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Electricity Retailer Trading Portfolio Optimization Considering Risk Assessment in Chinese Electricity Market

Bo Sun, Fan Wang*, Jingdong Xie, Xin Sun

College of Economics and Management, Shanghai University of Electric Power, Yangpu District, Shanghai 200120

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ABSTRACT

The Chinese electricity market underwent a significant reform in 2015 resulting in its complete liberalization on the sell-side. Electricity retailers now seeking to adapt to the electricity market are focused on trading portfolio optimization based on risk assessment, which can be performed by classifying and combining possible electricity purchases and sales on mid-long-term and spot markets. The scenario method is used in this study to simulate random risk variables (the real-time price and user demand), then a comprehensive decision-making/risk assessment model for electricity trading portfolio optimization is established with the goal of profit maximization. The conditional value-at-risk (CVaR) serves as the risk assessment index for electricity purchases and sales. Four combinations of electricity trading modes are assessed as a case study. The most basic trading mode is significantly affected by the risk aversion factor in regards to purchases scale and expected profit, which validates the proposed model. The time-of-use (TOU) price and real-time price guaranteeing the bottom and top price as a transaction mode are found to affect the scale of electricity purchases and the expected profit of the electricity retailer. Proportional distribution plans for three respective retail transactions are determined according to electricity retailers' different attitudes toward risk.

1. Introduction

In March 2015, the Central Committee of the Communist Party of China and the State Council issued "Several Opinions on Further Deepening the Reform of the Electric Power System (Document No. 9 issued by the General Office of the CPC Central Committee [2015])" to reform China's power system. The reform targeted the sell-side of "multi-channel cultivation of the competitive main players in the electricity retail market and the orderly opening of the electricity retail transactions to social capital" as one of the most important tasks [1]. Liberalizing the electricity retail market, encouraging further competition, and forming a new "multi-buyer-multi-seller" structure are notable development trends after the reform of China's power sales system. Reforms also may serve to improve the quality of electricity retail services and the satisfaction of power users while ensuring safe and reliable energy supply. Appropriate reform may also optimize the allocation of resources.

Electricity market-oriented transactions also began alongside this reform. The system initially centered on mid-long-term physical transactions, and the trading frequency was annual and monthly. A spot market was then gradually established. Mid-long-term market transactions are now conducted nationwide on the Chinese electricity market while the electricity spot market is in the early stages of development, and it has only been piloted in certain provinces (e.g., Guangdong). The electricity financial market (such as options market and futures market, etc.) has not yet begun to be constructed. At present, mid-long-term transactions in China mainly include annual bilateral transactions, monthly bilateral transactions, monthly concentrated bidding transactions and monthly nominal quotation transactions [2]. The electricity spot market transactions in Guangdong Province include day-ahead market and real-time market transactions [3]. In a word, China currently adheres to mid-long-term transactions while vigorously advancing the construction of the electricity spot market.

Electricity retail transactions in China were liberalized after the introduction of a new power reform plan. Various types of electricity retailers have sprung up since entered an increasingly competitive market. New electricity retailers in China must swiftly gain a foothold in the complex and changing competitive electricity retail market if they are to effectively maximize their profits. Retailers that directly participate in Chinese electricity market-oriented transactions face risks inherent to frequent real-time price fluctuations and user demand uncertainty [4-5]. These retailers participate in a variety of transactions as they attempt to hedge risks. Today's electricity retailers in China must develop strategies for purchasing electricity from the current typical Chinese electricity market. They also face the problem of planning and

* Corresponding author
E-mail address: wang_fan_fiona@163.com (F. Wang).

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distribution of flexible and diverse electricity retail contracts as the retailers respond to various load characteristics and user purchases preferences. Therefore, it is necessary to study the optimization decisions made by the electricity retailer in terms of electricity purchases and sales at the same time. Risk must be reasonably allocated according to this optimization of electricity purchases and sales across the transaction portfolio. Ultimately, the retailer must secure the proper strategy to maximize profits while effectively avoiding risks.

The existing research on electricity retailers mainly centers on profit model discussion, marketing strategy formulation and bidding issues. Authors in [6] discussed the profit model of the electricity retailer under the background of new power reform according to the current development of Chinese electricity market. Authors in [7] studied the influence of distributed power on the marketing strategy of electricity retailers. Authors in [8] studied the decision-making problem of electricity retailers with multiple electricity purchases channels. Authors in [9] and [10] studied the effect of user price mechanism on bidding strategies of electricity retailers. The formulation of bidding strategies for electricity retailers was studied when conducting bilateral transactions and spot transactions respectively [11-12]. These studies did not involve decision-making problems of electricity retailers considering risk assessment. Authors in [13] considered a variety of electricity purchases businesses to model risk factors by conditional value-at-risk and determined the best electricity sales price for consumers and electricity purchases strategies on the retailer side. Authors in [14] have investigated risk management in electricity retailer's investment portfolios with multiple electricity purchases contracts, the goal of which is maximizing the return of the investment portfolio according to the drawdown risk. Authors in [15] compared models of different electricity purchases source combinations from the perspective of electricity retailers with the objective of maximizing returns and constraining risk within the day-ahead market. An inner-outer two-layer model system based on stochastic mixed-integer optimization was proposed for electricity retailer's day-ahead electricity market bidding decision-making which includes the conditional value-at-risk (CVaR) of profit in the objective function [16]. Authors in [17] studied the behavior of electricity retailers in purchasing and selling electricity from the perspective of risk control based on the portfolio optimization theory. Authors in [18] studied the impact of the real-time price uncertainty on the retailer's optimization of electricity purchases decisions.

However, the studies discussed above only deal with decisions on the supply-side and neglected the impact of the retail transactions in the sell-side or demand response on the electricity retailers' electricity purchases and sales strategies. Authors in [19] presented a model for optimizing retailer portfolios which includes risk-return optimization under Markowitz theory and places emphasis on the interaction between retailers and end-use customers. Authors in [20] focused on the impact of user demand elasticity on retailer profitability by considering the user demand response. Authors in [21] proposed a real-time pricing (RTP) framework for various users and provided various risk-based strategies for electricity retailers by implementing downside risk constraints method. A stochastic profit maximization model for the demand response aggregator has also been proposed, in which risk is taken into account as per the CVaR measure [22]. Authors in [23] built the Capital Asset Pricing Model (CAPM) to determine the retail electricity price for end users and used the Risk Adjusted Recovery on Capital (RAROC) to quantify the price risk involved. Other researchers have designed electricity price packages for electricity retailers by enhancing the stickiness of the users [24]. Authors in [25] studied the impact of demand response on power system optimization decision in different markets: day-ahead market and real-time market. These studies only focused on demand-side issues.

There has been a great deal of research on electricity retailers, but in the context of the Chinese electricity market, few previous researches have considered the influence of both the supply- and sell-side on electricity retailers. The researches discussed above mainly focused on risk assessment on the supply-side and on various bidding strategies. They proposed electricity purchases strategies applicable to multi-level electricity markets and corresponding risk management methods. Although CVaR has been occasionally utilized, CVaR models in the literature do not involve both electricity purchases and sales transactions. Sell-side transactions optimization and user demand responses may be used to improve the electricity retailer's transaction strategies, but these approaches generally do not consider electricity retail contracts. In actuality, the electricity retailer's management must target optimization strategies to both the supply-side and sell-side, so the optimization of single-side transactions is not sufficient to ensure the stable and sustainable development of electricity retailers.

Therefore, the transactions in supply- and sell-side, including retail contracts and demand and price elasticity, in the current Chinese electricity market are investigated in this paper. Transactions on both the supply-side and sell-side were combined to model various portfolios. A set of the electricity purchases and sales transaction portfolio can be obtained through changing the ratio operator of each retail transaction (implementing one or more types of transactions on the sell-side). The goal is to optimize the combination and proportional distribution of the electricity retailer in the market and to determine the impact of retail proportions on the profits of the electricity retailer.

The contributions of this paper can be summarized as follows.

1) Current transaction models for electricity purchases in the Chinese electricity market are summarized, including the mid-long-term market, day-ahead market, and real-time market. Retail transactions including the fixed price, time-of-use (TOU) price (different electricity prices during different periods), and real-time price guaranteeing the bottom and top price are reviewed.
2) On the basis of the current Chinese electricity market with multi-level electricity market and different retail contract transactions, a comprehensive electricity trading optimization model of decision-making and risk assessment for both the supply- and sell-side based on CVaR is established.
3) Recommendations for electricity purchases and sales strategies are proffered to electricity retailers with different risk attitudes. These recommendations also involve proportional distribution plans tailored specially to three respective retail transactions.

The rest of this paper is organized as follows. In Section 2, retailers' transactions are defined according to the supply-side and sell-side. Section 3 presents the comprehensive model of decision-making and risk assessment for electricity trading optimization based on CVaR. The case study and its results are reported in Section 4. Section 5 provides a brief summary and conclusion.

2. Analysis of China's electricity retailers

To comprehensively investigate electricity trading optimization of electricity retailers based on the current Chinese electricity market, this study was conducted under the following assumptions:

1) The subject is assumed to be an independent electricity retailer. Other types of electricity retailers (e.g., those with distribution system operation rights, those with self-supplying power plants and comprehensive energy retailers) are not considered to compete in the electricity market. The electricity retailers' own plans are emphasized for maximizing profitability in their electricity transactions.
2) It is assumed here that the electricity retailer only conducts electricity transactions, not value-added business. Today's Chinese electricity market is in the initial stages of construction. Its retailers mainly rely on electricity transactions to gain profits; the electricity transactions are the retailers' primary function and value-added business only plays an auxiliary role. Value-added business may play a more important role as the market further develops.
3) It is assumed that the electricity purchases market includes mid-long-term, day-ahead and real-time markets on a time scale. Only

bilateral contract transactions are considered in the mid-long-term market. Other financial markets (e.g., options markets) do not currently exist in Chinese electricity market.

2.1. Electricity transaction modes

In the electricity markets, a retailer has the role of a mediator entity that purchases electricity from supply-side and sells it on the sell-side to those consumers that do not participate directly in the electricity markets. The basic core business conducted by electricity retailers is electricity trading currently, though they also are engaged in some value-added business which encompass fault handling, user equipment maintenance, energy-saving services, etc. This paper focuses on electricity transaction practices. Electricity transactions of electricity retailers take place on the supply-side and the sell-side.

On the supply-side, electricity retailers can purchase electricity by signing different physical contracts according to their own needs in multi-level electricity market. The retailer purchases a certain amount of electricity in the mid-long-term market and the day-ahead market in advance, then strikes a balance between the purchased electricity and the electricity for sale through the real-time market.

On the sell-side, end users are consumers. To best cater to the preferences of the majority of users, the electricity retailer provides them with a variety of price packages. The sell-side transaction of electricity retailers can be divided into fixed price, TOU price, and real-time price guaranteeing the bottom and top price contracts. The transaction model of the electricity retailer is shown in Fig. 1.

2.2. Transactions on supply-side

In the Chinese electricity market, the supply-side transactions are mainly conducted in the mid-long-term market, day-ahead market, and real-time market.

2.2.1. Electricity purchases in the mid-long-term market

The mid-long-term electricity purchases transactions of the electricity retailer referred to in this paper are bilateral contract transactions. Purchases are made in the mid-long-term market based on a contract signed by the supplying and demanding parties in advance. The physical delivery of electricity at a fixed price is agreed upon in the contract within a certain period of time. The price and quantity of such a contract are determined after signing; thus, this purchases behavior occurs prior to the spot market and can be used to hedge the volatility and variability of spot market prices [26]. In the electricity purchases and sales strategies discussed here, "mid-long-term transactions" between electricity retailers and generators mainly refer to retailer purchases made by signing various bilateral mid-long-term contracts with generators according to user demand forecasts in the jurisdiction area (mainly annual bilateral and monthly bilateral transactions). These contracts result in the satisfaction of long-term user demand [27].

The purchases cost of the electricity retailer in the mid-long-term market is formulated as follows:

$$C_{\mathrm{B}} = \sum_{t \in T} L_{\mathrm{B}}^{t} \cdot p_{\mathrm{B}} \tag{1}$$

where T is the entire observation period; C_{B} is the purchases cost of the retailer in the mid-long-term market during the observation period; t is the basic observation period; L_{B}^{t} is the contract electricity of the transaction in the mid-long-term market during the t^{th} period; p_{B} is the transaction contract price in the mid-long-term market.

2.2.2. Electricity purchases in the day-ahead market

The "day-ahead market" refers to a trading market one day prior to the real-time operation. It is an important aspect of the electricity spot market. The retailer purchases electricity through centralized trading in the day-ahead market according to the forecasted user demand for the subsequent day. This serves to balance the deviation between the mid-long-term transactions of the retailer and the user demand.

The purchases cost of the electricity retailer in the day-ahead market is formulated as follows:

$$C_{\mathrm{D}} = \sum_{t \in T} L_{\mathrm{D}}^{t} \cdot p_{\mathrm{D}}^{t} \tag{2}$$

where C_{D} is the purchases cost of the electricity retailer in the day-ahead market during the whole observation period; L_{D}^{t} is the contract electricity of the transaction in the day-ahead market during the t^{th} period; p_{D}^{t} is the day-ahead market clearing price during the t^{th} period.

2.2.3. Electricity purchases in the real-time market

The "real-time market" usually refers to a trading market wherein power is delivered immediately [28]. Factors such as weather changes, grid accidents, rapid changes in power due to the intermittency of renewable energy, and load fluctuations during actual operation may cause large deviations between the electricity planned to be purchased in advance and the real-time demand for electricity. It is crucial to resolve the imbalance between power supply and demand in the operation of the power grid in the real-time market. The real-time market is generally organized and implemented periodically by State Grid Dispatching Center, which directs the operation of the grid at certain intervals; its main role is not to trade electricity, but to ensure a real-time balance in power generation and consumption across the grid while ensuring operational safety. The real-time market also plays an important role in providing adjustments and price signals to manage congestion as well as offering auxiliary services to swiftly mitigate any power scarcity.

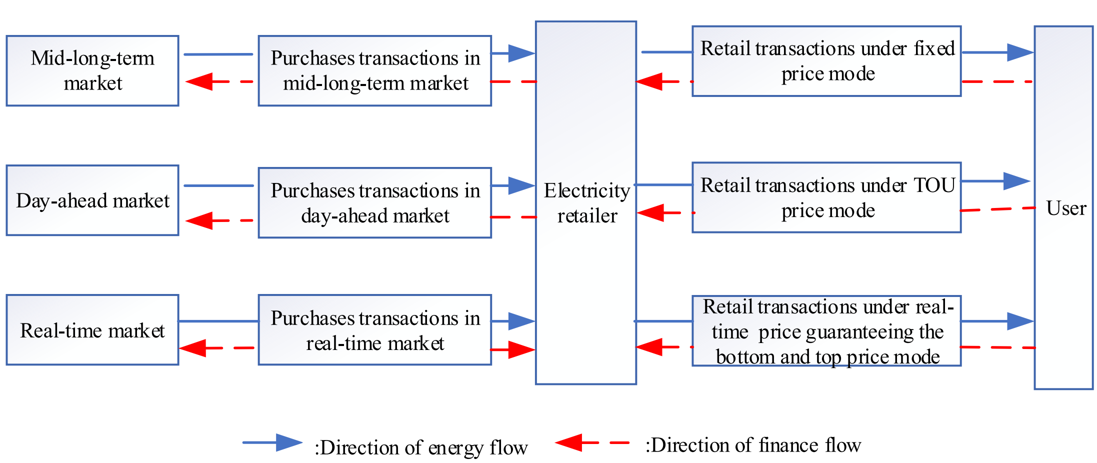

Fig. 1. Electricity transaction modes of electricity retailer

The electricity retailer makes purchases in the real-time market to balance any deviation between the electricity purchased according to the plan in advance and the users' real-time demand within individual trading periods. The real-time market is a centralized place for electricity trading. Its most essential characteristics include uncertainty and randomness. The scenario method [29] was used in this study to simulate real-time prices. A set of real-time price scenarios Λ can be expressed as follows:

$$\Lambda = \{p_R^t(\omega): t = 1, 2, ..., N, \forall\ \omega \in \Omega\} \tag{3}$$

where $p_R^t(\omega)$ is the real-time price during the t^{th} period under the ω^{th} scenario; N is the number of trading sessions in the real-time market.

It is assumed that the electricity retailer is a price-taker in the real-time market which purchases and sells electricity at a real-time price according to its own needs. When the electricity purchased by the retailers in the mid-long-term market and the day-ahead market falls below the user demand, the retailers must purchase electricity in the real-time market, and now the value of the purchased electricity is positive. Otherwise, the retailers can sell electricity in the real-time market, and now the value of the purchased electricity is negative. If the electricity purchased by the retailers in the mid-long-term market and the day-ahead market precisely meets the user demand, then the retailers do not need to trade in the real-time market. The purchases cost of the electricity retailer in the real-time market during the period N and under the ω^{th} scenario is expressed as follows:

$$C_R(\omega) = \sum_{t=1}^{N} [L_B^t + L_D^t - L_t(\omega)]\cdot p_R^t(\omega) \tag{4}$$

where $C_R(\omega)$ is the purchases cost of the electricity retailer in the real-time market under the ω^{th} scenario, which may be a positive value, negative value, or zero; $L_t(\omega)$ is the user demand during the t^{th} period under the ω^{th} scenario.

2.2.4. Electricity retailers' deviation assessment model

Assuming that the amount of electricity in contract signed by the electricity retailer in the mid-long-term market is L_B, the amount of electricity traded in the day-ahead market is recorded as L_D, and the actual electricity consumption of the user that the electricity retailer agent for in the month under the ω^{th} scenario is recorded as $L(\omega)$, so:

$$\Delta L(\omega) = L(\omega) - L_B - L_D \tag{5}$$

where $\Delta L(\omega)$ is the electricity deviation of the electricity retailer under the ω^{th} scenario. The amount of electricity that the retailer needs is evaluated based on the deviation as-assessed. When $\Delta L(\omega) \neq 0$, there is deviation under the ω^{th} scenario. At this time, the additional cost of the electricity retailer consists of two parts: the deviation as-evaluated (penalty fee) and the deviation of trades in the real-time market, which may be positive, negative, or zero [30].

$$C^{pe}(\omega) = p^{pe}\cdot\Delta L(\omega) + \sum_{t=1}^{T} p_R^t(\omega)\cdot\Delta L(\omega) \tag{6}$$

where $C^{pe}(\omega)$ is the additional cost of the electricity retailer under the ω^{th} scenario; p^{pe} is the unit assessment cost of the electricity deviation.

2.3. Transactions on sell-side

By providing users with a diverse array of services, electricity retailers can enhance user loyalty while expanding the scale of their users. This is the key to ensuring continued profitability. There are three typical differentiated electricity price contracts on today's Chinese electricity market: the fixed price contracts, TOU price contract, and real-time price guaranteeing the bottom and top price contract.

2.3.1. Retail transactions under fixed price mode

If the user selects a fixed price contract offered by the electricity retailer, then the electricity price stipulated in the contract is fixed, and the electricity price remains unchanged throughout the contract period. Here, the price of the fixed price contract with the user is set as p_{con}.

2.3.2. Retail transactions under TOU price mode

Unlike the fixed price, the TOU price load curve can be divided into peak, flat, and valley periods each featuring a different electricity price based on the half-ladder membership function principle [31].

The TOU price is calculated as follows:

$$p_{fen}(t) = \begin{cases} p_p^t,\ t \in T_p \\ p_s^t,\ t \in T_s \\ p_r^t,\ t \in T_r \end{cases} \tag{7}$$

where $p_{fen}(t)$ is the TOU price during the t^{th} period; T_p, T_r, T_s are the collection of peak load periods, valley load periods, and flat load periods in a day, respectively; p_p^t, p_r^t, p_s^t are the retail price of peak load periods, valley load periods, and flat load periods, respectively.

2.3.3. Retail transactions under real-time price guaranteeing the bottom and top price mode

The contract referred to here as "real-time price guaranteeing the bottom and top price" stipulates a maximum and minimum electricity transaction price which do not change during the contract period. The electricity retail price varies as per the real-time market. When the linked price is lower than the maximum price and higher than the minimum price, the retail price is a real-time price linked to market. When the linked price is higher than the maximum, the maximum price is adopted by the retailer as the retail price; conversely, when the linked price is lower than the minimum price, the minimum price is adopted. The real-time price guaranteeing the bottom and top price for the electricity retailer is denoted as $\hat{p}$:

$$\hat{p} = \begin{cases} p_{max},\ p_{ss}(t) \geq p_{max} \\ p_{ss}(t),\ p_{min} \leq p_{ss}(t) \leq p_{max} \\ p_{min},\ p_{ss}(t) \leq p_{min} \end{cases} \tag{8}$$

where p_{max} is the maximum retail price (top price); p_{min} is the minimum retail price (bottom price); $p_{ss}(t)$ is the linked price which is lower than the top price and higher than the bottom price.

Price variations under this contract, as mentioned above, follow the real-time market. The sharing ratio of the profit between the electricity retailer and the user is agreed upon in advance. Based on profit sharing, the user's linked price can be expressed as:

$$p_{ss}(t) = p_e(t) - \eta[p_e(t) - p_R^t] \tag{9}$$

where $p_e(t)$ is the electricity price of the user during the t^{th} period according to the grid company's catalog electricity price; η is the sharing ratio of the profit agreed upon between the electricity retailer and the user.

2.3.4. User demand elasticity based on price elasticity coefficient

The incentive effect of the retail contract price mechanism on users' electricity consumption behavior is examined here from the perspective of the electricity retailer. The demand and price elasticity under the retail contract mode is defined accordingly. The demand and price elasticity based on the elastic coefficient refers to the user's adjustments of his own electricity consumption in response to the electricity price signal [32]. The electricity retailer guides the user to change this consumption behavior by changing the retail contract price. Based on the user demand under the fixed price, the user demand under the TOU price and the real-time price guaranteeing the bottom and top price can be expressed as:

$$L_{2,t}(\omega) = L_{1,t}(\omega)(1 + \sum_{z=1,z\neq t}^{T} \varepsilon_{zt}\frac{p_{fen}(z) - p_{fen}(t)}{p_{con}(t)} + \varepsilon_{tt}\frac{p_{fen}(t) - p_{con}(t)}{p_{con}(t)}) \tag{10}$$

$$L_{3,t}(\omega) = L_{1,t}(\omega)(1 + \sum_{z=1,z\neq t}^{T} \varepsilon_{zt}\frac{\hat{p}(z) - \hat{p}(t)}{p_{con}(t)} + \varepsilon_{tt}\frac{\hat{p}(t) - p_{con}(t)}{p_{con}(t)}) \tag{11}$$

where $L_{1,t}(\omega)$ is the user demand under fixed price mode during the t^{th} period and under the ω^{th} scenario; $L_{2,t}(\omega)$ is the user demand under TOU price mode during the t^{th} period and under the ω^{th} scenario, when $t \in T_p$, $L_{2,t}(\omega) = L_{p,t}(\omega)$, which indicates the actual user demand in the peak period during the t^{th} period and under the ω^{th} scenario, when $t \in T_r$, $L_{2,t}(\omega) = L_{r,t}(\omega)$, which indicates the actual user demand in the valley period during the t^{th} period and under the ω^{th} scenario, when $t \in T_s$, $L_{2,t}(\omega) = L_{s,t}(\omega)$, which indicates the actual user demand in the flat period during the t^{th} period and under the ω^{th} scenario; $L_{3,t}(\omega)$ is the user demand under real-time price guaranteeing the bottom and top price mode during the t^{th} period and under the ω^{th} scenario, when $t \in T_1$, $L_{3,t}(\omega) = L_{\max,t}(\omega)$, which indicates the actual user demand during the top period during the t^{th} period and under the ω^{th} scenario, when $t \in T_2$, $L_{3,t}(\omega) = L_{ss,t}(\omega)$, which indicates the actual user demand during the real-time period during the t^{th} period and under the ω^{th} scenario, when $t \in T_3$, $L_{3,t}(\omega) = L_{\min,t}(\omega)$, which indicates the actual user demand during the bottom period during the t^{th} period and under the ω^{th} scenario,; ε_{zt} is the user's cross-elasticity coefficient during the z^{th} and t^{th} period; ε_{tt} is the user's self-elasticity coefficient during the t^{th} period; $p_{fen}(z)$ is the TOU price during the z^{th} period; $\hat{p}(z)$ is the real-time price guaranteeing the bottom and top price during the z^{th} period.

2.3.5. User satisfaction model

The electricity consumption of users is affected by the sales price provided by the electricity retailer. User satisfaction with electricity cost is defined here as a ratio of the difference between the electricity cost under the retail contract price of the selected transactions and the cost under the catalog price of the power grid company to the cost under the catalog price of the power grid company. The user satisfaction rate can be expressed as follows:

$$m_{\text{con}} = \frac{\sum_{t\in T} p_e(t)L(t)\Delta t - \sum_{t\in T} p_{\text{con}}L(t)\Delta t}{\sum_{t\in T} p_e(t)L(t)\Delta t} \times 100\% \tag{12}$$

$$m_{fen} = \frac{\sum_{t\in T} p_e(t)L(t)\Delta t - \sum_{t\in T} p_{fen}^{t}L(t)\Delta t}{\sum_{t\in T} p_e(t)L(t)\Delta t} \times 100\% \tag{13}$$

$$m_{ss} = \frac{\sum_{t\in T} p_e(t)L(t)\Delta t - \sum_{t\in T} p_{ss}(t)L(t)\Delta t}{\sum_{t\in T} p_e(t)L(t)\Delta t} \times 100\% \tag{14}$$

where m_{con} is the user's satisfaction rate under a fixed price contract; m_{fen} is the user's satisfaction rate under the TOU price contract; m_{ss} is the user's satisfaction rate under the real-time price guaranteeing the bottom and top price contract; $L(t)$ is the user demand during the t^{th} period.

3. Risk assessment and decision-making model based on CVaR

The fluctuations of real-time market prices and the uncertainty of user demand are the main risk factors in the electricity transactions. Both are continuous random variables, so decision-making and risk assessment problems facing the electricity retailer can be transformed into a decision-making problem of random planning. A typical scenario is established in this study by simulating electricity prices in the real-time market with dynamic user demand under the risk factors discussed above. The CVaR variable is used to secure an electricity purchases and sales strategy that maximizes the profit of different electricity retailer's transaction portfolios under certain risk constraints.

Based on the description of the electricity purchases transactions mentioned above, the cost of the electricity retailer, accounting for an assessment of electricity deviation under the ω^{th} scenario, can be expressed as:

$$C(\omega) = C_{\text{B}} + C_{\text{D}} + C_{\text{R}}(\omega) + C_{pe}(\omega) \tag{15}$$

where $C(\omega)$ is the total cost of the electricity retailer in all markets under the ω^{th} scenario.

The electricity retailer provides users with a variety of retail contracts and settles electricity bills with users according to the prices agreed upon therein. $F(\omega)$ denotes the income (profit) of the electricity retailer under the ω^{th} scenario, which is expressed as follows:

$$\begin{aligned} F(\omega) = {} & \rho_1(\omega)\cdot \sum_{t\in T} p_{\text{con}}L_{1,t}(\omega)\Delta t \\ & + \rho_2(\omega)\cdot\big(p_{\text{p}}\cdot \sum_{t\in T_{\text{p}}} L_{\text{p},t}(\omega)\Delta t + p_{\text{r}}\cdot \sum_{t\in T_{\text{r}}} L_{\text{r},t}(\omega)\Delta t + p_{\text{s}}\cdot \sum_{t\in T_{\text{s}}} L_{\text{s},t}(\omega)\Delta t\big) \\ & + \rho_3(\omega)\cdot\big(p_{\max} \sum_{t\in T_1} L_{\max,t}(\omega)\Delta t + \sum_{t\in T_2} p_{ss}(t)L_{ss,t}(\omega)\Delta t + p_{\min} \sum_{t\in T_3} L_{\min,t}(\omega)\Delta t\big) \end{aligned} \tag{16}$$

where $\forall\omega\varepsilon\Omega$ satisfies the following:

$$\begin{aligned} \sum_{t\in T} L_t(\omega) &= \sum_{t\in T_{\text{p}}} L_{\text{p},t}(\omega) + \sum_{t\in T_{\text{r}}} L_{\text{r},t}(\omega) + \sum_{t\in T_{\text{s}}} L_{\text{s},t}(\omega) \\ &= \sum_{t\in T_1} L_{\max,t}(\omega) + \sum_{t\in T_2} L_{ss,t}(\omega) + \sum_{t\in T_3} L_{\min,t}(\omega) \end{aligned} \tag{17}$$

$\rho_1(\omega)$, $\rho_2(\omega)$, $\rho_3(\omega)$ are the ratio operators assigned by the retailer to the three electricity transactions under the ω^{th} scenario; When the user chooses the transaction of TOU price contract, $L_{\text{p},t}(\omega)$, $L_{\text{r},t}(\omega)$, $L_{\text{s},t}(\omega)$ indicate the user's actual demand in the peak period, valley period, and flat period during the t^{th} period and under the ω^{th} scenario; T_1, T_2, T_3 are the set of time periods for the top price, real-time price, and bottom price under the real-time price guaranteeing the bottom and top price contract. When the user chooses the real-time price guaranteeing the bottom and top price contract, $L_{\max,t}(\omega)$, $L_{ss,t}(\omega)$, $L_{\min,t}(\omega)$ are his or her actual user demand in the top period, real-time period, and bottom period during the t^{th} period and under the ω^{th} scenario.

The profit of the electricity retailer when implementing multiple retail contracts simultaneously under the ω^{th} scenario can be expressed as follows:

$$W(\omega) = F(\omega) - C(\omega) \tag{18}$$

where $W(\omega)$ is the profit of the electricity retailer under the ω^{th} scenario.

The expected profit of the electricity retailer is the sum of the product of the electricity retailer's profit and the corresponding probability under all scenarios:

$$W = \sum_{\omega} \pi(\omega)\cdot W(\omega) \tag{19}$$

where W is the expected profit of the electricity retailer.

The electricity purchases and sales losses of the electricity retailer under the ω^{th}scenario is characterized here as the inverse of the retailer's profit:

$$G(\omega) = -W(\omega) \tag{20}$$

Because the electricity purchases and sales model of the electricity retailer must reflect (and constrain) the electricity purchases and sales loss through the CVaR method [33], $G(\omega)$ in the electricity purchases and sales CVaR model of the retailer is considered here to be equivalent to the loss function $f(W, R_i)$ of Formula (A8) in Appendix A (which is the standard derivation of the CVaR methodology). F_{VaR} is the maximum risk loss that a retailer may incur in the electricity market while the confidence level is β, which is equivalent to the loss value α of Formula (A8) in Appendix A. The sample set of risk factors is Ω.

The electricity purchases and sales model of the electricity retailer based on the CVaR is:

$$F_{\text{CVaR}} = F_{\text{VaR}} + \frac{1}{(1-\beta)} \sum_{\omega} \pi(\omega)\cdot[G(\omega) - F_{\text{VaR}}]^{+} \tag{21}$$

$$[G(\omega) - F_{\text{VaR}}]^{+} = \max\{0, G(\omega) - F_{\text{VaR}}\} \tag{22}$$

The virtual variable z_ω can be used to transform optimization problems into linear programming problems:

$$F_{\mathrm{CVaR}} = F_{\mathrm{VaR}} + \frac{1}{1-\beta}\sum_{\omega}\pi(\omega)\cdot z_{\omega} \tag{23}$$

$$s.\ t.\ z_{\omega} \geq 0,\ z_{\omega} \geq G(\omega) - F_{\mathrm{VaR}} \tag{24}$$

When the electricity retailer formulates a trading strategy, it attempts to maximize profit and minimize the risk of loss. The objective function is:

$$\max W - \delta F_{\mathrm{CVaR}} \tag{25}$$

where δ is a risk aversion factor related to the attitude of the electricity retailer. For risk-averse electricity retailers δ is larger and for risk-preferring electricity retailers is smaller.

There are various methods for measuring returns and risks under the portfolio theory. The fundamental goal of any such method is to construct a portfolio optimization model with returns or risks as targets or constraints. A set of solutions with the least risk at the same level of return or the greatest return at the same level of risk are secured as the optimal solution.

Assume x is a decision vector, $\phi(x)$ is a risk function, $W(x)$ is a profit function, and X is a decision feasible set in which $x \in X$, γ is a risk factor parameter, ε is a limited return level, τ is a limited risk level, and a confidence level $0 < \beta < 1$ has been given. Investors inherently seek the greatest possible return at the least possible risk. Existing combination optimization models applicable to the electricity market include the following.

An optimization problem that comprehensively considers increasing returns and reducing risks to obtain maximum utility $\min \phi(x) - \gamma W(x), \gamma \geq 0$.

An optimization problem with the lowest risk under the constraints of the expected level of portfolio returnsmin $\phi(x)$, $W(x) \geq \varepsilon$.

An optimization problem with the largest portfolio returns under the constraints of certain risk levelsmin$[-W(x)]$, $\phi(x) \leq \tau$. This produces the same effective frontier when the parameters ε, τ, and γ are changed under certain conditions, that is, x^* is the same optimal solution of the three problems under certain conditions.

(a) Objective function

According to the above situation 3), under the constraints of the CVaR, the maximum expected revenue of the electricity retailer (with minimal loss) is the objective function of the electricity retailer's electricity purchases and sales decision-making:

$$\min(-W) \tag{26}$$

(b) Constraints

$$\delta\cdot\left[F_{VaR} + \frac{1}{1-\beta}\sum_{\omega}\pi(\omega)\cdot z_{\omega}\right] \leq \xi \tag{27}$$

$$z_{\omega} \geq 0,\ z_{\omega} \geq G(\omega) - F_{\mathrm{VaR}}\ \ \forall\ \omega \in \Omega \tag{28}$$

$$p_{\mathrm{p}}^{t} \geq p_{\mathrm{s}}^{t} \geq p_{\mathrm{r}}^{t} \geq C_e \tag{29}$$

$$\eta^{\min} \leq \eta \leq \eta^{\max} \tag{30}$$

$$m_{\mathrm{con}} \geq m_{\min} \tag{31}$$

$$m_{fen} \geq m_{\min} \tag{32}$$

$$m_{ss} \geq m_{\min} \tag{33}$$

where δ is a risk aversion factor; ξ is the upper limit of the electricity purchases and sales risk of the electricity retailer; $p_{\mathrm{r}}^{t} \geq C_e$ indicates that the valley price should be greater than the marginal cost C_e of the system during the valley period. $\eta^{\max}$ and $\eta^{\min}$ are, respectively, the upper and lower limits of the profit-sharing percentage agreed upon between the electricity retailer and the user. $m_{\min}$ represents the minimum user satisfaction with electricity bill expenditures.

In summary, the objective function is a minimization of the electricity purchases and sales losses of the electricity retailer represented by Formula (26). Formulas (27)-(33) are the constraints. A comprehensive model of decision-making and risk assessment for the optimization of electricity transaction practices based on CVaR is thus established. As discussed in detail below, MATLAB was used to call the CPLEX solver to operate this model to validate it via case study.

4. Case study

4.1. Data

The planning period selected for this analysis is 30 days. (The basic period is 15 min, which is the duration of the "real-time market" totaling 2,880 periods.) Four sets of real-time market price and user demand under fixed price mode scenarios were simulated according to historical data for a typical area [34] (Appendix B Fig. 1 and Fig. 2). Assuming that the probability of each real-time price scenario and corresponding user demand scenario is 1/4, the average expected real-time market price is \$48.56/(MW•h), and the purchases price of the electricity retailer in the mid-long-term market is \$25/(MW•h). The user's self-elasticity coefficient and cross-elasticity coefficient are -0.415 and 0.145, respectively. It is assumed that within one planning period, the user does not change his or her electricity retailer. The confidence level is $\alpha = 0.95$ and the user's satisfaction rate does not fall below 2%.

Based on the above parameters, different electricity transaction models were formed in this study by limiting the values of ρ_1, ρ_2, and ρ_3 before conduction separate risk assessments and decision-making operations.

4.2. Mode 1

In Mode 1, $\rho_1 = 1$ and $\rho_2 = \rho_3 = 0$; the electricity retailer only conducts fixed price contracts. All types of electricity purchases contracts are included in the supply-side. The retailer mainly faces the risks of real-time market price volatility and user demand uncertainty. This is the most basic transaction mode for electricity trading of the electricity retailer in the market environment.

The impact of risk factors on the electricity retailer's electricity purchases and sales strategies was assessed as reported below. The purchases scales of the electricity retailer in different markets under different risk aversion factors δ were calculated with a unit assessment cost of electricity deviation of \$50/(MW•h). The results are shown in Table 1.

As shown in Table 1, as the risk aversion factor δ of the electricity retailer gradually increases, the electricity retailer gradually reduces the amount of electricity purchased in the real-time market but increases the amount of electricity purchased in the mid-long-term market. The negative values indicate instances where the electricity retailer sells rather than purchases electricity on the real-time market. The retailer's risk level has decreased alongside a decrease in expected profit. This is because the risk of real-time market price fluctuations and higher corresponding penalty costs grow as the company trades more electricity in the real-time market, leading to a greater risk of loss.

Risk-preferred electricity retailers are willing to risk substantial loss and can expect to obtain greater profit by appropriately increasing the proportion of electricity purchased in the real-time market. Conversely, risk-averse electricity retailers must expand the scale of the electricity purchased in the mid-long-term market to maintain stable profits while avoiding large price fluctuations. Ensuring profitability is dependent on accurate prediction of user demand and minimal deviation in electricity service. The electricity purchases and sales strategy of the retailer in this mode is optimal in Mode 1 when the fixed price is \$58.8/(MW•h).

The impact of the unit assessment cost of electricity deviation on the retailer's electricity purchases and sales strategy was also assessed in this study. The results with a risk aversion factor of 2 are shown in Table 2. The negative values indicate that the electricity retailer is selling electricity rather than purchasing electricity in the real-time market. A higher unit assessment cost of electricity deviation results in a smaller scale of electricity purchased in the real-time market, higher penalty fees for the retailer, and a lower expected profit for the retailer. Therefore, when the unit assessment cost of electricity deviation on the

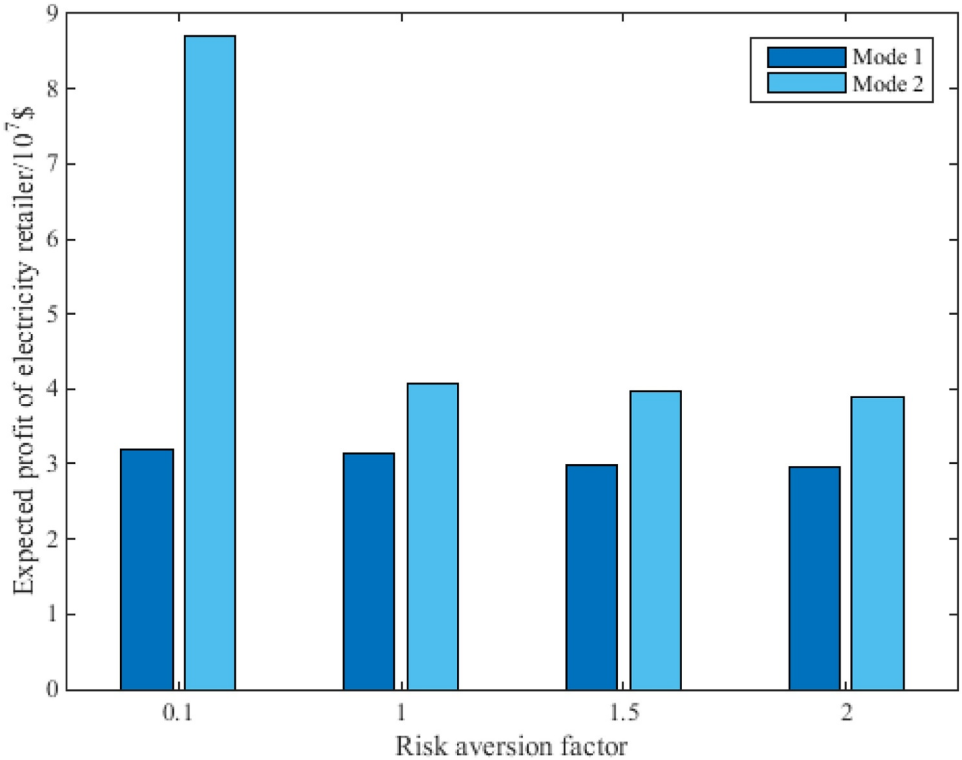

Fig. 2. Expected profit of the electricity retailer under constant risk aversion factors (Mode 1, Mode 2)

retailer side is high, it is necessary to reduce transactions in the real-time market by improving the accuracy of user demand predictions or properly implementing user demand responses to ensure profitability.

Finally, when δ=2, the purchases scales of the electricity retailer in different markets at different purchases electricity prices in the mid-long-term electricity market were calculated as shown in Table 3.

Table 3 shows that under the same circumstances (unchanged δ), as the price of electricity in the mid-long-term market increases, the optimal electricity purchases and sales strategy of the retailer is to reduce the electricity purchased in the mid-long-term market while stabilizing the retail contract price. This prevents reduction in expected profit or intensifying risk levels for the retailer. When the prices of various types of electricity retail contracts remain unchanged, the total user demand remains unchanged as well while the electricity purchases activity in the mid-long-term market decreases. This forces the retailer to purchase more electricity in the real-time market, to bear greater risk of price fluctuations in the real-time market, and to experience a decrease in both profit and risk level. Whether to purchase cheap electricity in the mid-long-term market is key as the retailer seeks to improve its financial competitiveness under Mode 1.

4.3. Mode 2

In Mode 2, $\rho_2 = 1$ and $\rho_1 = \rho_3 = 0$; the retailer only conducts transaction of the TOU price contracts. All types of electricity purchases contracts are included in the supply-side. When the unit assessment cost of the electricity deviation is \$50/(MW•h), the expected profit of the electricity retailer under different risk aversion factors δ were calculated as shown in Table 4.

Table. 2
Expected profit of the electricity retailer under different unit assessment costs of electricity deviation

p	Electricity purchased in real-time market /(10^6MW•h)	Expected profit of the electricity retailer/ (10^7\$)	Penalty costs/ (10^7\$)
5	-0.01	2.99	0.005
50	-0.01	2.96	0.05
500	-0.0019	2.90	0.950

Table 4 shows that as the risk aversion factor increases, the trading activity among retailers in the real-time market gradually decreases. This is determined by the demand for real-time market price hedging. When the risk which the retailer can afford decreases, the risks caused by the fluctuations of real-time market price must be hedged as effectively as possible.

Fig. 2 shows that under the same risk aversion factor, the expected profit under the TOU price contract is higher than the expected profit under the fixed price contract. This is because the price and demand elasticity are taken into account. When the retailer implements the former contract, economic leverage effectively mobilizes users to “cut the peaks” and “fill the valleys” to reasonably bear the cost of electricity. This reduces the purchases cost of the retailer thereby increasing

Table. 1
Scale of electricity purchased by the electricity retailer in different markets under different risk aversion factors in Mode 1

δ	Electricity purchased in mid-long-term market/(10^6MW•h)	Electricity purchased in day-ahead market/(10^6MW•h)	Electricity purchased in real-time market/(10^6MW•h)	Expected profit of the electricity retailer/ (10^7\$)	Penalty costs/ (10^7\$)
0.1	1.02	0.76	-0.04	3.19	0.20
1	1.38	0.40	-0.03	3.13	0.15
1.5	1.74	0.02	-0.02	2.98	0.10
2	1.75	0.01	-0.01	2.96	0.05

Table. 3
Scale of electricity purchased by the electricity retailer at different purchases prices in mid-long-term markets

Purchases price in mid-long-term market/ ($)	Electricity purchased in mid-long-term market/(10^6MW•h)	Electricity purchased in day-ahead market/(10^6MW•h)	Electricity purchased in real-time market/(10^6MW•h)	Expected profit of the electricity retailer/ ($10^7$$)	Fixed price / ($/(MW•h))
25	1.64	0.10	0.04	2.96	58.8
30	1.53	0.11	0.10	2.93	58.8
40	1.32	0.11	0.31	2.85	58.8
50	1.18	0.11	0.45	2.79	58.8

Table. 4
Expected profit of the electricity retailer under different risk aversion factors in Mode 2

δ	Electricity purchased in real-time market/(10^6MW•h)	Expected profit of the electricity retailer/($10^7$$)
0.1	0.04	8.75
1	0.03	4.18
1.5	0.02	3.99
2	0.01	3.92

Table. 5
Expected profit of the electricity retailer under different risk aversion factors in Mode 3

δ	Expected profit of the electricity retailer/ ($10^7$$)	Real-time price guaranteeing the bottom and top price / ($/(MW•h))	
		Bottom price/ ($/(MW•h))	Top price/ ($/(MW•h))
0.1	7.53	47.3	215.60
1	3.39	45.58	78.71
1.5	3.15	41.86	75.57
2	2.95	40	74.00

the expected profit. Therefore, electricity retailers can appropriately utilize such contracts to optimize their retail structures and maximize profits. The electricity purchases and sales strategy in Mode 2 is optimal when the TOU price is $215.6/(MW•h) in the peak period, $103.7/(MW•h) in the flat period, and $49/(MW•h) in the valley period.

4.4. Mode 3

In Mode 3, $\rho_3 = 1$ and $\rho_1 = \rho_2 = 0$; the electricity retailer only conducts transaction of the real-time price guaranteeing the bottom and top price contracts. All types of electricity purchases contracts are included in the supply-side. When the unit assessment cost of the electricity deviation is $50/(MW•h) and the sharing ratio is 0.3, the expected profit of the electricity retailer under different risk aversion factors δ were calculated as shown in Table 5.

Table 5 shows that the variation trend of expected profit of the electricity retailer with the risk aversion factors in Mode 3 is the same as that in Mode 1, which is, as the risk aversion factor δ of the electricity retailer gradually increases, the expected profit of the retailer will decrease. The results differ significantly when comparing the expected profit of the electricity retailer in Mode 1 and Mode 3 under various risk aversion factors. The expected profit and penalty costs of the electricity retailer under the same risk aversion factors under Modes 1 and 3 are shown in Fig. 3.

The user demand changes as the electricity price changes when demand and price factors are elastic. As shown in Fig. 3, under any risk aversion, compared with Mode 1, the penalty costs of the electricity retailer in Mode 3 is reduced as the expected profit is increased. The user demand links to the electricity price. Once the user perceives a signal of the price change, he adjusts his own demand accordingly, which is quite beneficial for the electricity retailer. The retailers can guide users to reduce or increase their electricity demand through price signals, thereby reducing their own electricity deviations while reducing penalty costs and increasing expected profit.

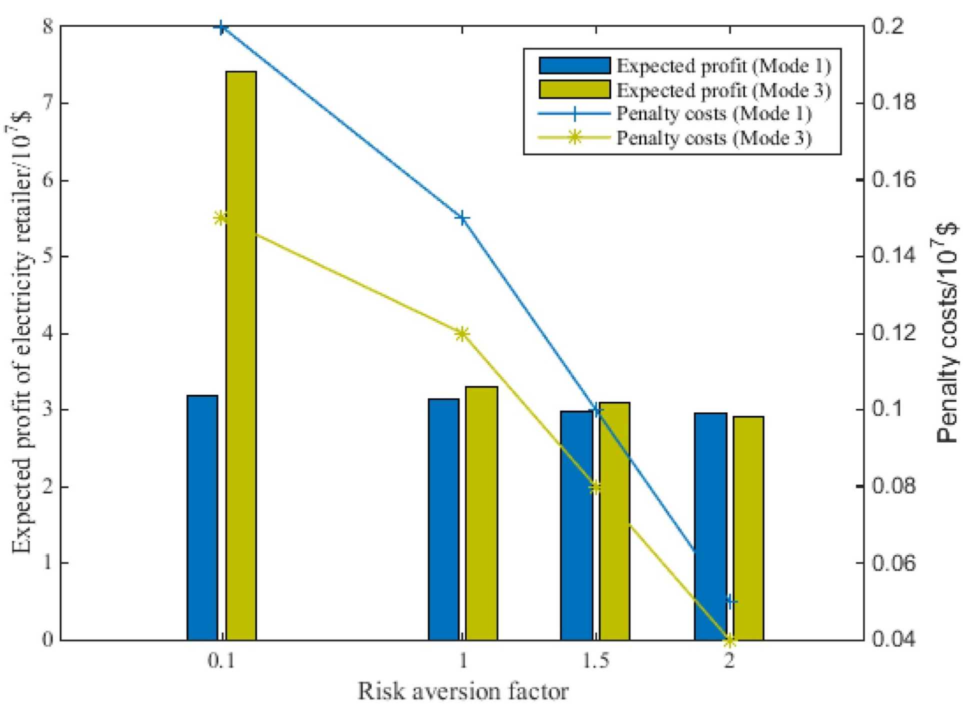

Fig. 3. Expected profit and penalty costs of the electricity retailer under constant risk aversion factors (Mode 1, Mode 3)

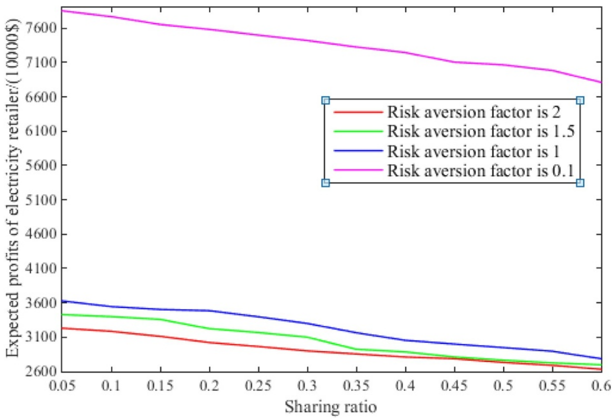

Fig. 4. Relationship between electricity retailer's expected profit and sharing ratio

Fig. 3 also suggests that under a small risk aversion factor, the expected profit under the real-time price guaranteeing the bottom and top price contract is higher than the expected profit under a fixed price contract. This difference is exacerbated by any decrease in the risk aversion factor. Under a larger risk aversion factor, however, the expected profit under the real-time price guaranteeing the bottom and top price contract is a bit lower than that under the fixed price contract. The real-time price guaranteeing the bottom and top price is linked with the real-time market price, which makes the retail price variable. A smaller risk aversion factor indicates greater risk for the retailer. The risks and price-related uncertainties in the real-time electricity market are passed down to the user via a market linkage mechanism. To a certain extent, risk-sharing between the retailer and user is realized in this case as the purchases cost of the retailer is reduced. The profit of the retailer increases significantly under this scenario.

This has certain significance for the retailer in terms of its business structure. For risk-preferred retailers, the real-time price guaranteeing the bottom and top price contract results in higher expected profit. In Mode 3, the electricity purchases and sales strategy are optimal when the real-time price guaranteeing the bottom and top price is \$47.3/(MW•h) in the bottom period and \$215.6/(MW•h) in the top period.

The linkage mechanism is reflected in a profit-sharing scenario where the real-time price guaranteeing the bottom and top price is linked to the real-time price under a set agreement between the retailer and user. Different sharing ratios have different effects on the retailer's electricity purchases strategies in this case. Fig. 2 shows the expected profit of the retailer with increase in sharing ratio under different risk aversion factors.

As shown in Fig. 4, a smaller sharing ratio benefits the retailer's profitability regardless of its attitude towards risk, provided its goal is to ensure user satisfaction.

4.5. Mode 4

In Mode 4, $0 \leq \rho_1 \leq 1$, $0 \leq \rho_2 \leq 1$, $0 \leq \rho_3 \leq 1$, and $\rho_1 + \rho_2 + \rho_3 = 1$ denotes the electricity retailer conducting fixed price, TOU price, and real-time price guaranteeing the bottom and top price contracts simultaneously. When the fixed price is \$58.8/(MW•h), the prices in the peak period, flat period, and the valley period of the TOU price are \$215.6/(MW•h), \$103.7/(MW•h), and \$49/(MW•h), respectively; the prices in the top period and the bottom period are \$215.6/(MW•h), and \$47.3/(MW•h), respectively. Fig. 5 shows the expected profit of the electricity retailer under the same risk aversion factors in Mode 1 to Mode 4.

Fig. 5 shows that under any risk aversion factor, the expected profit of the retailer in Mode 4 are higher than in any of the three modes discussed above. Regardless of the risk attitude of the electricity retailer, conducting multiple electricity retail contracts simultaneously plays a significant role in increasing expected profit. Multiple electricity retail contracts better meet the needs of different users, which improves revenue.

The proportion of these three types of contract under different risk aversion factors is shown in Table 6.

Table 6 shows that the proportion of fixed price contracts gradually increases (and the proportion of the other two contract types gradually decrease) as the risk aversion factor increases, as a lower tolerance for risk indicates a greater priority for price stability. The TOU and especially the real-time price guaranteeing the bottom and top price contracts are not desirable for the retailer in pursuit of steady income in this context due to their uncertainty. The TOU price contract consistently accounts for a large proportion of the total contracts for similar reasons as discussed in Mode 2: it is a transaction practice that consistently leads to maximum profit.

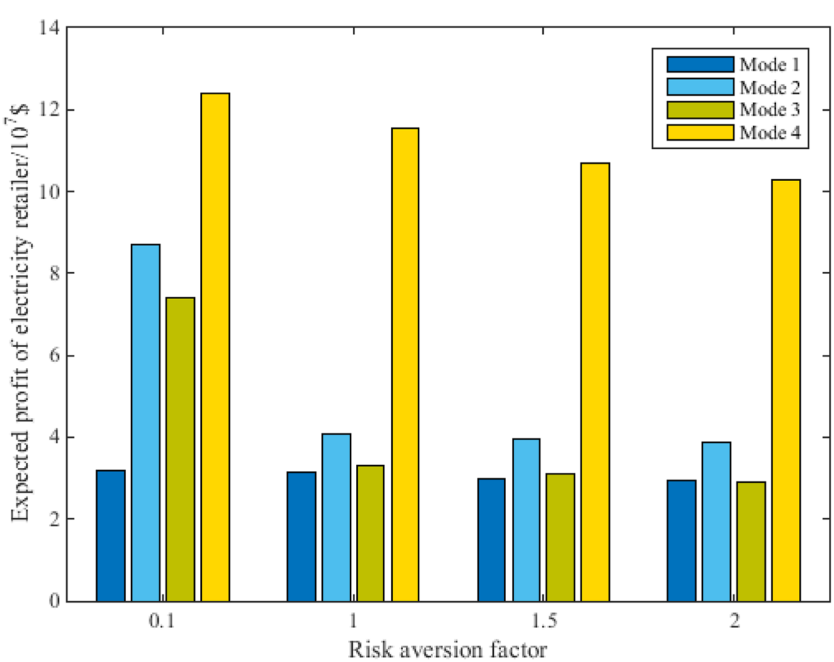

Fig. 5. Expected profit of the electricity retailer under constant aversion factors (Modes 1 to 4)

Table. 6
Proportion of electricity retail transaction types under different risk aversion factors

δ	Expected profit of the electricity retailer/ ($10^7$$)	Proportion of real-time price guaranteeing the bottom and top price contract	Proportion of TOU price contract	Proportion of fixed price contract
0.1	12.56	0.047	0.831	0.122
1	11.63	0.029	0.724	0.247
1.5	10.82	0.023	0.688	0.289
2	10.35	0.020	0.671	0.309

Therefore, for risk-preferred companies, the proportion of real-time price guaranteeing the bottom and top price transaction and TOU price contracts can be appropriately increased in order to maximize the expected profit. For risk-averse electricity retailers, profit will be relatively low but stable when the proportion of fixed price contracts is increased.

5. Conclusion

A comprehensive decision-making and risk assessment model was established in this study for the optimization of electricity transaction practices based on CVaR. Three types of transaction practices were assessed on the supply-side and the sell-side of the electricity retailer/user relationship with consideration of deviations in electricity. Different modes of electricity transactions are formed as different contracts are enacted. These modes are selected on a case-by-case basis as the retailer seeks to minimize loss, maximize profit, and ensure user satisfaction.

The primary conclusions of this study can be summarized as follows.

1) The amount of electricity purchased in multi-level electricity market is affected by the retailer's risk aversion factor, and retailers with different risk attitudes have different electricity purchases strategies. Risk-averse retailers will benefit from enhancing the accuracy of user demand forecasting. The key to financial competitiveness is obtaining cheap electricity from the mid-long-term market.
2) The TOU price can obviously increase the expected profit of the electricity retailer. In effect, considering the demand and price elasticity, the TOU price contract is an effective means of demand-side management.
3) The real-time price guaranteeing the bottom and top price can transfer risk from some extent from the retailer to the user. It is recommended that risk-preferred electricity retailers implement this contract to maximize profitability.
4) The electricity retailer maximizes profits when conducting all types of contracts simultaneously. Risk-preferred companies may increase the proportion of real-time price guaranteeing the bottom and top price and TOU price contracts while risk-averse retailers may benefit from increasing their proportion of fixed price contracts.

The results presented in this paper may assist China's electricity retailers to develop new ideas, enrich their electricity transactions, and enhance the vitality of the electricity market. This work also may provide theoretical guidance for China's retailers as they navigate a relatively newly liberalized sell-side. Sound, effective electricity trading practices benefit not only electricity retailers with different risk attitudes, but also assist in reforming Chinese electricity market. In the future, with the continuous development of the transactions on sell-side, retailers can carry out demand-side management and provide integrated energy services to manage risk and enhance competitiveness.

CRediT authorship contribution statement

Bo Sun: Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Fan Wang:** Software, Writing - original draft, Data curation, Investigation. **Jingdong Xie:** Supervision, Project administration. **Xin Sun:** Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that couldhave appeared to influence the work reported in this paper.

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Appendix A

Standard Derivation of the CVaR Methodology

CVaR refers to the average portfolio loss under the condition that the loss of the portfolio is greater than a given value-at-risk (VaR) value. The VaR alone does not allow for consistent risk measurements. The CVaR has been applied to risk assessment in the electricity retail scenario.

In general, $f(W, \xi)$ indicates the loss corresponding to the decision vector (portfolio) $W \in \wp \subset R^n$ and risk factor (random vector) $\xi \in R^n$. For convenience, it may be assumed that $\xi \in R^n$ is a continuous random vector. For a given portfolio W, the probability of loss which does not exceed α is:

$$\psi(W, \alpha): =P(f(W, \xi) \leq \alpha) \tag{A1}$$

The VaR corresponding to the portfolio W and a given confidence level β is:

$$VaR_\beta(W): =\inf\{\alpha \in R, \psi(W, \alpha) \geq \beta\} \tag{A2}$$

Under the assumption that $\psi(W, \alpha)$ is continuous, then

$$P(f(W, \xi) \leq VaR_\beta(W)) = \psi(W, VaR(W)) = \beta \tag{A3}$$

CVaR is defined as the conditional expectation that the loss exceeds VaR, which is expressed as:

$$CVaR_\beta(W): =E[f(W, \xi)|f(W, \xi)\geq VaR_\beta(W)] = \frac{1}{1-\beta}\int_{VaR_\beta(W)}^{+\infty} xp(x)dx \tag{A4}$$

where E is the expectation operator and $p(x)$ is the density function of loss $f(W, \xi)$.

The definition of CVaR is defined as the following equivalent:

$$CVaR_{\beta}(W) = \min_{\alpha} F_{\beta}(W, \alpha) \tag{A5}$$

where $F_{\beta}(W, \alpha)$ is defined as:

$$F_{\beta}(W, \alpha) := \alpha + \frac{1}{1-\beta} E[(f(W, \xi) - \alpha)^{+}] \tag{A6}$$

and $(z)^{+} = \max\{z, 0\}$. Minimizing the CVaR of $W \in \wp \subset R^{n}$ is equivalent to minimizing $F_{\beta}(W, \alpha)$ of $(W, \alpha) \in \wp \times R$, which is formulated as follows:

$$\min_{W \in \wp} CVaR_{\beta}(W) = \min_{(W,\alpha) \in \wp \times R} F_{\beta}(W, \alpha) \tag{A7}$$

Moreover, when $\wp$ is a convex set and $f(W, \xi)$ is a convex function, Formula. (A7) is a convex programming problem.

The CVaR is applied here to resolve portfolio optimization problems. The first step in this task is to find an estimate of the density function of the loss $f(W, \xi)$ or risk factor ξ. When ξ is a given sample set, $\{R_1, R_2, ..., R_T\}$, $F_{\beta}(W, \alpha)$ can be estimated; T represents the sample size. Estimating $F_{\beta}(W, \alpha)$ as follows:

$$\tilde{F}_{\beta}(W, \alpha) := \alpha + \frac{1}{(1-\beta)T} \sum_{i=1}^{T} (f(W, R_i) - \alpha)^{+} \tag{A8}$$

Appendix B

Fig. 6, Fig. 7,

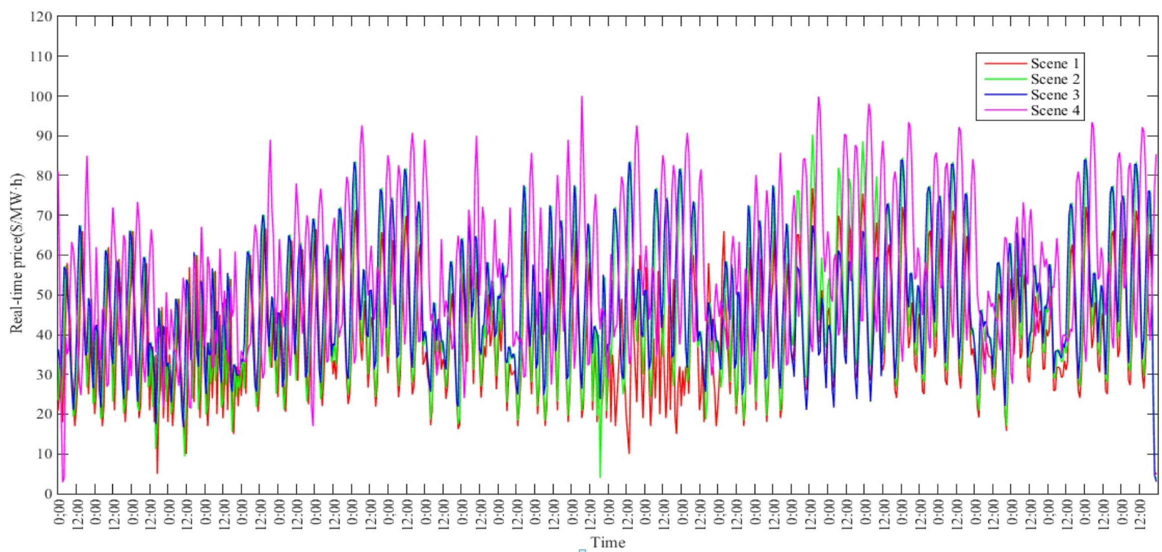

Fig. 6. Real-time electricity price in 4 scenes (30 days)

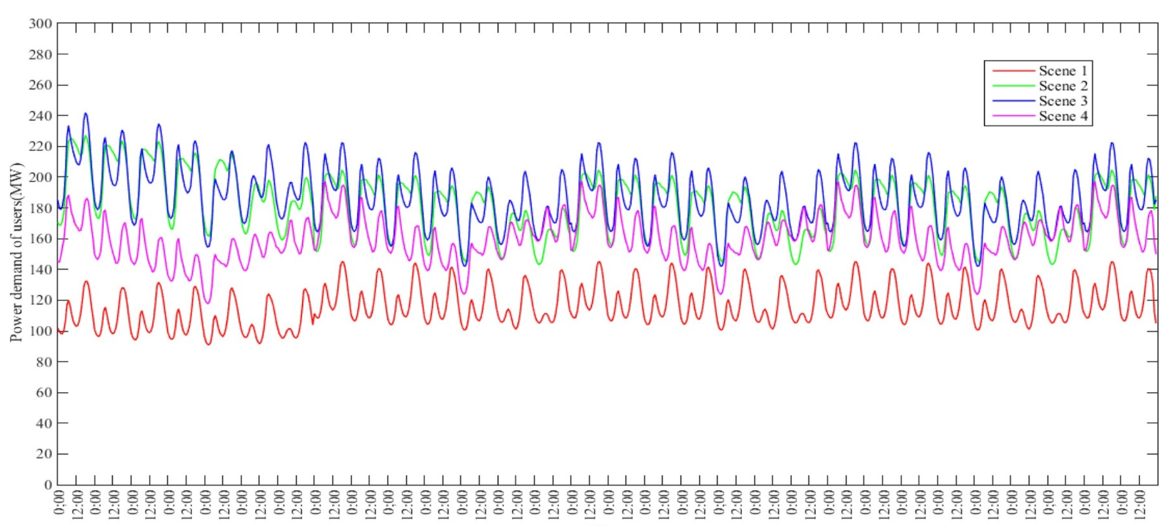

Fig. 7. Power demand of users in 4 scenes (30 days)

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