthen the connection mechanism between agent power purchase activities and the medium- to long-term electricity market and spot market. Given the uncertainty in the electricity demand of agent users and market prices, a reasonable allocation of power purchase proportions in multi-time scales and multi-product electricity trading can help reduce cash flow risks for grid enterprises and promote the safe and stable operation of the electricity market. The optimal strategy is determined using the Monte Carlo simulation method, and the effectiveness of the proposed model and method is validated through numerical examples. The results demonstrate a reduction in conditional risk value and other relevant indicators, providing grid enterprises with valuable references for mitigating trading risks and formulating agent power purchase strategies.

Keyword: Electricity market; Transaction Decision Model; Power grid enterprise; Proxy electricity purchase; CVaR

1 Introduce (Background)

In October 2021, the National Development and Reform Commission (NDRC) of China successively issued the *Notice on Further Deepening the Market-oriented Reform of Coal-fired Power Generation On-grid Electricity Pricing* and the *Notice on Organizing the Work of Grid Enterprise Agent Power Purchase*, which clearly stated the need to establish and improve market-based power purchase methods for grid enterprises, effectively manage market price fluctuations, and ensure the smooth implementation of the agent power purchase mechanism. In September 2023, the NDRC and the National Energy Administration (NEA) of China issued the "Basic Rules for Electricity Spot Market (Trial)" (referred to as the "Basic Rules"), which stipulate that grid enterprise agent power purchasers should participate equally in spot trading

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and bear responsibilities and obligations fairly.

To ensure the fair operation of the electricity market and avoid the situation where grid enterprises act as both referees and players, in the electricity market, grid enterprise agent power purchases primarily participate by not declaring transaction prices but accepting the market-determined prices. In the medium- to long-term market, the settlement of grid enterprise agent power purchase transactions is based on medium- to long-term time-of-day prices. In the spot market, the settlement of actual deviation electricity quantities in agent power purchase transactions is based on spot market prices. Although grid enterprise agent power purchases cannot actively participate in the electricity market, they can still implement transaction strategies for agent power purchase through position management of electricity market trading varieties across various time scales.

However, in the current situation, grid enterprise agent power purchasers face the following challenges in their power purchase activities for industrial and commercial users:(1)The difficulty lies in the grid enterprises' challenge to connect their medium- to long-term time-of-day trading decisions with the spot market in order to ensure the stability of agent power purchase prices to a certain extent and reduce cash flow risks; (2)The uncertainty surrounding industrial and commercial user demand and market prices adds greater pressure to the accuracy of grid enterprises' power purchase decision parameter predictions.Taking all factors into account, it has become a critical issue for grid enterprise agent power purchasers to carefully assess risks, develop appropriate market trading strategies, and reduce cash flow risks while participating in medium- to long-term time-of-day trading that connects with the spot market. Addressing these challenges is vital for enhancing the stability of the electricity market and is an urgent area of research and resolution for grid enterprises.

Indeed, the current research on market trading strategies primarily focuses on market participants, including power generation companies, electricity retailers, and wholesale electricity users. However, there has been a lack of research specifically focused on grid enterprise agent power purchase strategies.Reference [1] proposes an approach for formulating medium- to long-term trading strategies based on trading varieties and trading time sequences. Reference [2] presents transaction strategies for distributed renewable energy aggregation participating in the electricity market under dynamic pricing schemes. Reference [3] establishes an analytical model using Monte Carlo simulation to quantify the impact of different trading strategies on the revenue of electricity retailers, thereby identifying the most profitable trading scheme. Reference [4] focuses on energy storage retailers and investigates how to develop optimal trading strategies considering both the purchase and sale of electricity as bilateral demand response. It should be noted that grid enterprise agent power purchase strategies differ from those of market-oriented entities. While market-oriented entities typically aim to maximize their profits, grid enterprises, acting as referees, should prioritize minimizing business risks when engaging in agent power purchase activities.

The current research, both domestically and internationally, on risk measurement models predominantly includes ARCH models, GARCH models, VaR models, and CVaR models. Reference [5] systematically investigates multiple GARCH models for risk value measurement and provides insights into the applicable scenarios for GARCH models. Reference [6] examines the influence of background risk on portfolio selection within the framework of mean-VaR and mean-CVaR. Based on the literature survey, it is believed that the CVaR method addresses the shortcomings of other risk assessment methods by considering the inadequacies in capturing the fat-tailed nature of returns. Additionally, CVaR exhibits convexity and is computationally simpler, making it easier to optimize investment strategies based on CVaR. When dealing with the high price volatility in the electricity market, CVaR enables comprehensive and intuitive risk measurement of trading strategies.

This article aims to develop an optimal power purchase decision model for grid enterprise agent users in the medium- to long-term time-of-day trading market, considering the uncertainties of user electricity demand and market trading prices. The model takes into account the conditional value at risk (CVaR) and focuses on minimizing risk while maximizing expected returns. Firstly, the article constructs pricing and trading models for grid enterprise agent power purchase in the medium- to long-term time-of-day trading market. Next, using Monte Carlo simulation, the model solves for the power purchase costs that minimize risk under the expected return and determines the optimal power purchase proportions for different time periods within the medium- to long-term time-of-day trading. Finally, the effectiveness of the model is demonstrated through numerical examples.

2 Research method

The fundamentals of CVaR

When X represents an investment portfolio vector and a random vector $Y \epsilon R^m$ (R^m Representing an m-dimensional real number space) represents the stochastic factors of the market, the loss function of X can be expressed as $f(X,Y)$; Assuming that the joint probability density function of Y is represented by $p(Y)$, for a given X, the probability value of $f(X,Y)$ caused by Y not exceeds a certain threshold value α (α represents a specific loss level) is:

$$\Psi(X,\alpha)=\int_{f(X,Y)} p(Y)dY \tag{1}$$

Where, $X \in \Omega$, Ω is a subset of n-dimensional real number space R^n , and $\Psi(X,\alpha)$ represents the feasible set of investment portfolio; $\Psi(X,\alpha)$ is the loss cumulative distribution function under X, and $\Psi(X,\alpha)$ is nondecreasing and right-continuous with respect to α .

When the confidence level β that caused $f(X,Y)$ by Y does not exceed the threshold value α , Let $\alpha_\beta(X)$ and $\phi_\beta(X)$ respectively represent the VaR (Value at Risk) and CVaR (Conditional Value at Risk) values associated with the loss function $f(X,Y)$ of investment portfolio X. The values a and b can be respectively calculated using equations (2) and (3):

$$\alpha_\beta(X) = \min\{\alpha \in R:\ \Psi(X,\alpha) \geqslant \beta\} \tag{2}$$

$$\phi_\beta(X) = \frac{1}{1-\beta}\int_{f(X,Y) \geqslant \alpha_\beta(X)} f(X,Y)\,p(Y)\,dY \tag{3}$$

The value $\phi_\beta(X)$ obtained from equation (3) is the CVaR (Conditional Value at Risk) value when the loss exceeds $\alpha_\beta(X)$. Due to the difficulty in obtaining an analytical expression for $\alpha_\beta(X)$, a literature proposes an approximate method by introducing a transformation function $F_\beta(X,\alpha)$ to replace $\phi_\beta(X)$ in order to simplify the calculation of CVaR.

$$F_\beta(X,\alpha) = \alpha + \frac{1}{1-\beta}\int_{Y \in R^m} (f(X,Y)-\alpha)^+\, p(Y)\,dY \tag{4}$$

In the equation, $(f(X,Y)-\alpha)^+$ represents the substitution of $\max\{f(X,Y)-\alpha, 0\}$

When obtaining an analytical expression for $p(Y)$ is challenging, it is common to estimate the integral term in equation (4) using historical data of Y or Monte Carlo simulation sample data. Let $Y_1, Y_2, \ldots, Y_N$ be N sample data points of Y, then the estimated value of function $F_\beta(X,\alpha)$ is:

$$\widehat{F}_\beta(X,\alpha) = \alpha + \frac{1}{N(1-\beta)}\sum_{k=1}^{N} (f(X,Y_k)-\alpha)^+ \tag{5}$$

3 Risk control model for proxy purchasing of electricity under medium- to long-term time segmentation trading

Assuming that the next-month commercial proxy purchasing price P_i includes the next-month average on-grid electricity price P_a, historical deviation electricity cost discount P_{bias}, and other additional charges P_{add}.

$$P_i = P_a + P_{bias} + P_{add} \tag{6}$$

In the next month, the total electricity consumption of commercial proxy purchasing is denoted as Q_{all}. Considering the policy of prioritizing power dispatch for proxy purchasing, a portion of the generated electricity, denoted as Q_{prior}, is allocated to the commercial proxy purchasing business at a price of P_{prior}. Therefore, the cash flow generated by the prioritized power dispatch is denoted as $C_{prior\ cashflow}$.

$$C_{prior\ cashflow} = Q_{prior}(P_i - P_{prior}) \tag{7}$$

In addition to the prioritized electricity quantity, the remaining electricity quantity needs to be acquired from the medium- to long-term time segmentation market. Let $\overrightarrow{P_{buy}}$ represent the comprehensive purchasing price for the three medium- to long-term time segmentation markets, including the annual, monthly, and intra-month markets for the following month. The expression can be given as:

$$\overrightarrow{P_{buy}} = \left\{ \sum_{t=1}^{T_1} \sum_{V_Y=1}^{V_Y} P_{v,t}^{Y}, \sum_{t=1}^{T_2} \sum_{V_M=1}^{V_M} P_{v,t}^{M}, \sum_{d=i}^{D} \sum_{t=1}^{T_3} \sum_{V_D=1}^{V_D} P_{v,t}^{D} \right\} \tag{8}$$

Where T_1 represents the total number of time segments in the medium- to long-term annual trading, V_Y represents the number of trading varieties in the annual trading, $P_{v,t}^{Y}$ represents the annual trading price for trading variety v in time segment t. T_2 represents the total number of time segments in the medium- to long-term monthly trading, V_M represents the number of trading varieties in the monthly trading, $P_{v,t}^{M}$ represents the monthly trading price for trading variety v in time segment t. T_3 represents the total number of time segments in the medium- to long-term intra-month trading, D represents the total number of trading days within a month, V_D represents the number of trading varieties in the intra-month trading, and $P_{v,t}^{D}$ represents the intra-month trading price for trading variety v in time segment t.

$\vec{x}$ represents the purchasing ratio for the next month in the three medium- to long-term time segmentation markets, including the annual, monthly, and intra-month markets. The expression can be given as:

$$\vec{x} = \left\{ \sum_{t=1}^{T} \sum_{V_Y=1}^{V_Y} x_{v,t}^{Y}, \sum_{t=1}^{T} \sum_{V_m=1}^{V_M} x_{v,t}^{m}, \sum_{t=1}^{T} \sum_{V_d=1}^{V_D} x_{v,t}^{d} \right\} \tag{9}$$

$x_{v,t}^{Y}$ represents the annual purchasing ratio for trading variety v in time segment t. $x_{v,t}^{m}$ represents the monthly purchasing ratio for trading variety v in time segment t. $x_{v,t}^{d}$ represents the intra-month purchasing ratio for trading variety v in time segment t.

The cash flow generated from the proxy purchasing of electricity by the grid enterprise from medium- to long-term time segmentation trading is denoted as $C_{buy\ cashflow}$.

$$C_{buy\ cashflow} = (Q_{all} - Q_{prior}) \cdot \vec{x} \cdot \left(P_i - \overrightarrow{P_{buy}}\right)^T \tag{10}$$

The revenue generated from the proxy purchasing of electricity by the grid enterprise in the next month can be represented as:

$$
\begin{aligned}
\mathrm{Pro} &= \mathrm{C}_{\text{buy cashflow}} + C_{prior\ cashflow} \\
&= \left(Q_{all} - Q_{prior}\right) \cdot \vec{x} \cdot \left(P_i - \overrightarrow{P_{buy}}\right)^T + Q_{prior}\left(P_i - P_{prior}\right) \\
&= \left(Q_{all} - Q_{prior}\right) \cdot \left\{ \sum_{t=1}^{T} \sum_{V_Y=1}^{V_Y} x_{v,t}^{Y}, \sum_{t=1}^{T} \sum_{V_m=1}^{V_M} x_{v,t}^{m}, \sum_{t=1}^{T} \sum_{V_d=1}^{V_D} x_{v,t}^{d} \right\} \\
&\cdot \left\{ P_i - \left\{ \sum_{t=1}^{T_1} \sum_{V_Y=1}^{V_Y} P_{v,t}^{Y}, \sum_{t=1}^{T_2} \sum_{V_M=1}^{V_M} P_{v,t}^{M}, \sum_{d=i}^{D} \sum_{t=1}^{T_3} \sum_{V_D=1}^{V_D} P_{v,t}^{D} \right\} \right\}^T \\
&+ Q_{prior}\left(P_i - P_{prior}\right)
\end{aligned} \tag{11}
$$

The expected revenue from the proxy purchasing of electricity by the grid enterprise in the next month is:

$$
\mathrm{E(Pro)} = \mathrm{E}\left(\mathrm{C}_{\text{buy cashflow}} + C_{prior\ cashflow}\right) \tag{12}
$$

Where $\bar{y} = \begin{Bmatrix} Q_{all}, \sum_{t=1}^{T_1} \sum_{V_Y=1}^{V_Y} P_{v,t}^{Y}, \sum_{t=1}^{T_2} \sum_{V_M=1}^{V_M} P_{v,t}^{M}, \\ \sum_{d=i}^{D} \sum_{t=1}^{T_3} \sum_{V_D=1}^{V_D} P_{v,t}^{D} \end{Bmatrix}$ is the market factor and $\mathrm{p}(\bar{y})\mathrm{represent}\bar{y}$ is the density function of $\mathrm{p}(\bar{y})\mathrm{represent}\bar{y}$, the conditional value at risk (CVaR) of the proxy purchasing of electricity by the grid enterprise in the next month is:

$$
CVaR_k = E[f(P_i, \bar{x}, \bar{y}) | f(P_i, \bar{x}, \bar{y}) \geq VaR_k] \tag{13}
$$

To avoid losses in the cash flow of the grid enterprise, it is necessary to minimize the aforementioned conditional value at risk. In addition, various constraints need to be further considered, as shown in the following formula:

$$
\begin{cases}
\sum_{t} x_t = 1 \\
\beta_t^{historical} \cdot (1 - \delta_t^{+}) \leq x_t \leq \beta_t^{historical} \cdot (1 + \delta_t^{+}) \\
z_j = \sum_{t} \left(-x_j \cdot \epsilon_{j,t}\right) - y
\end{cases} \tag{14}
$$

Where $\beta_t^{historical}$ represents the typical decomposition ratio of medium- to long-term electricity obtained in time segment t, and δ_t^{+} represents the adjustment range of the medium- to long-term decomposition curve based on the typical decomposition ratio.

4 Example analysis

Using the Monte Carlo simulation method and taking the electricity quantity and prices of the next month in a specific region as the base data, 40,000 combinations of selling prices and trading strategies were randomly selected under 2,000 market scenarios. A total of 2,105 combinations that satisfy the constraints were obtained. The minimum-risk strategy resulted in a user electricity price of 354.32 yuan. The long-term time segmentation trading strategy is shown in the figure 1 below.

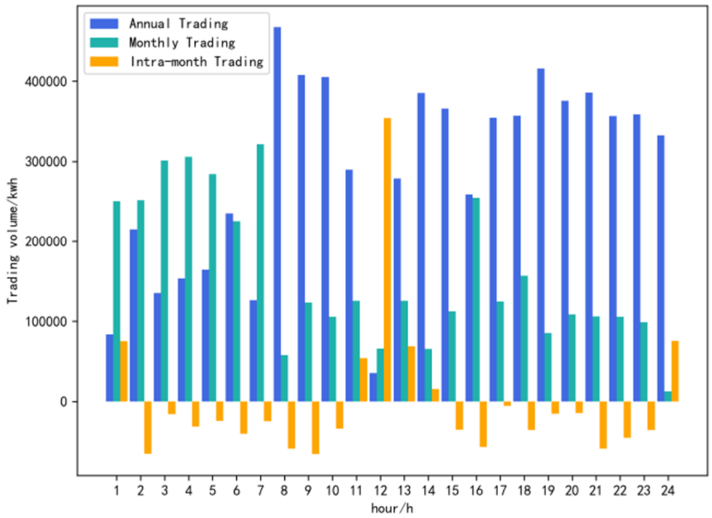

Figure 1. Long-term time segmentation trading decisions considering CVaR.

Where the total purchasing ratios for annual trading, monthly trading, and intra-month trading are 64.31%, 35.98%, and -0.29% respectively, the proportion of medium- to long-term trading in each time segment is shown in the table below. Under this trading strategy, the CVaR is 65412.35, and the expected profit is 1.8526 million yuan. The proportions of medium- to long-term time segmentation trading is shown in the Table 1 below.

Table 1. Proportions of medium- to long-term time segmentation trading considering CVaR.

Time segment	Annual - Trading	Monthly - Trading	Intra-month - Trading
1	20.40%	61.19%	18.42%
2	53.64%	62.67%	-16.30%
3	32.15%	71.59%	-3.74%
4	35.90%	71.46%	-7.35%
5	38.73%	66.96%	-5.69%
6	55.95%	53.61%	-9.56%
7	29.88%	75.92%	-5.80%
8	100.18%	12.41%	-12.59%
9	87.58%	26.53%	-14.10%
10	84.96%	22.19%	-7.15%
11	61.71%	26.76%	11.53%
12	7.78%	14.45%	77.77%
13	58.88%	26.58%	14.53%
14	82.60%	14.02%	3.38%
15	82.59%	25.40%	-8.00%
16	56.66%	55.79%	-12.45%
17	74.87%	26.29%	-1.16%

18	74.63%	32.79%	-7.42%
19	85.60%	17.59%	-3.19%
20	79.96%	23.15%	-3.10%
21	89.15%	24.47%	-13.62%
22	85.49%	25.37%	-10.86%
23	85.05%	23.41%	-8.46%
24	79.00%	3.03%	17.97%

5 Conclusion and findings

Due to the nature of the current grid enterprise, the proxy purchasing of electricity business typically does not involve spot market declaration. Instead, it participates in the electricity spot market by accepting spot market prices through the deviation volume. In the context of an increasingly improved connection mechanism between the medium- to long-term electricity market and the spot market, this paper focuses on the proxy purchasing of electricity by grid enterprises for commercial users and proposes a decision-making method for medium- to long-term time segmentation trading, considering conditional value at risk. Unlike market participants who aim to maximize profits in electricity market bidding, the proxy purchasing behavior of grid enterprises pays more attention to the cash flow risk level of the grid enterprise. By utilizing conditional value at risk in trading decision design, the cash flow risk level of the grid enterprise can be effectively reduced. This provides guidance and decision-making basis for the proxy purchasing strategy of grid enterprises for commercial users, facilitating medium- to long-term purchasing decisions and effectively mitigating market risks.

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