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# Optimization of Electricity Purchase and Sales Strategies of Electricity Retailers under the Condition of Limited Clean Energy Consumption

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**ABSTRACT**

In the process of my country's energy transition, the clean energy of hydropower, wind power and photovoltaic power generation has ushered in great development, but due to the randomness and volatility of its output, it has caused a certain waste of clean energy power generation resources. Regarding the purchase and sale of electricity by electricity retailers under the condition of limited clean energy consumption, this paper establishes a quantitative model of clean energy restricted electricity from the perspective of power system supply and demand balance. Then it analyzes the source-charge dual uncertain factors in the electricity retailer purchasing and selling scenarios in the mid- to long-term electricity market and the day-ahead market. Through the multi-scenario analysis method, the uncertain clean energy consumption and the user's power demand are combined to form the electricity retailer's electricity purchase and sales scene, and the typical scene is obtained by using the hierarchical clustering algorithm. This paper establishes a electricity retailer's risk decision model for purchasing and selling electricity in the mid- and long-term market and reduce-abandonment market, and takes the maximum profit expectation of the electricity retailer from purchasing and selling electricity as the objective function. At the same time, in the medium and long-term electricity market and the day-ahead market, the electricity retailer's purchase cost, electricity sales income, deviation assessment cost and electricity purchase and sale risk are considered. The molecular results show that electricity retailers can obtain considerable profits in the reduce-abandonment market by optimizing their own electricity purchase and sales strategies, on the premise of balancing profits and risks.

**KEYWORDS**

Electricity retailer; electricity purchase and sale strategy; clean energy consumption

## 1 Introduction

At present, the reform of the global energy structure is in full swing, and vigorous development of clean energy has become an irreversible trend of the times. Facing the increasingly serious contradiction between energy development and utilization and the deterioration of resources and environment, China is vigorously developing low-carbon energy and renewable energy, reducing its dependence on traditional fossil energy, and building a comprehensive energy supply system with clean energy as the core.

While the energy transition has brought rapid development to the clean energy industry, it has also brought enormous challenges. The output of clean energy units, mainly hydropower, wind power and photovoltaic power generation, is affected by the characteristics of water power, wind power, and light resources in the natural environment. Due to the seasonal rotation and the alternation of day and night, it presents seasonal and periodical fluctuation characteristics. The distribution of clean energy resources and load demand have the characteristics of reverse distribution in the spatial and temporal dimensions. During the superimposed period of the flood season and the strong wind season, the imbalance between power supply and demand is prominent, and clean energy consumption is difficult [1].

Under the condition that the consumption of clean energy is limited, electricity retailers can not only purchase electricity through the monthly wholesale market, but also purchase electricity through the reduce-abandonment market. The market is organized by the electricity trading center when it predicts the difficulty of clean energy consumption. However, the output of clean energy units such as hydropower, wind power and photovoltaic power generation is affected by the distribution of water, wind, and light resources in the natural environment. Due to seasonal rotation and day-night alternation, it presents seasonal and time-period fluctuation characteristics. The theoretical maximum output and the amount of electricity to be consumed are great uncertainty [2,3]. In the reduce-abandonment market, the changes in the electricity to be consumed by clean energy will affect the electricity generators' declared electricity volume and declared price in the electricity wholesale market, resulting in the uncertainty of the market clearing electricity price and clearing electricity volume.

For electricity retailers, the profit from purchasing and selling electricity comes from the difference between the price of electricity purchased and sold in the retail market and the wholesale market [4]. The fluctuation of electricity purchase price will directly affect the electricity purchase cost of electricity retailers, which will bring certain risks to the electricity retailer's electricity purchase and sale strategy [5,6]. This paper firstly uses the multi-scenario analysis method to combine the uncertain time-based clean energy consumption limited electricity consumption and user electricity demand data into different electricity purchase and sale scenarios, and based on the scene clustering technology, the many electricity purchase and sale scenarios are simplified into several categories typical electricity purchase and sale scenarios, so as to convert uncertain parameters into multiple deterministic parameters that are easy to solve. Then, considering various electricity purchase and sale scenarios and their occurrence probability [7,8], analyze and calculate the profit and loss of electricity retailers in various typical scenarios. And the conditional value-at-risk (CVaR) method is used to evaluate the loss risk and comprehensively evaluate the profit risk level, and finally make the optimal purchase and sale decision under the condition of balancing profit and risk [9].

## 2 Analysis of the Limited Consumption of Clean Energy

The four links of power generation, transmission, distribution and utilization in the power system are carried out at the same time and completed in an instant, and the power load has obvious randomness [10,11]. In order to ensure the real-time balance of the system, the conventional power output must be adjusted to dynamically track the load changes. Only when the system regulation ability is greater than the load change, the power system can operate safely and stably [12]. After a high proportion of wind, photovoltaic power generating units and radial hydropower generating units with no adjustment capability are connected to the power system, conventional units not only need to track the load changes on the user side, but also stabilize the power generation side wind, photovoltaic power output and radial hydropower output fluctuations, to ensure the dynamic balance of power generation and electricity consumption in the power system [13]. When the regulation capacity provided by the conventional units in the system is not enough to balance load changes and clean energy output fluctuations [14], wind, photovoltaic power generation units and radial hydroelectric units without regulation capacity will reduce the output level, resulting in abandoned water, wind and photovoltaic power [15]. Therefore, the limited consumption of clean energy is closely related to the situation of clean energy power generation resources, system adjustment capacity, and load demand level [16]. When there is no line blockage in the power system in the area, the actual power generation of clean energy is the difference between the "total system load curve and external power curve" and the minimum technical output of the thermal power unit [17]. The clean energy power generation resources are better in the flood season and strong wind season, and the theoretical maximum power generation is greater than the actual power generation of clean energy, that is, the consumption of clean energy is limited [18]. The limited amount of clean energy consumption is the difference between the theoretical maximum power generation and the actual power generation, as shown in Fig. 1.

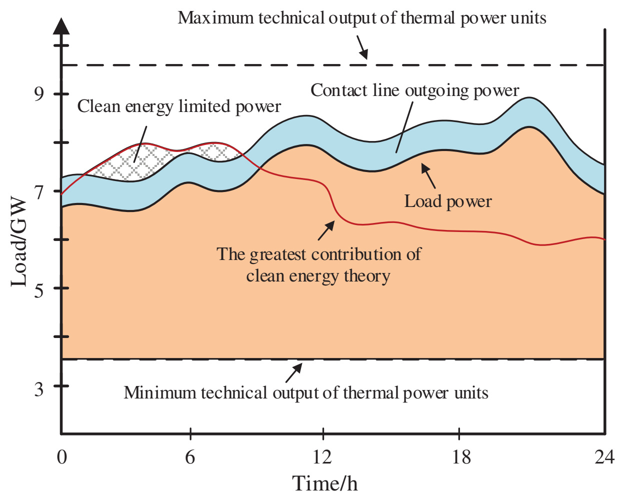


**Figure 1:** Clean energy consumes limited electricity

For any time $t$, the restricted power consumption of new energy in the area can be expressed as:

$$P_{con}(t) = P_{pre}(t) - \left( P_L(t) + P_{out}(t) - \sum_{i=1}^{N_1} P_{f,i,\min} \right) \tag{1}$$

$$P_{f,i,\min} = (1 - \alpha_i) P_{f,i,\max} \tag{2}$$

In the above equations, $P_{con}(t)$ is the limited power consumed by clean energy in the area at time $t$; $P_{\text{pre}}(t)$ is the theoretical maximum output of clean energy units in the area at time $t$; $P_{f,i,\min}$ and $P_{f,i,\max}$ represent the minimum and maximum technical output of the i-th thermal power unit, respectively; $N_1$ is the total number of thermal power units in the region. The $\alpha_i$ is the peak shaving depth of the i-th thermal power unit. $P_L(t)$ is the load demand power in the area; $P_{out}(t)$ is the power delivered to the outside of the area at time $t$.

Integrating Eq. (1), the limited electricity consumption of clean energy in period $t$ can be expressed as:

$$Q_{con} = \int P_{con}(t)\,\mathrm{d}t = Q_{pre} + \int \left[ \sum_{i=1}^{N_1} (1-\alpha_i) P_{g,i,\max} - P_L(t) - P_{out}(t) \right] \mathrm{d}t \tag{3}$$

$$Q_{pre} = Q_{h,pre} + Q_{w,pre} + Q_{p,pre} \tag{4}$$

In the above equations: $Q_{pre}$ is the theoretical maximum power generation of clean energy in time period $t$, which is composed of the theoretical maximum output of wind turbines $Q_{w,pre}$, the theoretical maximum output of photovoltaic units $Q_{p,pre}$ and the theoretical maximum output of hydropower units $Q_{h,pre}$.

Considering that the consumption of clean energy is limited in the period $T$, in order to increase the consumption of electricity, the power system usually uses the capacity of the tie line channel to the greatest extent to send electricity, that is:

$$P_{out}(t) = P_{out}^{\max}, \quad \forall t \in T \tag{5}$$

In the above equation: $P_{out}^{\max}$ is the maximum transmission power sent out by the tie line within the time period $T$.

To sum up, the limited electricity consumption of clean energy in period $T$ can be expressed as:

$$Q_{con} = Q_{pre} + T \cdot \sum_{i=1}^{N_1} (1-\alpha_i) P_{g,i,\max} - Q_L - T \cdot P_{out}^{\max} \tag{6}$$

In the above equation: $Q_L$ represents the load power consumption in the period $T$.

## 3 Electricity Retailer's Operation Mode to Promote New Energy Consumption

### *3.1 Operational Framework of Electricity Retailers Considering Reduce-Abandonment Market*

In general, electricity retailers only participate in medium and long-term transactions. Electricity retailers purchase electricity through centralized bidding, bilateral negotiation and other transaction modes in the wholesale market, and sell electricity to retail users through bilateral negotiation in the retail market, and their income comes from the price difference between the wholesale market and the retail market.

During the period when the consumption of clean energy is limited, the Electricity Trading Center organized reduce-abandonment transactions a few days ago. The electricity retailer purchases the electricity to be consumed at a lower price in the reduce-abandonment market. Through demand-side flexible resource management, users are encouraged to increase the response electricity on the basis of maintaining the original purchased electricity and complete the electricity purchase and sale transaction of the clean energy to be consumed. By designing a reasonable demand response mechanism and optimizing incentive pricing decisions, the interest rate difference between the purchase and sale of electricity can be used to obtain sufficient profits and achieve a win-win situation for clean energy generators, electricity retailers and electricity users. The service objects of electricity retailers are composed of general industrial and commercial users, large industrial users, adjustable loads, electric vehicle users, and energy storage equipment. The operation mode of electricity retailers under the condition of restricted clean energy consumption is shown in Fig. 2.

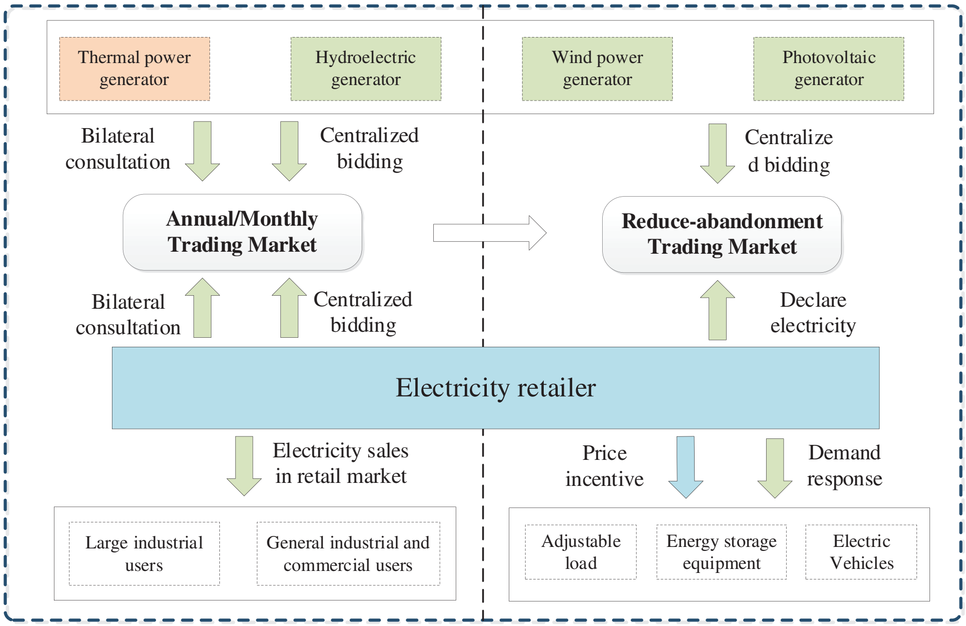


**Figure 2:** The operation mode of electricity retailer considering new energy consumption

### *3.2 The Clearing Process of Reduce-Abandonment Market Unilateral Centralized Bidding*

The reduce-abandonment market adopts unilateral centralized bidding transaction on the power generation side, and clears it according to the unified price difference. The clearing calculation principle is based on "priority of price difference, priority of time and priority of environmental protection". The transaction organization process is as follows:

(1) The demander's electricity declaration. According to their own electricity demand, electricity retailers and major electricity users declare the electricity quantity through the electricity trading center platform, and obtain the total demand electricity $Q_L$ of the reduce-abandonment market through the summary of the electricity trading center.

(2) Power generators bid unilaterally. Power generators declare electricity and prices through the power trading center platform. Suppose a total of n clean energy power generators participate in the reduction and abandonment session, and the electricity and price declared by the i-th clean energy power generator are $Q_i$ and $\lambda_i$, respectively. Under different conditions of limited clean energy consumption, the amount of electricity to be consumed by the clean power generation units is different. When there is a lot of electricity to be consumed, the market price competition is fierce. In order to sell more electricity for profit, the power generator will lower its own quotation, otherwise, the power generator will raise its own quotation. Therefore, the declared price of clean energy generators is expressed by a linear function as:

$$\lambda_i = \alpha_i \cdot Q_{con} + \lambda_i^{mon} \tag{7}$$

In the above equation: $\lambda_i^{mon}$ is the average electricity selling price of clean energy generator i in the monthly electricity market; $\alpha_i$ is the correlation coefficient between the declared electricity price of clean energy generator i and the restricted electricity consumption of clean energy, and

$\alpha_i \cdot Q_{con}$ is the price reduction rate of clean energy generators based on monthly electricity sales prices due to limited consumption, of which $\alpha_i \leq 0$.

The electricity trading center sorts the declared electricity quantities according to the order of the declared price from low to high. When the above conditions are all the same, the electricity trading center will combine and sort multiple declared electricity quantities with the same conditions, thereby forming a seller's electricity quantity declaration queue with monotonically increasing prices.

(3) The transaction price is cleared. The electricity trading center takes the electricity data from the declared electricity quantity queue in sequence according to the price, and increases the pre-transaction electricity quantity queue data accordingly. When the declared power of the first m power generators in the seller's declared power queue satisfies the Eq. (8), that is, when the total pre-transaction power is equal to the total demand for the reduce-abandonment market, the clearing calculation is ended.

$$\begin{cases} \sum_{i=1}^{m-1} Q_i < Q_L \\ \sum_{i=1}^{m} Q_i \geq Q_L \end{cases} \tag{8}$$

The reduce-abandonment market clearing price is equal to the last quotation entered into the transaction volume queue, that is, the declared electricity price $\lambda_m$ of the m-th power generator, and all transaction volumes are settled according to the unified clearing price. For the combined declared electricity volume of different clean energy generators, the electricity trading center will allocate the transaction volume to different clean energy generators according to the proportion of the declared electricity volume.

(4) Safety check. The power trading center forms an unconstrained transaction result according to the pre-transaction volume of each market entity, and submits it to the power dispatching agency for safety verification. After the verification, the official clearing result will be formed, which will be announced by the trading center.

## 4 Optimization of Electricity Purchase and Sale Strategies of Electricity Retailers under the Condition of Limited New Energy Consumption

### *4.1 Cluster Analysis of Electricity Retailer's Electricity Purchase and Sale Scenarios*

The profit of electricity retailers comes from the difference between the purchase and sale of electricity in the retail market and the wholesale market. In the above-mentioned mid-to long-term and reduce-abandonment electricity purchase and sale business in the two-tier market, due to the uncertainty in the consumption of restricted electricity by new energy sources and the uncertainty of users' electricity demand, the profits of electricity retailers are also faced with uncertain risks. In this paper, the electricity purchase and sale scenario is composed of new energy consumption limited electricity consumption and user electricity demand during each period of the special execution day. Assuming that a total of T times of reduce-abandonment market are organized in the decision-making cycle, all electricity purchase and sale scenarios are expressed as:

$$S_T = [\omega_1, \omega_2, \omega_3, \cdots, \omega_t, \cdots, \omega_T]^T \tag{9}$$

$$\omega_t = \left[Q_{v,t}^{pre}, Q_{n,t}^{pre}, Q_{p,t}^{pre}, Q_{v,t}, Q_{n,t}, Q_{p,t}\right] \tag{10}$$

In the above equations: $S_T$ represents the set of electricity purchase and sale scenarios of all electricity retailers; $\omega_t$ represents the electricity retailer purchase and sale scenarios on the t day; $Q_{v,t}^{pre}$, $Q_{\mathrm{n},t}^{pre}$, and $Q_{p,t}^{pre}$ represent the limited power during the new energy valley period, the normal period, and the peak period, respectively; $Q_{v,t}$, $Q_{n,t}$, and $Q_{p,t}$ respectively represent the load electricity consumption of the electricity retailer's agent users during the valley period, the normal period and the peak period.

Since it is difficult to determine the number of clustering results in the clustering of electricity purchase and sales scenarios, this paper uses the hierarchical clustering algorithm in structural clustering to cluster all scenarios. The collection of electricity purchase and sales scenarios after clustering is:

$$S_T^* = [\omega_1, \omega_2, \cdots, \omega_t, \cdots, \omega_{T^*}] \tag{11}$$

In the above equation: $S_T^*$ represents the set of all electricity retailer's electricity purchase and sale scenarios after clustering; $T^*$ represents the number of categories of scene clustering.

### *4.2 Electricity Retailer's Electricity Purchase Cost Model by Time Period*

The electricity purchase cost of electricity retailers includes the mid- to long-term monthly wholesale market electricity purchase cost and the day-to-day special demand response electricity purchase cost. The medium and long-term monthly market is mainly divided into bilateral negotiation transactions and centralized bidding transactions.

The centralized bidding transaction adopts the high-low matching method for clearing. The prices declared by power generators are sorted from high to low, and the prices declared by electricity retailers are sorted from low to high and matched and cleared. The clearing price is the average value of the declared prices of both parties. Since it is the period when clean energy is to be consumed, thermal power usually operates in the minimum mode, and the supply capacity of the electricity market is greater than the demanded electricity. Therefore, it is assumed that the electricity retailer declares that the demanded electricity can be fully traded. The electricity purchase costs of electricity retailers in this market are:

$$C^{mon} = \sum_{i=1}^{N_1} \lambda_{sb,i}^{mon} Q_{sb,i}^{mon} + \lambda_{jz}^{mon} Q_{jz}^{mon} \tag{12}$$

In the above equation: $C^{\mathrm{mon}}$ is the electricity purchase cost of electricity retailers in the mid- to long-term monthly wholesale market; $N_1$ is the total number of generators participating in the mid- to long-term monthly market; $\lambda_{sb,i}^{mon}$ and $Q_{sb,i}^{mon}$ are respectively the electricity purchase price and electricity purchase amount signed by the electricity retailer and the i-th power generator in the bilateral negotiation contract in the medium and long-term monthly wholesale market; $\lambda_{jz}^{mon}$ is the market clearing price matched by the centralized bidding mode in the medium and long-term monthly wholesale market; $Q_{jz}^{mon}$ is the declared electricity quantity of electricity retailers in the centralized bidding mode.

Electricity retailers purchased electricity through bilateral negotiation transactions and unilateral centralized bidding transactions in a reduce-abandonment market recently. After the bilateral negotiation transaction is completed, the electricity retailer declares the demand for electricity, and forms a transaction listing. The electricity generators obtain electricity through price competition, and clear the market according to the declared price. The electricity purchase cost of the electricity retailer in the reduce-abandonment market is:

$$C_t^{day}(\omega) = C_t^v(\omega) + C_t^n(\omega) + C_t^p(\omega) = \sum_{i=1}^{N_2} \lambda_t^{\oplus}(\omega)\, Q_{i,t}^{\oplus}(\omega) \tag{13}$$

In the equation: $C_t^{day}(\omega)$ is the electricity purchase cost of the electricity retailer's reduce-abandonment market on the day under the scenario; $C_t^v(\omega)$, $C_t^n(\omega)$, and $C_t^p(\omega)$ are the electricity purchase costs in the valley period, the normal period, and the peak period of the reduce-abandonment market, respectively; $N_2$ is the total number of generators participating in the reduce-abandonment market; The superscript $\oplus = v, n, p$ indicates the period type, Among them, $\lambda_t^v(\omega)$, $\lambda_t^n(\omega)$, and $\lambda_t^p(\omega)$ represent the unified clearing price during the reduce-abandonment market valley period, normal period, and peak period on the t day; $Q_{i,t}^v(\omega)$, $Q_{i,t}^n(\omega)$, and $Q_{i,t}^p(\omega)$ are the electricity traded by the power generator with the electricity retailer during the valley period, the normal period, and the peak period of the i-th day.

### *4.3 Electricity Retailer's Electricity Sales Revenue Model by Time Period*

The electricity retailer's electricity sales revenue also includes the monthly electricity sales revenue and the previous day's special demand response electricity sales revenue. In monthly electricity sales, electricity retailers usually sign a fixed-price package contract with users at the end of the previous month, and the contract price is executed within a month and remains unchanged. Then the monthly electricity sales revenue of the electricity retailer can be expressed as:

$$\pi^{mon}(\omega) = \sum_{k=1}^{K_1} \lambda_{sb,k}^{mon} Q_{sb,k}^{mon} \tag{14}$$

In the equation: $K_1$ is the number of users who have signed monthly bilateral contracts with the electricity retailer; $\lambda_{sb,k}^{mon}$ is the electricity sales price signed by the electricity retailer and the kth user in the monthly retail market; $Q_{sb,k}^{mon}$ is the monthly electricity consumption of user $k$.

In the day-ahead demand-response power sales, in order to encourage power users with flexible resources to increase their power purchases, electricity retailers will give users economic incentives according to the step-by-step incentive price. At this time, the power sales revenue can be expressed as:

$$\pi_t^{day}(\omega) = \sum_{n=1}^{N} K_2 \int_{\theta_{n-1}}^{\theta_n} \left(\lambda_{sb,\theta}^{mon} - P_n\right) Q_n \mathrm{d}\theta \tag{15}$$

In the equation: N is the number of optional incentive grades provided by the electricity retailer, $n = 1, 2, \ldots, N$; $K_2$ is the total number of users participating in the demand response incentive of the electricity retailer on the t day.

### *4.4 A Cost Model for Evaluating the Deviation of Electricity Retailers by Time Period*

During the actual purchase and sale of electricity by electricity retailers, there is uncertainty in the actual electricity consumption of users, which causes a certain deviation between the total electricity consumption of the electricity retailer's electricity purchase contract and the actual total electricity consumption. When the deviation between the electricity demand curve declared by the electricity retailer in the reduce-abandonment market and the actual electricity consumption curve exceeds a certain range, the electricity retailer will be punished by the electricity trading center. The deviation assessment cost of the electricity retailer is composed of the deviation assessment cost of each time period, which can be expressed as:

$$C^p(\omega) = \sum_{t=1}^{T_2} \sum C^p_{\oplus,t}(\omega) \oplus = v, n, p \tag{16}$$

$$C^p_{\oplus,t}(\omega) = \begin{cases} k_1 \left( Q_{\oplus,t}(\omega) - \sum_{i=1}^{N_2} Q^{\oplus}_{i,t}(\omega) \right) \\ 0 \\ k_2 \left( \sum_{i=1}^{N_2} Q^{\oplus}_{i,t}(\omega) - Q_{\oplus,t}(\omega) \right) \end{cases} \tag{17}$$

In the above equations: $C^p_{\oplus,t}(\omega)$ are the deviation assessment cost of electricity retailers during valley hours, normal hours, and peak hours; $Q_{\oplus,t}(\omega)$ is the electricity consumption of all the proxy users of the electricity retailer during the valley period, the normal period and the peak period of the t day; T is the number of days in the decision-making cycle for the reduce-abandonment market transaction; $k_1$ and $k_2$ are the positive and negative deviation assessment coefficients of the electricity trading center for electricity retailers, respectively. When $Q_{\oplus,t}(\omega) > (1+\delta)\sum_{i=1}^{N_2} Q^{\oplus}_{i,t}(\omega)$, it is positive deviation assessment, when $Q_{\oplus,t}(\omega) < (1-\delta)\sum_{i=1}^{N_2} Q^{\oplus}_{i,t}(\omega)$, it is negative deviation assessment; $\delta$ represents the proportion of electricity that is exempt from assessment.

## 4.5 An Optimal Decision-Making Model Considering the Uncertainty of Clean Energy Consumption-Limited Scenarios

### 4.5.1 Optimization Decision Objective Function

In scenario $\omega$, the electricity retailer's profit from purchase and sale of electricity in the medium and long-term and reduce-abandonment market are:

$$\pi(\omega) = \pi^{mon}(\omega) + \sum_{t=1}^{T_2} \pi_t^{day}(\omega) - C^{mon} - \sum_{t=1}^{T_2} C_t^{day}(\omega) - C^p(\omega) \tag{18}$$

Then the expected profit function of the electricity retailer is the sum of the products of all scenario profits and scenario probabilities:

$$E = \sum_{\omega} \rho(\omega)\pi(\omega) \tag{19}$$

In view of the uncertainty of the results of the reduce-abandonment market caused by the uncertainty of the amount of electricity to be consumed by clean energy sources, electricity retailers may face certain losses in their demand response incentives. In this paper, the loss of electricity purchase and sale of electricity retailers is defined as the difference between the actual profit of a certain scenario and the expected profit of all scenarios, that is:

$$F(\omega) = \pi(\omega) - E \tag{20}$$

In this paper, the conditional value-at-risk (CVaR) method is used to describe the loss of this part of the profit. Then the CVaR of the electricity retailer's electricity purchase and sale income can be expressed as [19]:

$$C_{vaR} = F_{VaR} + (1-\mu)^{-1} \sum_{\omega} \rho_\omega \cdot \max\left(F(\omega) - F_{VaR}, 0\right) \tag{21}$$

$$b\{\psi \leq F_{VaR}\} = \mu \tag{22}$$

In the above equations: $\mu$ is the confidence level; $\psi$ is the loss of electricity purchase and sale of electricity retailers; $F_{VaR}$ represents the maximum loss that electricity retailers may face when implementing demand response incentives when the confidence level is $\mu$.

When electricity retailers make decisions on purchasing and selling electricity and incentivizing pricing, they must consider the costs and benefits of the mid-to-long-term market and the reduce-abandonment market, and take into account the risk of loss from implementing demand response incentives. Therefore, the objective function of the electricity retailer's decision to purchase and sell electricity is:

$$\max [E - \tau C_{vaR}] \tag{23}$$

In the above equation: k is the risk aversion coefficient of the electricity retailer. The larger the k is, the less the power retailer can accept the risk of loss. On the contrary, the smaller the k is, the stronger the risk tolerance of the electricity retailer is.

### *4.5.2 Optimizing Decision Constraints*

(a) Individual Rational Constraints

Introduce individual rational constraints in mechanism design to motivate users to voluntarily participate in demand response. It shows that the formulation of incentive electricity price must make the profit obtained by voluntary participation users at least greater than 0 [20], and its mathematical expression is as follows:

$$P_n Q_n - C(Q_n, \theta) \geq 0 \tag{24}$$

(b) Incentive Compatibility Constraint

Rational users, in order to pursue the maximization of demand response revenue, will inevitably choose the most suitable incentive gear for themselves, then:

$$P_n Q_n - C(Q_n, \theta) \geq P_k Q_k - C(Q_k, \theta), k \neq n \tag{25}$$

(c) Incentive Price Constraint

Only when the set incentive price $P_n$ is less than $\lambda_{sb,\theta}^{mon} - \lambda_t(\omega)$, the electricity retailer can benefit from the demand response, then:

$$0 < P_n < P_k < \lambda_{sb,\theta}^{mon} - \lambda_t(\omega) \tag{26}$$

(d) Market Purchase and Sale of Electricity and Electricity Balance Constraints

$$\sum_{i=1}^{N_1} Q_{sb,i}^{mon} + Q_{jz}^{mon} + \sum_{t=1}^{T_2}\sum_{i=1}^{N_2} Q_{i,t}(\omega) = \sum_{k=1}^{K_1} Q_{sb,k}^{mon}(\omega) + \sum_{t=1}^{T_2}\sum_{n=1}^{N} K_2 [F(\theta_n) - F(\theta_{n-1})] Q_n \tag{27}$$

$$Q_{i,t}(\omega) = \sum Q_{i,t}^{\oplus}(\omega) \quad \oplus = v, n, p \tag{28}$$

(e) Power Generation Capacity Constraints

The electricity sales of clean power generators in the reduce-abandonment market must meet the constraints of the maximum power generation capacity.

$$0 \leq \sum_{i=1}^{N_2} Q_{i,t}^{\oplus}(\omega) \leq Q_{\oplus,t}^{pre}(\omega) \quad \oplus = v, n, p \tag{29}$$

In the above equation: $Q_{i,t}^{\oplus}(\omega)$ represents the electricity sold by the clean energy generator i in the valley period, the normal period and the peak period of the t-th day under the scenario $\omega$.

(f) User Responds to Battery Constraints

$$0 < Q_{DR,t} + Q_{k,t}^{mon}(\omega) \leq Q_{DR,k}^{\max} \tag{30}$$

In the above equation: $Q_{DR,t}^{\max}$ represents the maximum value of the demand-response power that the user can provide in the time period t.

(g) Deviation Power Constraint

$$\left| Q_{\oplus,t}(\omega) - \sum_{i=1}^{N_2} Q_{i,t}^{\oplus}(\omega) \right| \leq Q_p^{\max} \quad \oplus = v, n, p \tag{31}$$

In the above equation: $Q_p^{\max}$ represents the maximum deviation quantity of electricity retailer specified by the electricity trading center.

## 5 Simulation and Numerical Results

It is assumed that the electricity retailer's bilateral negotiated contract price with all electricity users in the retail market is 502 yuan/MWh. In the mid-to-long-term electricity wholesale market, the electricity price for the bilateral negotiation between electricity retailers and generators is 315 yuan/MWh, and the clearing price for centralized bidding transactions is 329 yuan/MWh. The proportion of electricity that is exempted from the monthly electricity purchase and sale by the electricity trading center for electricity retailers is $\delta = 3\%$, the assessment coefficient for positive deviation is $k_1 = 0.1$, and the assessment coefficient for negative deviation is $k_2 = 0.3$.

### *5.1 Scene Clustering Results and Evaluation*

Referring to the power generation and consumption data of the power system in a high-proportion clean energy area, the daily clean energy power data and user load data are obtained. After generating all the scene sets, the hierarchical clustering algorithm is used to cluster the scenes. The clustering tree diagram is shown in Fig. 3.

It can be seen from the clustering dendrogram that when the number of sample categories is 3, the distance between classes is the largest, and the clustering effect is the best. The clustering results are shown in Table 1.

Scenario 1 is an extreme situation where a large amount of water and electricity is coming from hydropower, the electricity to be consumed by clean energy reaches a peak, and the load demand is low. The frequency is higher; in scenario 3, there is less clean energy to be consumed, and the load demand is higher, so the price of electricity for the reduce-abandonment market is higher.

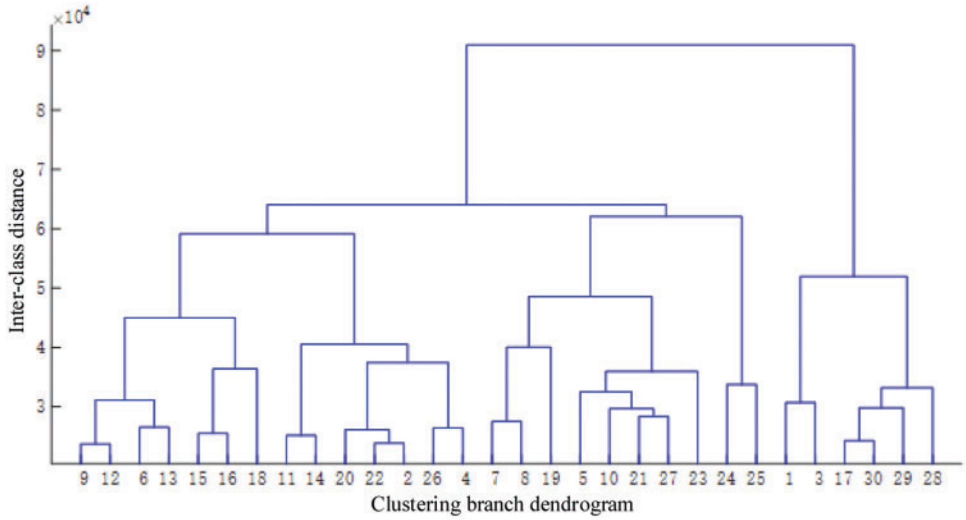


**Figure 3:** Hierarchical clustering dendrogram

**Table 1:** Clustering results of electricity retailer's electricity purchase and sale scenarios under the condition of limited clean energy consumption

| Typical scene | Typical scenario 1 | Typical scenario 2 | Typical scenario 3 |
|---|---|---|---|
| $Q_t^{pre}$ (MWh) | 9.5 | 7.1 | 6.2 |
| $Q_{L,t}$ (MWh) | 3.9 | 3.1 | 4.8 |
| $\lambda_t^g$ (yuan/MWh) | 268 | 273 | 277 |
| $\lambda_t^p$ (yuan/MWh) | 271 | 275 | 282 |
| $\lambda_t^f$ (yuan/MWh) | 273 | 278 | 285 |
| $\lambda_t^j$ (yuan/MWh) | 274 | 281 | 287 |
| Scenario probability | 0.054 | 0.830 | 0.116 |

### *5.2 The Influence of Different Risk Aversion Coefficients on the Profit of Electricity Retailer's Purchase and Sale of Electricity*

For different types of users with flexible resources, different demand response elasticity coefficients are set, and the influence of different demand elasticity coefficients on the profit of electricity purchase and sale of electricity retailers is analyzed.

As can be seen from Fig. 4, with the increase of the elastic coefficient of electricity user demand, the demand response power generated by the user also increases, and the incentive cost invested by the electricity retailer also continues to rise. However, on the other hand, the increase in the amount of electricity in response to user demand enables electricity retailers to declare more listed electricity in the reduce-abandonment market a few days ago, and their profits are also increasing by taking advantage of the price difference between electricity purchases and sales. Therefore, electricity retailers can increase the enthusiasm of users to respond to demand and expand the scale of demand response, so as to obtain greater profits in the reduction and abandonment session.

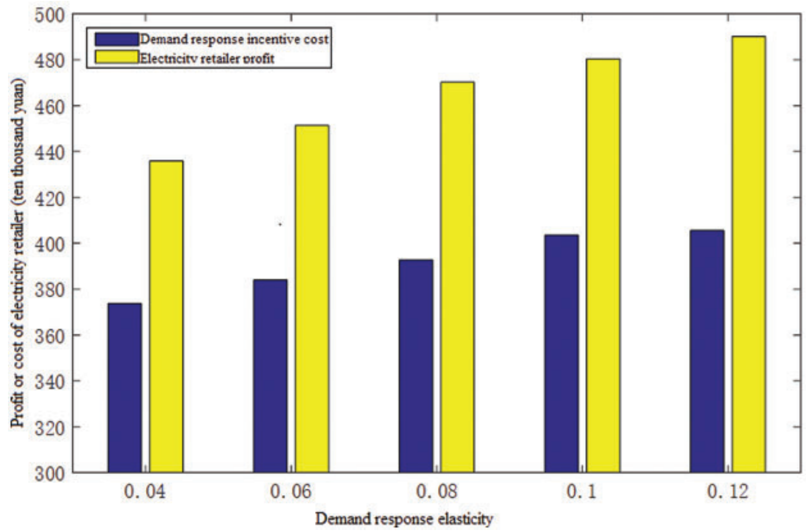


**Figure 4:** Changes in the profit of electricity retailers from purchasing and selling electricity under different elasticities of demand

## 6 Conclusion

Aiming at the problem of electricity retailer's purchase and sale of electricity under the condition of limited clean energy consumption, this paper firstly analyzes the source-load dual uncertainty factors in the electricity retailer's mid- to long-term electricity market and the process of special electricity purchase and sale in the past few days. Then, through the multi-scenario analysis method, the uncertain clean energy consumption limited power consumption and user electricity demand are composed of different electricity purchase and sales scenarios, and the hierarchical clustering algorithm is used to obtain typical electricity purchase scenarios. Then, considering the electricity retailer's electricity purchase cost, deviation assessment cost, electricity sales revenue and electricity purchase and sales risk, and taking the maximum profit expectation of electricity retailer's electricity purchase and sales as the objective function, establishes the electricity retailer's mid- and long-term market-days in the reduce-abandonment market. The risk decision model of purchasing and selling electricity. The influence of relevant factors on the profit of electricity purchase and sale of electricity retailers is analyzed by numerical example simulation, and the following conclusions are obtained: Under the condition of limited consumption of clean energy, electricity retailers can make considerable profits in the medium and long-term and reduce-abandonment market by using the demand response mechanism to fully utilize the flexible resources of users and optimize their own electricity purchase and sale strategies on the premise of balancing profits and risks. At the same time, the incentive-based demand response carried out by electricity retailers can also absorb clean energy electricity in the system, achieving a win-win situation among power generators, electricity retailers and demand response users.

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