# Robust Purchase and Sale transactions Optimization Strategy for Electricity Retailers with Energy Storage System Considering Two-Stage Demand Response

Liwei Ju[a,b], Jing Wu[a], Hongyu Lin[a,b], Qinliang Tan[a], Gen Li[c], Zhongfu Tan[a], Jiayu Li[a]

a North China Electric Power University, Beijing, China, 102206

*b* Beijing Energy Development Research Base, Beijing 102206, China

*c* Cardiff University, Cardiff, CF24 3AA, United Kingdom

*Corresponding authors: hdlw_ju@ncepu.edu.cn (L. Ju); Lig9@cardiff.ac.uk (G. Li) Tel.: +86-176-0016-0816

**Abstract:** A new two-stage demand response is designed for the electricity retailers with energy storage system (ESS-ER) in the deregulated power market. The ESS-ER could response to the output of different power sources by adjusting the charging-discharging behavior according to the bidding power price. The paper models the two-stage demand response for electric power retailers and proposed a two-layer coordinated optimal model for the purchase and sale of the electric power retailers. In the upper layer model, the conditional value at risk method and robust stochastic theory are applied to describe the uncertainty influence of wind power and Photovoltaic (PV) power, and the minimum whole cost of power purchasing is taken as the objective. In the lower-layer, the power consumption behaviors of different customers are considered to get the maximum revenue of power selling by implementing differentiated demand response. Then, to solve the two-layer mathematical model, the lower-layer model is converted into the Karush-Kuhn-Tucker (KKT) optimality conditions. The results show that: (1) The two-stage demand response could smooth the curves of power purchasing and terminal users' load, which could bring more flexible transaction space. (2) The proposed two-layer transaction model could balance the cost and risk of power purchasing, bringing more trading opportunities for wind power and PV, which can also reduce the energy consumption cost of the end-users. (3) By introducing the risk cost coefficient, confidence degree and robust coefficient, the decision-makers can adjust the power trading behaviors, and establish the optimal power trading scheme in line with their expected situation. (4) When higher energy storage capacity is set, the efficiency of demand response rises. When the capacity ratio of wind to energy storage is 4:1, the efficiency of demand response reaches the best. When larger energy storage capacity is set, the demand response turns to be more effective. However, when the capacity ratio of wind and PV to energy storage is 4:1, the effect of demand response reaches the best. Overall, the proposed model could provide an effective tool for power retailers in China's electric power market.

**Key words**: Electricity retailers; demand response; uncertainty; purchase and sale transaction; robust;

## 0 Introduction

To improve the operating efficiency of electricity market and break up the monopoly, a significant restructuring process for power industry has been initiated in many countries since the 1990s [1]. In China, two power system reforms have been carried out. The first power industry reform was implemented according to Power System Reform Plan (No.5 Document), including separating the vertical integration power corporation (State Power Corporation, SPC) into two parts: power generation enterprises and power grids enterprises in 2002 [2]. After the reformation, the operating efficiency of the electricity market and competitiveness among power generation companies were enhanced significantly. However, the electricity sales market was still dominated by the State Grid Corporation of China (SGCC) and the China Southern Power Grid (CSG). The second power industry reform began with the launch of the Further Deepening the Reform of Electric Power System (No.9 Document) in 2015 [3]. With further implementation, the distribution market and the retail market were introduced to the existing electricity market. Power retailers become new participants into this market, which will bring the competition to the retail side.

In the deregulated power market, the electric power retailers can purchase electricity through contracts or spot transactions from the power generation companies or the power pool market [4]. Then, the purchased power will be sold to the terminal users. Additionally, electricity retailers sign contracts with users at a pre-agreed selling price, which indicates major part of the power retailers in connecting power suppliers and terminal users. The main operating benefits are determined by the price difference between purchase and sale. In addition, the smart grid technology has become more mature in recent years. Demand response (DR) is introduced to encourage users to optimize their power consumption behaviors through flexible price policies, bringing benefits and improving the operation efficiency of the supply side [5]. For power retailers, the power purchase cost can reduce with energy storage system involved. As the implementer of DR, power retailers should consider how to maximize the benefits by power distribution. Therefore, the optimal strategy of power purchase and sale considering DR involved in both purchase and retail side is studied, promoting electricity retailers to participate in the electricity market.

DR can be used to encourage the end-users to respond to the system dispatching by implementing differentiated tariff policies to mitigate market and public-grid issues [6]. When power retailers participate in or implement DR, the risk of price fluctuation and power supply shortage reduces, and the operating efficiency and the reliability of energy supply improves. In recent years, many scholars at home and abroad have carried out research on the basic concept, classification and technology of DR. Huang et al. [7] divided the demand response into the price-based demand response (PBDR) and the incentive-based demand response (IBDR). Luo et al. [8] integrated the IBDR problem with other distributed energy resources in the form of the virtual power plant. Eissa .[9] presented a first-time real-time incentive demand response problem is smart grid used by “i-Energy” management system. Athanasios et al.[10] introduced an integrated model that perform the simulation of the day-ahead electricity market, and estimates the income and price elasticities of electricity demand for estimating the retailers’ profitability with demand responsive consumers. Yoon et al. [11] proposes an online-learning-based strategy for a distribution system operator-based electricity retailer to determine optimal retail prices, considering the optimal operations of data-driven demand response using the explicit an artificial neural network (ANN) model.

For electricity retailers, the purpose of flexible trading in the power market is to achieve the lowest power purchase cost and the greatest selling benefits. With the development of the power system reformation, the user-centered management theory needs to be implemented further, requiring more research on DR and the retailers’ decision-making on power purchase and sale behaviors [12]. First of all, in terms of power purchase, due to the uncertainty and high economics of clean energy power generation, the declared price and the controllability of different power generators should be considered. Ben et al. [13] investigates the impacts of electricity market variations for electricity retailers on the Nordic stock market returns using hourly observations of electricity spot prices pairwise in aggregate market index and some sector indexes. Furthermore, Tom et al. [14] model consumer switching in retail electricity markets in New Zealand to identify important determinants of switching and estimate willingness to pay (WTP) for six non-price attributes. Boroumand et al. [15] discussed the potential benefits of optimal intra-day electricity hedging for the environment from the perspective of electricity retailers. Sayyad et al. [16] proposed a robust optimization approach to handle market price uncertainty in which the upper deviation from forecasted value of pool price will be considered for risk analysis for a retailer. .

Then, in power transaction, the electric power retailers sign agreements with different types of users, and as the implementer of DR, they set flexible selling prices to guide users’ load, and realize the optimal power distribution to obtain the maximum revenue at the same time. Maharjan et al. [17] aimed at maximizing the selling benefits, establishing a hierarchical system model for electric power retailers and customers.

| | |
|---|---|
| **Abbreviations** | |
| ESS-ER | Electricity retailers with Energy Storage System |
| DR | Demand response |
| IBDR | Incentive-based demand response |
| PBDR | Price-based demand response |
| WPP | Wind power plant |
| PV | Photovoltaic power |
| CVaR | Condition value at risk |
| KKT | Karush-kuhn-tucker |
| ES | Energy storage |
| IU | Industrial users |
| CU | Commercial users |
| AU | Commercial users |
| RU | Residential users |
| **Set** | |
| *t*, *s* | Index for time |
| z | Index for user |
| **Scalar** | |
| T | Optimization period, 24hour |
| K | Generator number |
| $\lambda$ | Risk aversion coefficient of the ESS-ER |
| $\alpha$ | Critical value of power purchase risk cost |
| $\beta$ | Confidence level |
| $M^{\text{on}}$, $M^{\text{off}}$ | Preparation time for the retail to be on-sale and off-sale |
| $r_{u,t}$ | Margin power purchased from uncontrollable generation sources at time $t$ |
| **Parameter** | |
| $e_{st}$ | Price elasticity of time $s$ to time $t$ |
| $L^{0}_{\text{ES},t}$ | Power purchase demands of ESS-ER before the PBDR at time $t$ |
| $P^{0}_{ES,t}$ | Power purchase price of ESS-ER at time $t$ before the PBDR |
| $\Delta P_{ES,t}$ | Variations of power purchased price of ESS-ER at time $t$ afer the PBDR. |
| $\Delta L^{+}_{zm,t}$ | Increasing IBDR output in the $m$-th interval at time $t$ |
| $\Delta L^{-}_{zm,t}$ | Reducing IBDR output in the $m$-th interval at time $t$ |
| $N_m$ | Number of intervals |
| $N_z$ | Number of IBDR users |

| | |
|---|---|
| $P^{-}_{k,t}$ | Compensation price at time $t$ that generator $k$ offers to the ESS-ER for power shortage |
| $P^{\text{UG}}_{t}$ | Power price of utility grid at time $t$ |
| $\Delta g^{+}$, $\Delta g^{-}$ | Limits of increase and decrease of electricity sold by generators |
| $\Delta L^{\max}_{ES,t}$, $\Delta L^{\min}_{ES,t}$ | Maximum and the minimum DR output of the retailer at time $t$ |
| $\Delta L^{\max}_{ES}$ | Upper limit of the total DR output of the retailer |
| $\Delta g^{\text{chr,R}}_{ES}$ | Rated discharging power of the energy storage system |
| $\Delta g^{\text{dis,R}}_{ES}$ | Rated charging power of the energy storage system |
| $S^{\max}_{ES}$ | Maximum capacity of the energy storage system |
| $g^{\max}_{t}$ | Maximum electricity available for sale at time $t$ |
| $P_{zt}$ | Electricity price for user $z$ at time $t$ |
| $P_{ut}$ | Revenue of the ESS-ER from selling surplus electricity at time $t$ |
| $P_{bt}$ | Electricity price for CU at time $t$ |
| $P^{0}_{t}$ | Electricity prices before PBDR at time $t$ |
| $P_{rt}$ | Electricity price for RU at time $t$ |
| $L^{\max}_{zt}$, $L^{\min}_{zt}$ | Maximum and minimum ramping power of user $z$ participating in PBDR at time $t$ |
| $\Delta L^{\text{IBDR,max}}_{z,t}$ | Maximum ramping power of user $z$ participating in IBDR at time $t$ |
| $\Delta L^{\text{IBDR,min}}_{z,t}$ | Minimum ramping power of user $z$ participating in IBDR at time $t$ |
| $\Delta L^{+,\max}_{zm,t}$ | Maximum IBDR output of user $z$ |
| $\Delta L^{-,\max}_{zm,t}$ | Maximum IBDR reduction of user $z$ |
| $\Delta L^{\min}_{zt}$, $\Delta L^{\max}_{zt}$ | Upper and lower PBDR output limits of user $z$ |
| $\Delta L^{\max}_{ES,t}$, $\Delta L^{\min}_{ES,t}$ | Upper and lower DR limits of the ESS-ER purchasing electricity at time $t$ |
| **Variables** | |
| $L_{\text{ES},t}$ | Power purchase demands of ESS-ER after the PBDR at time $t$ |
| $\Delta L_{\text{ES},t}$ | Variation of the power purchase demand of ESS-ER at time $t$ |
| $V\left(L_{\text{ES},t}\right)$ | Electric value of Power purchase demands $L_{\text{ES},t}$ of ESS-ER at time $t$ |
| $\pi^{\text{P}}$ | Unit net profit of the retailer |
| $\Delta L^{\text{IBDR}}_{z,t}$ | Agreed electricity of user z participating in the IBDR at time $t$ |
| $P^{\text{IBDR}}_{z,t}$ | IBDR price of user $z$ at time $t$ |
| $\Delta L^{+}_{zm,t}$ | Increasing IBDR output in the $m$-th interval at time $t$ |
| $\Delta L^{-}_{zm,t}$ | Reducing IBDR output in the $m$-th interval at time $t$ |
| $C_{ER}$ | Total power purchase cost of the ESS-ER |
| $g_{k,t}$ | Electricity quantity that the ESS-ER buys from generator $k$ at time $t$ |
| $g^{-}_{k,t}$ | Power shortage at time $t$ |
| $CVaR_{k,t}$ | Risk cost that the ESS-ER takes for power purchase from generator $k$ |

| | | | |
|---|---|---|---|
| $P_{k,t}$ | Power price at time $t$ that generator $k$ offers | $g_{u,t}$ | Electricity purchased by the ESS-ER from uncontrollable generation sources at time $t$ |
| $\eta_{\text{ex}}$ | Reserve purchase power coefficient of the ESS-ER for the electricity consumption growth at time $t$ | $C_{zt}^{DR}$ | Cost of the ESS-ER implementing DR to user $z$ at time $t$ |
| $g_{c,t}$ | Electricity purchased by the ESS-ER from controllable generation sources at time $t$ | $C_{it}^{DR}$ | DR costs generated by IU at time $t$ |
| $g_t$ | Electricity sold by generators at time $t$ | $C_{bt}^{DR}$ | DR costs generated by CU at time $t$ |
| $v_t$ | Operation state of generators at time $t$ | $C_{at}^{DR}$ | DR costs generated by AU at time $t$ |
| $T_{t-1}^{\text{on}}$, $T_{t-1}^{\text{off}}$ | Accumulated on-sale time and off-sale time of the retail at time t-1 | $C_{rt}^{DR}$ | DR costs generated by RU at time $t$ |
| $\Delta L_{ES,t}^{\text{pur}}$ | Power purchased of the electricity retailers at time $t$ | $C_t^{PBDR}$ | PBDR cost generated by users at time $t$ |
| $\Delta L_{ES,t}^{\text{se}}$ | Power sale of the electricity retailers at time $t$ | $C_t^{IBDR}$ | IBDR cost generated by users at time $t$ |
| $S_{ES,t-1}$ | Energy storage at time $t$-1 | $C_{bt}^{R}$ | Cost saving of CU |
| $g_t$ | Actual sold electricity at time $t$ | $P_t$ | Electricity prices after PBDR at time $t$ |
| $R$ | Sale revenue of the ESS-ER | $v_{zt}$ | States of user $z$ participating in PBDR at time $t$ |
| $X_{zt}$ | Sale proportion of the ESS-ER to user $z$ at time $t$ | $v_{zt}$ , $o_{zt}$ | States of user $z$ participating in IBDR at time $t$ |

Guo et al. [18] established a multi-objective unified power purchase model aiming at minimizing the total purchase cost and the conditional value at risk considering the load deviations. Algarvio et al. [19] developed a risk management and the optimization model for the portfolios of retailers operating in liberalized electricity markets using the Markowitz theory. Ottesen et al. [20] proposed a short-term decision models for aggregators considering power selling with prosumers reserve surplus power purchasing, in which the aggregator can control flexible energy units. Dai et al. [21] studied the real-time pricing scheme in smart grid with multiple retailers and multiple residential users using Stackelberg game.

Finally, in power purchase and sale linkage transaction, considering the increasing ability of users in responding to market price and incentive information, current research started from the DR of users, and established a double-layer decision-making model with the upper model of maximizing retailers' benefits and the lower of maximizing the utility of power consumption [22]. Current research also considered the alliance transaction of both the generation side and the user side, and put forward the optimization decision of alliance selection and pricing [23]. Fotouhi et al. [24] provided a risk management strategy for retailers to deal with the uncertainties in the day-ahead market and hedge the financial losses. Sekizaki et al. [25] presented an power retail market model in which elastic demands of users in a distribution network were traded at flexible selling prices offered by power retailers. Kettunen et al. [26] developed a multistage stochastic optimization approach for the power contract portfolio management, which accounted for uncertainties of both power prices and loads. Sayyad et al [27] proposed a real-time pricing model for electricity retailer in the smart grid with the presence of hydrogen storage systems and plug-in electric vehicles under pool market price.

In summary of the above literature, the following points are obtained: (1) The existing research mainly focused on the basic concept, mathematical model and technology of DR, lacking of trading application cases. Power retailers can be seen as participants of DR in the purchase side. Only Athanasios et al. [10] and Yoon et al. [11], regarding DR as goods between its providers and buyers, discussed its development mode. (2) Some research have considered the impact of the uncertainty of uncontrollable power supply such as electricity price volatility and wind or photovoltaic (PV) on power purchasing strategy, and put forward a variety of uncertainty decision-making models, but failed to consider that the retailers with energy storage system (ESS-ER) can also participate in DR, which can flexibly adjust the charging and discharging behaviors, so as to alleviate the above uncertainty risks. (3) Many researchers have studied the DR in the retailing side, and established the optimal selling strategy for a certain type of users. However, power retailers can always sign contracts with multiple types of users, divided by power consumption characteristics, such as industrial users, commercial users, agricultural users and so on. The electricity retailers can implement differentiated DR strategy based on various power consumption characteristics, so as to achieve the optimal power allocation. (4) Due to the lack of research on DR strategy in power purchase side and the specialization of the research on DR in power selling side, linkage DR transactions of power purchase and sale were absent. Considering the above highlights, the possible contributions of this paper could be summarized as following.

- Firstly, the power retailers with energy storage system (ESS-ER) are chosen as the research object, and a two-stage DR strategy is proposes, in which the ESS-ER will be regarded as a DR participant in power purchase side and a DR implementer in power sale/retail side. When the ESS-ER is taken as the DR participant, in order to meet the power demand, the purchase volume is set to be equal before and after the DR being carried out. However, when the ESS-ER is regarded as a DR implementer, the way to participate in DR, the revenue of different types of users and the profit space of the retailers are discussed.
- Secondly, a bi-level coordinated optimization model of power purchase and retail for the ESS-ER is proposed considering the two-stage demand response, including the combined power purchase optimization model in the upper layer and the optimal electricity allocation model in the lower layer. In the upper layer model, the generating uncertainties of wind power and PV are considered, and the influence degree of uncertain variables in objective function and constraints are measured by introducing CVaR and robust stochastic optimization theory. Meanwhile, assuming that retailers can participate in demand response in power purchase side by employing the energy storage system, the power purchase cost and risk cost may reduce. In the lower layer model, the complementarity and economy of different types of DR are considered, and an optimization strategy is established to maximize the revenue of the retailer and to achieve the optimal power allocation among different user types.
- Finally, in order to achieve the linkage transaction optimization of electricity retailers, the Karush-Kuhn-Tucker (KKT) condition is introduced in the lower layer model to transform the bi-level optimization model into a single-level comprehensive optimization model. The single-level comprehensive optimization model considers the characteristics of bilateral demand response in both purchase and retail sides, and is able to transform the power consumption information in the sale side into the purchase side immediately to achieve linkage optimization. By solving the model, the maximum power sale revenue and the minimum power purchase cost can be achieved at the same time, which is, the maximum net revenue of the power retailers.

The paper is laid out as follows: Section 1 introduces the operating strategies of the ESS-ER, including the development background and operation mode. Then, the two-stage demand response mathematical modeling for electricity retailer is completed in Section 3. Section 4 establishes a bi-level coordinated optimization model for retailers' power purchase and retail, including the combined power purchase optimization model in the upper and the optimal electricity allocation model in the lower. To solve the proposed bilevel model, the lower model is transformed to the KKT conditions of the upper model in Section 4. Then, a case study with the IEEE 30-bus system is conducted to verify the validity and applicability of the proposed model in Section 5. Section 6 highlights the contributions and conclusions of this paper.

The remainder of the paper is laid out as follows: Section 1 introduces the operating strategies of the ESS-ER, including the development background and operation mode. Then, the retailers with energy storage system are chosen as the research object, and the operation mode of the ESS-ER is discussed. Furthermore, when the retailers is pre-configured with energy storage system, two-stage demand response exist in the power purchase side and power sale side, therefore, the two-stage demand response mathematical modeling for electricity retailer is completed in Section 2. Section 3 establishes a bilevel coordinated optimization model for retailers' power purchase and retail, including the combined power purchase optimization model in the upper and the optimal electricity allocation model in the lower. To solve the proposed bilevel model, the lower model is transformed to the KKT conditions of the upper model in Section 4. Then, a case study with the IEEE 30-bus system is conducted to verify the validity and applicability of the proposed model in Section 5. Section 6 highlights the contributions and conclusions of this paper.

## 1 Operation strategies for the ESS-ER

### 1.1 Development of electricity retailers in China

The power system in China has experienced three vital stages of "integration", "generation-grid separation", and "three openings, one independence, and three enhancements" [3]. Before 2002, the State Grid Corporation of China was in charge of the electricity system that generation, transmission, distribution and retail were integrated. In 2002, the hard time for the corporation, to improve the flexibility and competitiveness of generation market, State Council of China proposed that power generation plants should be separated with the grid corporation, in the *Notice on electric power system reform plan (GF [2002] No.5)* [2]. In addition, 5 power generation groups and 2 grid corporations were started, as mentioned in the notice. In 2005, to intensify the flexibility and competitiveness of the market and reduce the cost of energy utilization, distribution and retail businesses would orderly be open to social capital in the *Opinions on further deepening the reform of electric power system (ZF [2015] No.9)*, and power generation/utilization plans which were not for public welfare or adjustment would also be orderly open [3]. Fig. 1 shows the development of the power system in China.

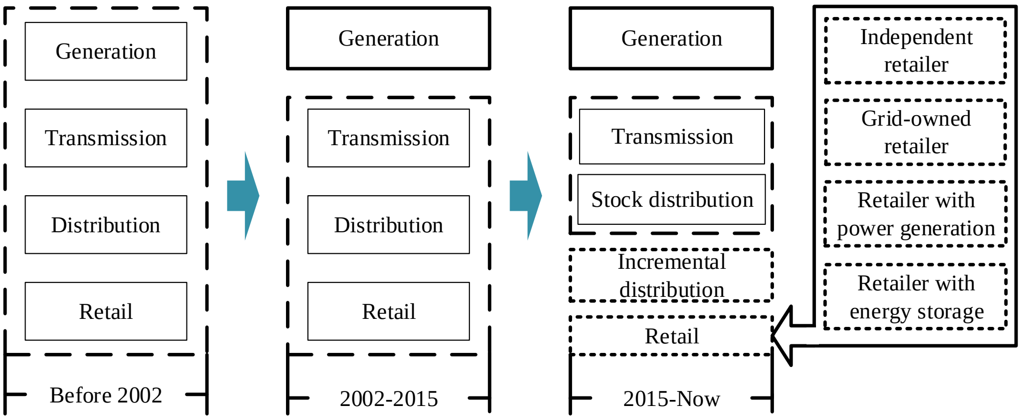


**Fig. 1 The development of electricity system in China**

With continuously open of power retail business, different types of power retailers form. Until December 2017, 3044 power retailers have been established in China [23]. According to the business type, power retailers are composed of independent retailers, grid-owned retailers, generator-owned retailers, and electricity power retailers with energy storage system (ESS-ERs). Different from the first three, ESS-ERs can offer both electricity service and ancillary services, such as peak regulation, frequency modulation, and reserve. Since ESS-ERs are able to charge and discharge via energy storage system, retailers become more flexible in the market. Therefore, this paper focuses on the purchase and sale strategies of the ESS-ERs.

### 1.2 Operation mode of the ESS-ER

Considering that the ESS-ER owns an energy storage system, the operation states (charging or discharging) can be adjusted according to the bidding power price of different types of power generation plants to cooperate with clean energy generation output. In addition, as an implementer of demand response (DR) in the retail side, the ESS-ER can encourage end users to adjust their power consumption behaviors. Therefore, ESS-ER can implement DR in both purchase and retail side. ESS-ERs do not only participate in PBDR for power purchase, but both PBDR and IBDR for power retail. Fig. 2 shows the operation mode of the ESS-ER.

According to Fig. 2, the operation mode of the ESS-ER includes power purchase and power retail, which makes the DR operating in two stages. The details are as follows.

➢ In power purchasing, the ESS-ER will use energy storage to charge and discharge to participate in PBDR, based on the bidding prices and purchase demand of different types of power generation plants. When the price is relatively low, the ESS-ER will increase its purchase quantity, otherwise, it will decrease to obtain DR revenue, thus realizing the objective of minimizing the power purchase cost.

➢ In power retailing, as an implementer of DR, the ESS-ER will sign agreements with different types of users to meet the load demands. Retailers participate in PBDR and IBDR by setting reasonable time-of-use (TOU) price and controllable load price for power allocation. In addition, extra power selling profits will be obtained by calling users' DR output to participate in power trading with public grid and ancillary services.

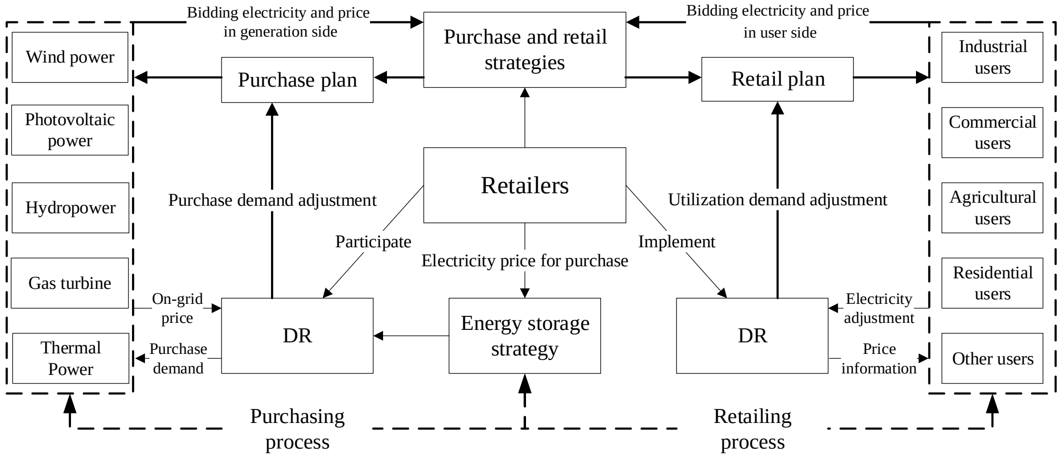


**Fig. 2 The operation mode of the ESS-ER**

## 2 Two-Stage Demand Response of the ESS-ER

### 2.1 DR strategy for power purchase

Without energy storage system, electric power retailers make power purchase plans only according to users' demands. If ESS is introduced, power retailers are able to participate in PBDR for power purchase. For example, according to the real-time electricity price of different types of power generators, the purchase demands can be adjusted by ESS to realize the minimum power purchase cost. The DR in power purchase only transfers the power demand among different periods, not reducing it. Fig. 3 shows the DR strategy for power purchase of the ESS-ER.

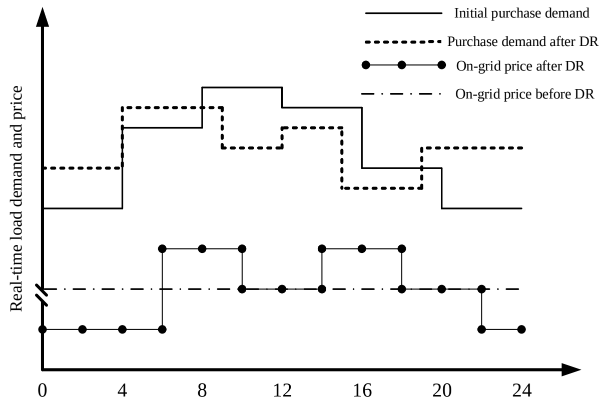


**Fig. 3 The DR strategy for power purchase of the ESS-ER**

According to Fig. 3, the ESS-ER will adjust its own electricity demand based on the real-time price if the TOU price is implemented. The calculation is as follows.

$$L_{\mathrm{ES},t} = L^{0}_{\mathrm{ES},t} + \Delta L_{\mathrm{ES},t} \tag{1}$$

Here, the price-demand elasticity matrix is introduced to stand for the PBDR.

$$e_{st}=\frac{\Delta L_{ES,s}/L^0_{ES,s}}{\Delta P_{ES,t}/P^0_{ES,t}}\begin{cases}e_{st}\le 0, s=t\\ e_{st}\ge 0, s\ne t\end{cases} \tag{2}$$

The calculation of load demand after the PBDR $L_{\mathrm{ES},t}$ refers to [28]. $V\left(L_{\mathrm{ES},t}\right)$ is set to be the electric value of $L_{\mathrm{ES},t}$, then the unit net profit $\pi^{\mathrm{P}}$ of the retailer is given by

$$\pi^{\mathrm{P}}=V\left(L_{\mathrm{ES},t}\right)-L_{\mathrm{ES},t}P_{\mathrm{ES},t} \tag{3}$$

In Eq. (3), the first and second derivatives of $P_{\mathrm{ES},t}$ are calculated, and $V\left(L_{\mathrm{ES},t}\right)$ is Taylor expanded.

$$\begin{aligned}V(L_{\mathrm{ES},t})&=V(L^0_{\mathrm{ES},t})+\frac{\partial V(L_{\mathrm{ES},t})}{\partial L_{\mathrm{ES},t}}[\Delta L_{\mathrm{ES},t}]+\frac{1}{2}\cdot\frac{\partial^2 V(L_{\mathrm{ES},t})}{\partial (L_{\mathrm{ES},t})^2}[\Delta L_{\mathrm{ES},t}]^2\\ &=V(L^0_{\mathrm{ES},t})+P^0_{\mathrm{ES},t}[\Delta L_{\mathrm{ES},t}]\{1+\frac{1}{2}\cdot\frac{\Delta L_{\mathrm{ES},t}}{e_{tt}L^0_{\mathrm{ES},t}}\}\end{aligned} \tag{4}$$

According to Eqs. (1) and (2), referring to the calculation method of demand variation after PBDR in [28] the power purchase demand after the PBDR can be calculated as follows.

$$L_{ES,t}=L^0_{ES,t}\times\left\{1+e_{tt}\times\frac{\Delta P_{ES,t}}{P_{ES,t}}+\sum_{\substack{s=1\\ s\ne t}}^{24}e_{st}\times\frac{\Delta P_{ES,s}}{P_{ES,s}}\right\} \tag{5}$$

The power purchase demand of the ESS-ER at different times after the PBDR can be obtained by using Eq. (5). Part of the power purchase demand in peak periods can be transferred to valley periods when the retailer has energy storage system and it participates in PBDR.

## 2.2 DR strategy for power retail

Power users include industrial users (IU), commercial users (CU), agricultural users (AU) and residential users (RU). Different kinds of users may have different DR means. Referring to [28], DR in retail side contains IBDR and PBDR. IBDR means that an ESS-ER signs agreement with users where load reduction, compensation and penalty (if the user breaks the agreement) are clearly determined, thus directly managing the users' power consumption behaviors. In this paper, it is assumed that the IBDR makes electricity quantity increase/reduce and the users get correspondingly paid, on the premise of the constraints of the users having been satisfied. Fig. 4 shows the IBDR bidding prices in retail side of the ESS-ER.

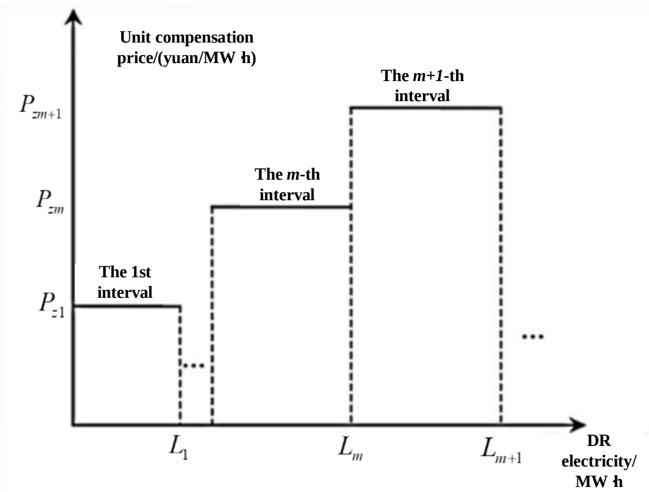


**Fig. 4 The IBDR bidding prices in retail side of the ESS-ER**

According to Fig. 4, the users will carry out IBDR step by step. The total IBDR dispatching cost is calculated as follows.

$$C_{\mathrm{IBDR}}=\sum_{t=1}^{T}\sum_{z\in IBDR,z=1}^{Z}\left[P_{z,t}^{\mathrm{IBDR}}\Delta L_{z,t}^{\mathrm{IBDR}}+\sum_{m=1}^{N_m}\left(P_{zm,t}^{+}\Delta L_{zm,t}^{+}+P_{zm,t}^{-}\Delta L_{zm,t}^{-}\right)\right] \quad (6)$$

Where $z\in IBDR$ means that user $z$ participates in IBDR. In this paper, four kinds of users participate in DR. Based on their power consumption behaviors, which DR they get involved in is determined as shown in Table 1.

**Table 1 Different kinds of users and their DR means**

| | PBDR | IBDR | Characteristics |
|---|---|---|---|
| Industrial users (IU) | Involved;<br>Load can be transferred, increased and decreased | Involved;<br>Load can be increased and decreased | Huge demand, flexible, proactive, and controllable;<br>Sensitive to cost |
| Commercial users (CU) | Involved;<br>Load can be decreased | Involved;<br>Load can be increased and decreased | Fixed electricity consumption time, proactive, and controllable;<br>Interested in excess economic profits |
| Agricultural users (AU) | Involved;<br>Load can be transferred | Not involved | Inelastic demand, flexible, but uncontrollable;<br>Hard to transfer and unable to reduce |
| Residential users (RU). | Not involved | Involved;<br>Load can be decreased | Inelastic demand, controllable, but hard to respond actively<br>Fixed electricity consumption time, but demand can be decreased |

## 3 Bi-level coordinated optimization model of the ESS-ER

Considering day-ahead operation results as decision making reference, this paper pays attention to the problem of purchase and retail coordinated optimization for the ESS-ER, i.e. how the ESS-ER costs the least and gains the most, thus operating in the globally optimal state.

### 3.1 Idea of the two-stage model

The two-stage optimization model for the purchase and retail of the ESS-ER is constructed based on the operation mode of the ESS-ER. The power retailing allocation optimization model in the lower layer can be transformed into the KKT conditions of the upper purchase portfolio optimization model, thus jointly optimizing the power purchase and retail of the ESS-ER and establishing the optimal trading strategy. Fig. 5 shows the diagram of the two-stage model construction.

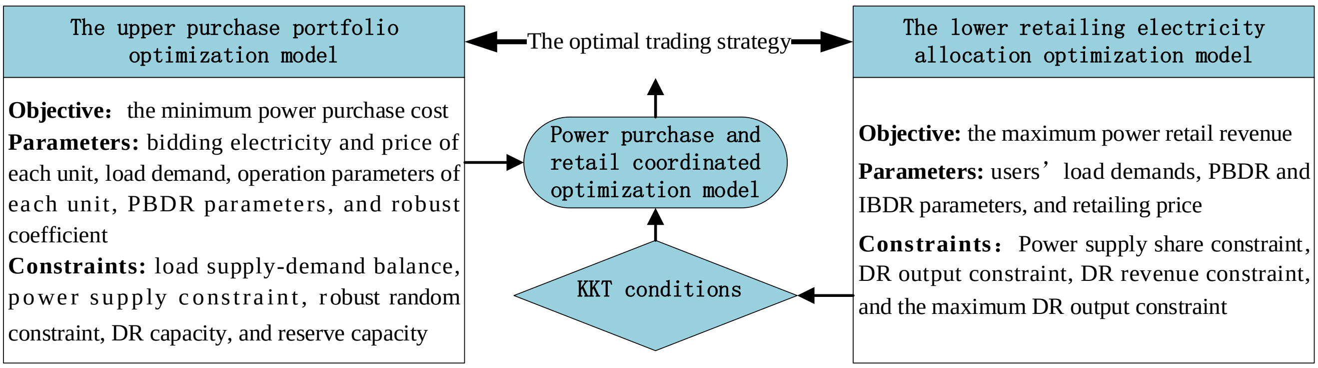


**Fig. 5 The two-stage optimization model construction**

According to Fig. 5, the two-stage coordinated optimization model for power purchase and retail of the ESS-ER are constructed as follows.

- In the upper layer model, the minimum power purchase cost is selected as the optimization objective, with the constraints including power supply constraints of each kind of power generators, load supply-demand balance, reserve capacity and so on. Finally, the purchase portfolio optimization model of the ESS-ER is built.

- In the lower layer model, the maximum power retail revenue is taken as optimization objective, with the constraints including users' DR output, power supply share, DR revenue and so on. Finally, the optimal power retailing allocation model of the ESS-ER is built.
- The objective and constraints of the lower model are transformed into Lagrangian function, and then the derivatives of the parameters of the Lagrange function are calculated, i.e. the lower model is transformed into the KKT conditions of the upper layer model. Thus, the two-stage model is changed into one-stage. Finally, the optimal power purchase and retail strategy is established.

## 3.2 Power purchase portfolio optimization model

In the day-ahead power market, all kinds of power generators bid based on their generation cost and reasonable revenue, and get their trading shares. Due to low marginal power generation cost, clean energy power generators have the price advantage to get better preferential access to share trading. However, since clean energy has strong uncertainty in power generating, retailers may face more risks of power shortage penalty and cost more for temporary power purchase, causing actual power generation from clean energy less than that in contract. In this paper, the CVaR method is introduced to measure the risk cost caused by clean energy power generators [29]. Therefore, the power purchase cost of the ESS-ER includes electricity cost, compensation for contracts breach from clean energy power generators, temporary power purchase cost, and power shortage risk cost. The objective is expressed as follows.

$$\min C_{ER}=\sum_{t=1}^{\mathrm{T}}\sum_{k=1}^{\mathrm{K}}\left\{(1-\lambda)\left[g_{k,t}P_{k,t}+g_{k,t}^{-}\left(P_t^{\mathrm{UG}}\text{-}P_{k,t}^{-}\right)\right]+\lambda CVaR_{k,t}\right\} \tag{7}$$

There is no risk cost if ESS-ERs purchase power from controllable power generation sources such as thermal power and gas turbines. However, the ESS-ER has to take uncertainty risk when purchasing power from uncontrollable sources, which is calculated as follows.

$$\sum_{t=1}^{\mathrm{T}}CVaR_{k,t}=\alpha+\frac{1}{1-\beta}\int_{\boldsymbol{g}\in\boldsymbol{R}^m}\left(f(\boldsymbol{G},\boldsymbol{g})-\alpha\right)^{+}p(\boldsymbol{g})d\boldsymbol{g} \tag{8}$$

Wherein, $\alpha$ is the critical value of power purchase risk cost, which is introduced for determining the risk status of power purchase transaction, and $f(\boldsymbol{G},\boldsymbol{g})$ equal to $g_{k,t}^{-}\left(P_t^{\mathrm{UG}}\text{-}P_{k,t}^{-}\right)$, used for calculating power purchase risk cost. $\boldsymbol{G}^T=[\boldsymbol{g}_1,\boldsymbol{g}_2,\boldsymbol{g}_3,\cdots,\boldsymbol{g}_T]$ stands for the decision vector and $\boldsymbol{g}^T=\left[\boldsymbol{g}_{WPP,t},\boldsymbol{g}_{PV,t},\boldsymbol{g}_{other,t}\right]$ stands for the electricity quantity vector purchased from uncontrollable generation sources, which is multivariate random vector. The distribution function of the multivariate random vector in Eq. (8) is difficult to determine. Usually, *N* samples $g_1,g_2,\cdots,g_N$. $\boldsymbol{g}$ is selected to replace expectations in the model solving process. The calculation is expressed as follows.

$$\sum_{t=1}^{\mathrm{T}}CVaR_{k,t}=\alpha+\frac{1}{N(1-\beta)}\sum_{n=1}^{N}\left(f(\boldsymbol{G},\boldsymbol{g})-\alpha\right)_n^{+} \tag{9}$$

Based on Eqs. (7)-(9), the set of power purchase objective is determined by reasonably setting risk aversion coefficient $\lambda$. In addition, power purchase trading also needs to consider constraints.

(1)Power purchase balance constraint

$$\sum_{u=1}^{\mathrm{U}}g_{u,t}\left(1-\varphi_{u,t}\right)+\sum_{c=1}^{\mathrm{C}}g_{c,t}\left(1-\varphi_{c,t}\right)+g_{k,t}^{-}=\left(1+\eta_{\mathrm{ex}}\right)L_{ES,t}^{0}+\Delta L_{ES,t} \tag{10}$$

Where $\eta_{\mathrm{ex}}$ is the reserve purchase power coefficient of the ESS-ER for the electricity consumption growth. The electricity consumption growth rate of China is about 4.9%,6.6% and 8.5% in 2016, 2017 and 2018, respectively [30]. If not considering the $\eta_{\mathrm{ex}}$, when the electricity consumption increase, the power shortage may happen, and the power shortage cost could be calculated as shown in Eq.(7). On the contrary, when the $\eta_{\mathrm{ex}}$ is set too higher, the surplus purchase power cost should be understood by the electivity retailers. How to choose $\eta_{\mathrm{ex}}$ should be researched by the sensitivity analysis. Strong uncertainty of $g_{u,t}$ will bring risks to power purchase decision making plans of the ESS-ER.

Therefore, the robust coefficient transformation constraint, i.e. Eq. (11), is introduced to provide a risk decision making means for different decision makers who have different attitudes towards risk. In other words, the random variables are transformed into interval distribution, and the constraints with robust coefficient and prediction error coefficient are constructed. Firstly, the variable for net power purchase demand $M_t$ is introduced as follows.

$$M_t = \sum_{c=1}^{\mathrm{C}} g_{c,t}\left(1-\varphi_{c,t}\right)-\left(L_{ES,t}^{0}+\Delta L_{ES,t}\right) \tag{11}$$

Where the prediction error coefficient of uncontrollable generation sources is set to be $e_{u,t}$. To facilitate analysis, set $G_{u,t}=\sum_{u=1}^{\mathrm{U}} g_{u,t}\left(1-\varphi_{u,t}\right)$. To ensure the constraints be satisfied when the uncertain variables reach the boundary, an auxiliary variable $\theta_{u,t}\,(\boldsymbol{\theta}\geq 0)$ is introduced and set to be $\theta_{u,t}\geq\left|G_{u,t}\pm e_{u,t}G_{u,t}\right|$, so Eq. (12) can be changed as follows.

$$-\left(g_{u,t}+e_{u,t}g_{u,t}\right)\leq -g_{u,t}+e_{u,t}\left|g_{u,t}\right|\leq -g_{u,t}+e_{u,t}\theta_{u,t}\leq M_t \tag{12}$$

The strongest random constraint can be determined via Eq. (12). However, extreme situations occur at very low probability, so a robust coefficient $\Gamma_u$, $\boldsymbol{\Gamma}\in[0,1]$, is introduced to enhance the flexibility of constraints as follows.

$$-\left(g_{u,t}+e_{u,t}g_{u,t}\right)\leq -g_{u,t}+\Gamma_{u,t}e_{u,t}\left|g_{u,t}\right|\leq -g_{u,t}+e_{u,t}\theta_{u,t}\leq M_t \tag{13}$$

(2) Power generation constraint

The electricity sold by all types of power generators shall not exceed the maximum electricity generation capacity. For controllable generation sources, i.e. thermal power and gas turbines, there are ramping constraints and startup/shutdown time constraints needed to consider. The constraints are as follows.

$$v_t\Delta g^{-}\leq g_t-g_{t-1}\leq v_t\Delta g^{+} \tag{14}$$

$$(T_{t-1}^{\mathrm{on}}-M^{\mathrm{on}})(v_{t-1}-v_t)\geq 0 \tag{15}$$

$$(T_{t-1}^{\mathrm{off}}-M^{\mathrm{off}})(v_t-v_{t-1})\geq 0 \tag{16}$$

(3) DR capacity constraint

To consume more clean energy power generation and decrease the total power purchase cost, the retail will adjust its purchase quantity and the portfolio through DR. For electricity retailers, the demand response behaviors mainly come from the energy storage, namely, the power retailers could use the ESD to purchase power in the load valley period and sell power in the load peak period. However, ESD has two operation modes, namely, the longest life cycle (LCC) mode and the optimum economic efficiency (OEE) mode.

The mainly objective of the OEE mode is to actively participate in energy conversion task and gain the maximum power transaction benefit, the detailed operation constraints are as following:

$$\Delta L_{ES,t}=\Delta L_{ES,t}^{\mathrm{pur}}+\Delta L_{ES,t}^{\mathrm{se}} \tag{17}$$

$$\Delta L_{ES,t}^{\min}\leq\Delta L_{ES,t}\leq\Delta L_{ES,t}^{\max} \tag{18}$$

$$\sum_{t=1}^{T}\Delta L_{ES,t}\leq\Delta L_{ES}^{\max} \tag{19}$$

The mainly objective of the LCC mode is to optimize the purchase-sale power by adjusting the operation strategy of the ESS, the purchase-sale power is infinitely near the rated discharging-charging power, which is better to improve the operation life of the systems. The detailed constraints are shown as follows.

$$\Delta L_{ES,t}^{\mathrm{pur}}\rightarrow\Delta g_{ES}^{\mathrm{dis,R}} \tag{20}$$

$$\Delta L_{ES,t}^{\text{sale}} \rightarrow \Delta g_{ES}^{\text{chr,R}} \tag{21}$$

$$\Delta L_{ES,t}^{\text{pur}} \bullet \Delta L_{ES,t}^{\text{sale}} = 0 \tag{22}$$

(4) Energy storage operation constraint

The energy storage system supports the DR operation of the retailer, which requires that power purchase for DR needs to be within the storage capacity. The constraint is as follows.

$$S_{ES,t} = \begin{cases} S_{ES,t\text{-}1} - \Delta L_{ES,t}^{\text{se}},\ in\ power\ sale \\ S_{ES,t\text{-}1} + \Delta L_{ES,t}^{\text{pur}},\ in\ power\ purchase \end{cases} \tag{23}$$

$$0 \le S_{ES,t-1} + \Delta L_{ES,t} \le S_{ES}^{\max} \tag{24}$$

$$\sum_{t=1}^{T} (S_{ES,0} + \Delta L_{ES,t}^{\text{pur}} - S_{ES,t}) = \sum_{t=1}^{T} \Delta L_{ES,t}^{\text{se}} \tag{25}$$

In, addition, to ensure that users' load demand can be satisfied, the power purchase should be matched with demand, i.e. $\sum_{t=1}^{T}\left(L_{\text{ES},t} - L_{\text{ES},t}^{0}\right) = 0$.

(5) Reserve capacity

Since clean energy power generators have strong uncertainty, the retailer will reserve some capacity to increase its power supply margin, thus avoiding high cost for power shortage. The constraint is expressed as follows.

$$g_t^{\max} - g_t + \Delta L_{ES,t} \ge r_{u,t} \cdot g_{u,t} \tag{26}$$

## 3.3 Electricity allocation optimization model

After making the optimal power purchase schedule, the ESS-ER will allocate the purchased power into four types of users based on their load demands, which is an investment portfolio issue. Therefore, it is critical to seek a path to implementing DR and achieving electricity allocation in different users optimally, thus gaining the maximum sale revenue.

$$\max R = \sum_{t=1}^{T}\sum_{z=1}^{Z}\left(P_{zt} X_{zt} L_{ES,t} - C_{zt}^{DR} + P_{ut}\left(1 - X_{zt}\right) L_{ES,t}\right) \tag{27}$$

According to Table 1, IU, CU, AU and RU have different DR strategies, so the costs are also different, which are calculated as follows.

$$C_{it}^{DR} = C_{it}^{PBDR} + C_{it}^{IBDR} = \sum_{t=1}^{T}\left\{\left(P_{it}^{0} L_{it}^{0} - P_{it} L_{it}\right) + \sum_{i \in IBDR, i=1}^{I}\left[P_{i,t}^{\text{IBDR}} \Delta L_{i,t}^{\text{IBDR}} + \sum_{m=1}^{N_m}\left(P_{im,t}^{+} \Delta L_{im,t}^{+} + P_{im,t}^{-} \Delta L_{im,t}^{-}\right)\right]\right\} \tag{28}$$

$$C_{bt}^{DR} = C_{bt}^{IBDR} + C_{bt}^{R} = \sum_{t=1}^{T}\left\{\sum_{b \in IBDR, b=1}^{B}\left[P_{b,t}^{\text{IBDR}} \Delta L_{b,t}^{\text{IBDR}} + \sum_{m=1}^{N_m}\left(P_{bm,t}^{+} \Delta L_{bm,t}^{+} + E_{bm,t}^{-} \Delta L_{bdm,t}^{-}\right)\right] + P_{bt}\left(\Delta L_{bm,t}^{-} - \Delta L_{bm,t}^{+}\right)\right\} \tag{29}$$

$$C_{at}^{DR} = C_{at}^{PBDR} = \sum_{t=1}^{T}\left\{\left(P_{at}^{0} L_{at}^{0} - P_{at} L_{at}\right)\right\} \tag{30}$$

$$C_{rt}^{DR} = C_{rt}^{IBDR} = \sum_{t=1}^{T}\left\{\sum_{r \in IBDR, r=1}^{R}\left[C_{rt} \Delta L_{rt}^{\text{IBDR}} + \sum_{m=1}^{N_m}\left(P_{rm,t}^{-} \Delta L_{rm,t}^{-}\right)\right] + P_{rt} \Delta L_{rm,t}^{-}\right\} \tag{31}$$

Where $z = \{i, b, a, r\}$. In China, the segmented electricity price is implemented for the residential users (RU), which is shown as follows.

$$P_{rt}=\begin{cases} P_{rt}^{1} & ,X_{rt}\le d \\ P_{rt}^{1}+P_{rt}^{1}d & ,d\le X_{rt}\le 2d \\ P_{rt}^{1}+2P_{rt}d & ,2d\le X_{rt}\le 3d \\ \vdots & \\ P_{rt}^{1}+(n-1)P_{rt}d, & (n-1)d\le X_{rt}\le nd \end{cases} \tag{32}$$

Where $d$ is the interval of the segmented power. $P_{rt}^{1}$ is the electricity price of the residential users in the first segmented interval. $n$ is number of the segmented interval.

(1) Power supply share constraints

The sum of power supply shares for all kinds of users is 1. Each share is set to be positive, and the power purchase of the ESS-ER matches with the retail.

$$\sum_{t=1}^{T}\sum_{z=1}^{z}X_{zt}=1, X_{zt}\ge 0 \tag{33}$$

$$\sum_{z=1}^{Z}\left(L_{zt}^{0}+v_{zt}\Delta L_{zt}\right)+\sum_{z=1}^{Z}o_{zt}\left(\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}+\Delta L_{zm,t}^{-}\right)=L_{ES,t} \tag{34}$$

(2) Users' DR constraints

$$L_{zt}^{\min}\le L_{zt}-L_{zt}^{0}\le L_{zt}^{\max} \tag{35}$$

$$\Delta L_{z,t}^{\mathrm{IBDR,min}}\le \Delta L_{z,t}^{\mathrm{IBDR}}-\Delta L_{z,t-1}^{\mathrm{IBDR}}\le \Delta L_{z,t}^{\mathrm{IBDR,max}} \tag{36}$$

$$0\le \Delta L_{zm,t}^{+}-\Delta L_{zm,t-1}^{+}\le \Delta L_{zm,t}^{+,\max} \tag{37}$$

$$0\le \Delta L_{zm,t}^{-}-\Delta L_{zm,t-1}^{-}\le \Delta L_{zm,t}^{-,\max} \tag{38}$$

In addition, there are startup/shutdown preparation time and maximum output constraints of users participating in DR, which are similar to Eqs. (15)-(23).

(3) DR revenue constraint

The intention for users to participate in DR is to reduce energy consumption cost, which requires that the cost needs to be lower after implementing DR. The constraint is shown as follows.

$$\sum_{t=1}^{T}\left\{v_{zt}P_{zt}L_{zt}\text{-}o_{zt}\sum_{i\in IBDR,i=1}^{N_i}\left[P_{z,t}^{\mathrm{IBDR}}\Delta L_{z,t}^{\mathrm{IBDR}}+\sum_{m=1}^{N_m}\left(P_{zm,t}^{+}\Delta L_{zm,t}^{+}+P_{zm,t}^{-}\Delta L_{zm,t}^{-}\right)\right]\right\}\le P_{zt}^{0}L_{zt}^{0} \tag{39}$$

(4) Users' maximum DR output constraints

In order to avoid the excessive DR participation of users, which may result in the output higher of DR beyond the peak regulation limitation of ESS, it is necessary to restrict the upper limit of DR output of all kinds of users, which are shown as follows.

$$\Delta L_{zt}^{\min}\le \Delta L_{zt}\le \Delta L_{zt}^{\max} \tag{40}$$

$$\Delta L_{ES,t}^{\min}\le \sum_{z=1}^{Z}\Delta L_{zt}\le \Delta L_{ES,t}^{\max} \tag{41}$$

$$\Delta L_{ES,t}^{\min}\le \sum_{z=1}^{Z}\left(\Delta L_{zt}+\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}-\Delta L_{zm,t}^{-}\right)\le \max\left\{\Delta L_{ES,t}^{\max},S_{ES,t}\right\} \tag{42}$$

Wherein, $\Delta L_{ES,t}^{\max}$ and $\Delta L_{ES,t}^{\min}$ are the upper and lower DR limits of the ESS-ER in power purchasing (which are also the maximum charging and discharging power of the energy storage system). Eqs. (41) and (42) are used to limit the total DR output produced by all kinds of users within the energy storage ability (capacity and charging/discharging power) of the ESS-ER.

## 4 KKT condition of the bi-level optimization model

The bi-level optimization model in this paper is proposed to study the economics of power purchase and sale transaction of the ESS-ER. Due to the difficulty brought by the coupling relationship among the upper, the lower, and the non-linear constraints, the bi-level model is transformed into single-level model. Based on section 3, the lower model involves a linear programming problem, so a Lagrangian function in the lower model is constructed, and then transformed to an added constraint of the upper layer model based on KKT conditions [31]. The Lagrangian function is proposed as follows.

$$\begin{aligned}
L=&\sum_{t=1}^{T}\sum_{z=1}^{Z}\left(C_{zt}^{DR}-P_{zt}X_{zt}L_{ES,t}\right)-\lambda_1\left(\sum_{t=1}^{T}\sum_{z=1}^{Z}X_{zt}-1\right)-\lambda_2\left(\sum_{z=1}^{Z}\left(L_{zt}^{0}+v_{zt}\Delta L_{zt}\right)+\sum_{z=1}^{Z}o_{zt}\left(\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}+\Delta L_{zm,t}^{-}\right)-L_{ES,t}\right)\\
&-v_1\left(L_{zt}-L_{zt}^{0}-L_{zt}^{\min}\right)-\mu_1\left(-\left(L_{zt}-L_{zt}^{0}-L_{zt}^{\max}\right)\right)-v_2\left(\Delta L_{z,t}^{\mathrm{IBDR}}-\Delta L_{z,t-1}^{\mathrm{IBDR}}-\Delta L_{z,t}^{\mathrm{IBDR,min}}\right)-\mu_2\left(-\left(\Delta L_{z,t-1}^{\mathrm{IBDR}}-\Delta L_{z,t-1}^{\mathrm{IBDR}}-\Delta L_{z,t}^{\mathrm{IBDR,max}}\right)\right)\\
&-\mu_3\left(-\left(\Delta L_{zm,t}^{+}-\Delta L_{zm,t-1}^{+}-\Delta L_{zm,t}^{+,\max}\right)\right)-\sigma_1\left(\Delta L_{zm,t}^{+}-\Delta L_{zm,t-1}^{+}\right)-\sigma_2\left(\Delta L_{zm,t}^{-}-\Delta L_{zm,t-1}^{-}\right)-\mu_4\left(-\left(\Delta L_{zm,t}^{-}-\Delta L_{zm,t-1}^{-}-\Delta L_{zm,t}^{-,\max}\right)\right)\\
&-\sigma_3\left(P_{zt}^{0}L_{zt}^{0}-\sum_{t=1}^{T}\left\{v_{zt}P_{zt}L_{zt}\text{-}o_{zt}\sum_{i\in IBDR,i=1}^{N_i}\left[P_{z,t}^{\mathrm{IBDR}}\Delta L_{z,t}^{\mathrm{IBDR}}+\sum_{m=1}^{N_m}\left(P_{zm,t}^{+}\Delta L_{zm,t}^{+}+P_{zm,t}^{-}\Delta L_{zm,t}^{-}\right)\right]\right\}\right)-v_4\left(\Delta L_{zt}-\Delta L_{zt}^{\min}\right)-\mu_5\left(\Delta L_{zt}^{\max}-\Delta L_{zt}\right)\\
&-v_5\left(\sum_{z=1}^{Z}\Delta L_{zt}-\Delta L_{ES,t}^{\min}\right)-\mu_6\left(\Delta L_{ES,t}^{\max}-\sum_{z=1}^{Z}\Delta L_{zt}\right)-v_6\left(\sum_{z=1}^{Z}\left(\Delta L_{zt}+\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}-\Delta L_{zm,t}^{-}\right)-\Delta L_{ES,t}^{\min}\right)\\
&-\mu_7\left(\Delta L_{ES,t}^{\max}-\sum_{z=1}^{Z}\left(\Delta L_{zt}+\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}-\Delta L_{zm,t}^{-}\right)\right)-\sigma_4\left(S_{ES,t}-\sum_{z=1}^{Z}\left(\Delta L_{zt}+\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}-\Delta L_{zm,t}^{-}\right)-S_{ES,t}\right)
\end{aligned} \tag{43}$$

Where $\lambda$, $\mu$, $\sigma$ and $\upsilon$ are the Lagrangian multipliers corresponding to constraints of the lower model. Further, $X_{zt}$, $\lambda$, $\mu$, $\sigma$ and $\upsilon$ are calculated, then the KKT conditions are obtained.

$$\sum_{t=1}^{T}\sum_{z=1}^{Z}\left(\frac{\partial C_{zt}^{DR}}{\partial X_{zt}}-P_{zt}L_{ES,t}\right)-\lambda_1=0 \tag{44}$$

$$\sum_{t=1}^{T}\sum_{z=1}^{Z}X_{zt}=1 \tag{45}$$

$$0\le\lambda_2\perp\left(\sum_{z=1}^{Z}\left(L_{zt}^{0}+v_{zt}\Delta L_{zt}\right)+\sum_{z=1}^{Z}o_{zt}\left(\Delta L_{z,t}^{\mathrm{IBDR}}+\Delta L_{zm,t}^{+}+\Delta L_{zm,t}^{-}\right)-L_{ES,t}\right)\ge 0 \tag{46}$$

$$0\le v_1\perp\left(L_{zt}-L_{zt}^{0}-L_{zt}^{\min}\right)\ge 0 \tag{47}$$

$$0\le\mu_1\perp\left(-\left(L_{zt}-L_{zt}^{0}-L_{zt}^{\max}\right)\right)\ge 0 \tag{48}$$

$$0\le v_2\perp\left(\Delta L_{z,t}^{\mathrm{IBDR}}-\Delta L_{z,t-1}^{\mathrm{IBDR}}-\Delta L_{z,t}^{\mathrm{IBDR,min}}\right)\ge 0 \tag{49}$$

$$0\le\mu_2\perp\left(-\left(\Delta L_{z,t-1}^{\mathrm{IBDR}}-\Delta L_{z,t-1}^{\mathrm{IBDR}}-\Delta L_{z,t}^{\mathrm{IBDR,max}}\right)\right)\ge 0 \tag{50}$$

$$0\le\mu_3\perp\left(-\left(\Delta L_{zm,t}^{+}-\Delta L_{zm,t-1}^{+}-\Delta L_{zm,t}^{+,\max}\right)\right)\ge 0 \tag{51}$$

$$0\le\sigma_1\perp\left(\Delta L_{zm,t}^{+}-\Delta L_{zm,t-1}^{+}\right)\ge 0 \tag{52}$$

$$0\le\sigma_2\perp\left(\Delta L_{zm,t}^{-}-\Delta L_{zm,t-1}^{-}\right)\ge 0 \tag{53}$$

$$0\le\mu_4\perp\left(-\left(\Delta L_{zm,t}^{-}-\Delta L_{zm,t-1}^{-}-\Delta L_{zm,t}^{-,\max}\right)\right)\ge 0 \tag{54}$$

$$0\le\sigma_3\perp\left\{P_{zt}^{0}L_{zt}^{0}-\sum_{t=1}^{T}\left\{v_{zt}P_{zt}L_{zt}\text{-}o_{zt}\sum_{i\in IBDR,i=1}^{N_i}\left[P_{z,t}^{\mathrm{IBDR}}\Delta L_{z,t}^{\mathrm{IBDR}}+\sum_{m=1}^{N_m}\left(P_{zm,t}^{+}\Delta L_{zm,t}^{+}+P_{zm,t}^{-}\Delta L_{zm,t}^{-}\right)\right]\right\}\right\}\ge 0 \tag{55}$$

$$0\le v_4\perp\left(\Delta L_{zt}-\Delta L_{zt}^{\min}\right)\ge 0 \tag{56}$$

$$0 \le \mu_5 \perp \left( \Delta L_{zt}^{\max} - \Delta L_{zt} \right) \ge 0 \tag{57}$$

$$0 \le \nu_5 \perp \left( \sum_{z=1}^{Z} \Delta L_{zt} - \Delta L_{ES,t}^{\min} \right) \ge 0 \tag{58}$$

$$0 \le \mu_6 \perp \left( \Delta L_{ES,t}^{\max} - \sum_{z=1}^{Z} \Delta L_{zt} \right) \ge 0 \tag{59}$$

$$0 \le \nu_6 \perp \left( \sum_{z=1}^{Z} \left( \Delta L_{zt} + \Delta L_{z,t}^{\mathrm{IBDR}} + \Delta L_{zm,t}^{+} - \Delta L_{zm,t}^{-} \right) - \Delta L_{ES,t}^{\min} \right) \ge 0 \tag{60}$$

$$0 \le \mu_7 \perp \left[ \Delta L_{ES,t}^{\max} - \sum_{z=1}^{Z} \left( \Delta L_{zt} + \Delta L_{z,t}^{\mathrm{IBDR}} + \Delta L_{zm,t}^{+} - \Delta L_{zm,t}^{-} \right) \right] \ge 0 \tag{61}$$

$$0 \le \sigma_4 \perp \left( S_{ES,t} - \sum_{z=1}^{Z} \left( \Delta L_{zt} + \Delta L_{z,t}^{\mathrm{IBDR}} + \Delta L_{zm,t}^{+} - \Delta L_{zm,t}^{-} \right) - S_{ES,t} \right) \ge 0 \tag{62}$$

Here, $0 \le a \perp b \ge 0$ equals $a \ge 0$, $b \ge 0$, $ab = 0$. Eqs. (46) to (62) are the mixed nonlinear complementarity problem in the lower layer model. After the KKT conditions being obtained, the power purchase and retailer trade optimization model for the ESS-ER is constructed based on Eqs. (7) to (24), and the optimal power purchase and retail strategy will be determined.

## 5 Case study

### 5.1 Basic data

The IEEE 30 node system is selected as the simulation system. 2×2MW WPP and 6×0.5MW PV are configured at node 2. 1×3MW WPP and 2×1MW PV are configured at node 5. 3×1MW CGT are configured at node 8. Therein, the CGT units are CENTAUR40, the up/down ramping power is 0.2 MW/h, and the startup/shutdown time is 0.15h. The CGT operation cost function is a quadratic function, and is linearized into a two-stage function with the slopes of 150 ¥/MW and 420 ¥/MW to facilitate the calculation [28]. Meanwhile, the ESS-ER with a 2MW·h energy storage system is connected to node 6, with the maximum charge/discharge power of 0.5MW and the charge/discharge loss of 0.4%. The initial operation model of the energy storage system is the OEE mode. Four types of users are IU, CU, AU and RU, with the accumulated maximum and minimum loads of 10.29 MW and 2.35 MW, respectively. Fig. 6 shows the load demand of different types of users.

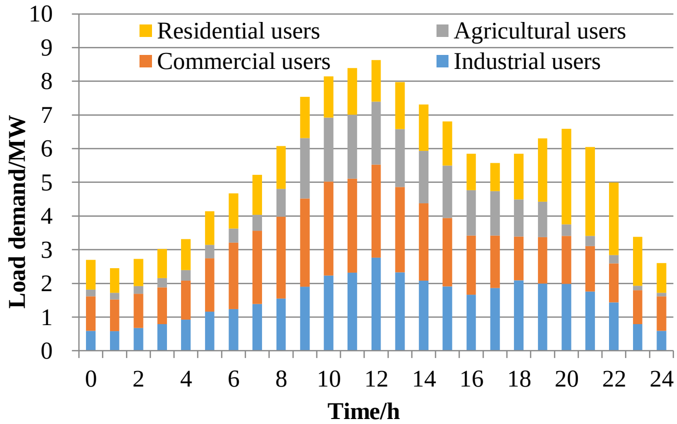


**Fig. 6 Load demand of different types of users**

As WPP and PV are greatly affected by external natural conditions, it is necessary to simulate the available output of WPP and PV. According to the output functions of WPP and PV detailed in Reference [32], cut-in wind speed, rated wind speed and cut-out wind speed are set to be 3m/s, 14m/s and 25m/s, respectively. The shape and scale parameters are set to be 2 and $2\bar{v}/\sqrt{\pi}$ , respectively. The average wind speed is $\bar{V}$ . The photovoltaic radiation intensity parameters are 0.45 and 9.42, and WPP rated output and PV rated output are both 4MW. Then, the scenario simulation of WPP and PV is performed by the simulation and reduction methods proposed in Reference [28], obtaining ten sets of typical output scenarios. The scenario that has the maximum probability of occurrence is selected as the input scenario. Fig. 7 show the available output of WPP and PV.

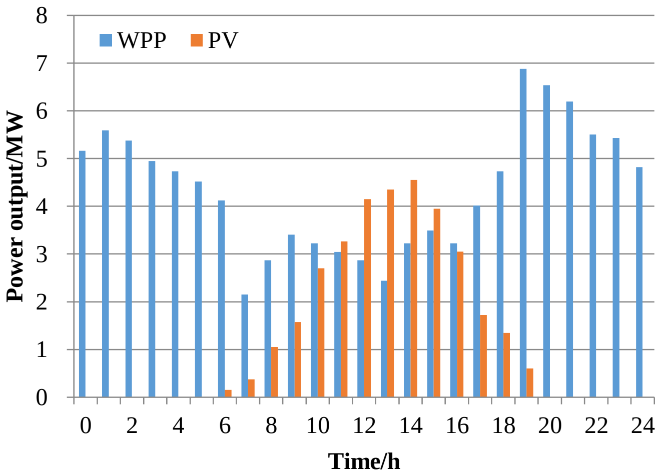


**Fig. 7 Available output of WPP and PV**

Energy storage has the flexible regulation performance, so the ESS-ER has strong regulation ability as a DR participant, which is similar to the IU. Here, the power demand elasticity of IU is selected as that of the ESS-ER during power purchasing, referring to [28]. Considering that the DR in power purchase side is mainly generated by energy storage, it is set that the TOU price is only carried out for the charge and discharge, and the rest power is settled according to the actual electricity transaction. When retailers implement DR, it is necessary to divide a day into peak, flat and valley periods for different types of users, and power demand elasticity coefficients are set based on Reference [32]. To avoid the phenomenon of “peak-valley upside down” caused by demand over-response, the load fluctuation generated by IBDR and PBDR shall be within ± 0.5MW, and the positive and negative peak regulation output provided by IBDR shall be within 0.5MW. Table 2 shows the DR parameters.

**Table 2 DR parameters**

| | | Time division | | | PBDR price/(¥/MW·h) | | | IBDR price/(¥/MW·h) | |
|---|---|---|---|---|---|---|---|---|---|
| | | Valley | Flat | Peak | Valley | Flat | Peak | Positive | Negative |
| ESS-ER (energy storage only) | | 0:00-5:00& 22:00-24:00 | 6:00-8:00& 15:00-18:00 | 9:00-14:00& 19:00-21:00 | 400 | 500 | 600 | - | - |
| User | IU | 0:00-5:00& 22:00-24:00 | 6:00-9:00& 14:00-16:00 | 10:00-13:00& 17:00-21:00 | 450 | 600 | 800 | 600 | 900 |
| | CU | 0:00-4:00& 22:00-24:00 | 5:00-6:00& 15:00-20:00 | 7:00-14:00 | 800 | 1200 | 1400 | 1000 | 1200 |
| | AU | 0:00-5:00& 20:00-24:00 | 6:00-8:00 | 9:00-19:00 | 400 | 500 | 600 | 550 | 650 |
| | RU | - | - | - | 350 | 350 | 350 | - | 540 |

The grid-connected prices of GT, WPP and PV are set to be 520¥/MW·h, 400¥/MW·h and 450¥/MW·h. Before implementing DR, the power prices of IU, CU, AU and RU are 380¥/MW·h, 1200¥/MW·h, 850¥/MW·h and 450¥/MW·h. Then, in order to analyze the influence of the price of segmented electricity on the power sales income, four equivalent segmented intervals are set. The power purchase cost and the initial risk weight coefficients are both set to be 0.5, the confidence level is set to be 0.9, the robust coefficient and prediction accuracy of WPP/PV are set to be 0.9. The compensation price for the retailer is set to be 1.2 times of the grid connected price when clean energy output is lower than the declared electricity, and the temporary power purchase price is set to be 900¥/MW·h. The surplus electricity of the retailer is used for utility peak regulation, which is paid at 2000¥/MW·h. The initial reserver purchase power coefficient $\eta_{ex}$ is 0.

In order to analyze the effects of DR on the ESS-ER, the effects of DR in power purchase side and in power retail side on power purchase and retail strategy are compared and analyzed, and four scenarios are set as follows.

- Scenario 1 (basic scenario) where DR is not taken into consideration. In this scenario, retailers does not implement ESS, so they do not participate in DR in both sides, and the optimal strategy is established under this situation.
- Scenario 2 where DR in power purchase side (PDR) is taken into consideration. In this scenario, retailers implement ESS, so it can participate in the PDR to cooperate with clean energy output, and the effects of DR on the optimal strategy are analyzed under this situation.
- Scenario 3 where DR in power retail side (RDR) is taken into consideration. In this scenario, retailers does not implement ESS, but the SDR is introduced to encourage users adjust their consumption behaviors, and the effects of DR on the optimal strategy are analyzed under this situation.
- Scenario 4 where DR in both power purchase side and retail side (PRDR) is taken into consideration. In this scenario, the coordinated effects of the PRDR on the optimal purchase and retail strategy are analyzed by comparing it with Scenarios 1 to 3.

The model is solved by the GAMS software using CPLEX 11.0 linear solver from ILOG_solver. The CPU time required for solving the problem for different case studies with an idea pad450 series laptop computer powered by core T6500 processor and 4 GB of RAM. When the optimization is MILP, the GAMs software could get a satisfactory solution quickly.

## 5.2 Transaction results

### 5.2.1 Scenario 1 where DR is not taken into consideration

In this subsection, the optimal power purchase strategy is established without DR. Because the grid-connected price consists of marginal cost and reasonable revenue of WPP and PV, the WPP and PV will get preferential access to power trade shares, and the rest demand is satisfied by CGT, which makes the minimum power purchase cost realized. Fig. 8 is the purchase strategy for retailers without DR.

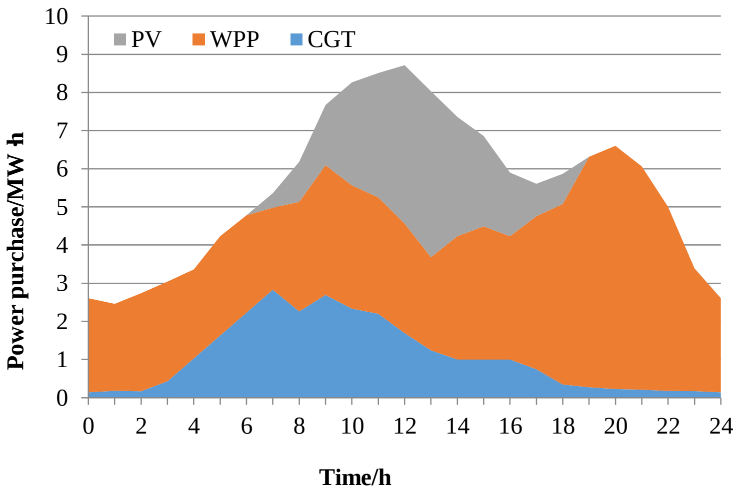


**Fig. 8 Purchase strategy of the retailer without involving DR**

According to Fig. 8, the WPP, PV and CGT supplied power to retailers to satisfy the power demand. Due to low output of PV at night, CGT obtained more electricity trade shares. During the day time, PV and WPP offered price lower than CGT during high power output period, so the retailer purchase power from PV and WPP preferentially. However, considering the uncertainties of wind power and PV generation, retailers had to take power shortage risk. Table 3 is the purchase strategies before and after considering the uncertainty.

**Table 3 Purchase strategies before and after considering the uncertainty**

| Model | Strategy/MW·h | Cost/MW·h | Objective function results/¥ |
| --- | --- | --- | --- |

| | CGT | WPP | PV | CGT | WPP | PV | Cost | CVaR | Comprehensive cost |
|---|---|---|---|---|---|---|---|---|---|
| Regular | 13.7 | 91.97 | 29.23 | 7124 | 36788 | 13154 | 57066 | 67936 | 67935.71 |
| CVaR and robust | 26.2 | 82.41 | 26.28 | 13624 | 32964 | 11826 | 58414 | 62143 | 62142.55 |

According to Table 3, if the uncertainty is not considered, retailers only aimed at the minimum power purchase cost. Meanwhile, more electricity is sold when considering uncertainty. However, it led to higher CVaR value, and higher comprehensive power purchase cost as well, which indicates that the proposed power purchase portfolio optimization model with CVaR and Robust theory reflected economic benefits and risk cost of WPP and PV, and has a better effect on establishing the purchase strategy with respect to cost and risk.

**5.2.2 Scenario 2 where the PDR is taken into consideration**

In this scenario, retailers adjusts its own power consumption by introducing the ESS, i.e. partial load demand in peak periods can be transferred to valley periods through PBDR, which smooths the distribution curve of the power purchase demand via "peak shaving and valley filling", and spares more room for clean power grid connection. Fig. 9 shows the distribution curve of power purchase demand of the ESS-ER before and after DR.

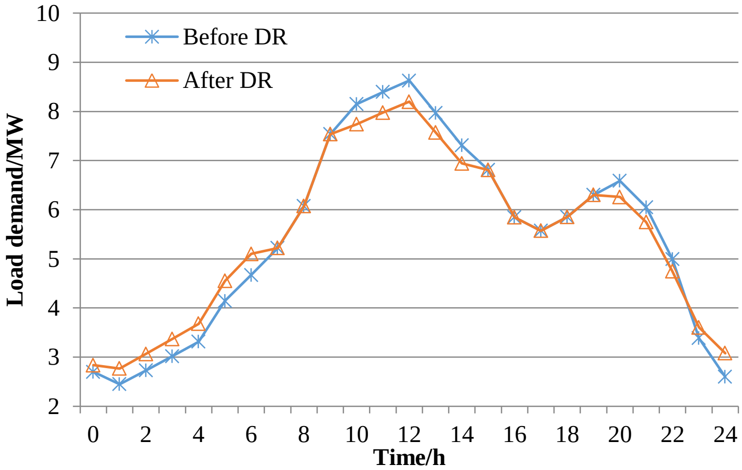


**Fig. 9 Power purchase demand of the ESS-ER before and after DR**

According to Fig. 9, after DR, the maximum load demand decreased by 0.43MW, the minimum load demand increased by 0.32 MW, and the peak-valley ratio decreased from 3.52 to 2.96. A smoother load demand curve makes the retailer purchase more electricity from WPP and PV. Table 4 shows the power purchase strategies of the retailers before and after DR.

**Table 4 Power purchase strategies of the retailer before and after DR**

| | Output/MW·h | | | PBDR/MW·h | | Power purchase demand | | | Objective results/¥ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | CGT | WPP | PV | Positive | Negative | Peak /MW | Valley /MW | Peak-valley ratio | Cost | CVaR | Toeal cost |
| Before DR | 26.20 | 82.41 | 26.28 | - | - | 8.63 | 2.45 | 3.52 | 58414 | 62143 | 62143 |
| After DR | 24.98 | 87.18 | 29.33 | 6 | -6 | 8.20 | 2.77 | 2.96 | 57421 | 59814 | 59814 |

According to Table 4, the retailers output ±6MW·h via DR, which made the demand curve smoother and spared more room for power generation of WPP and PV. The WPP and PV output increased by 4.77MW·h and 3.05MW·h respectively, while the CGT output decreased by 1.22MW·h. After the DR, because the output of WPP and PV increased, the power purchase cost decreased by 993¥, yet the CVaR decreased by 2329¥. Finally, the comprehensive cost decreased by 3326¥, which indicated that apart from decreasing power purchase cost, involving DR can also reduce the uncertainty risk cost from WPP and PV, thus realizing the minimum comprehensive purchase cost. Fig. 10 shows the power purchase strategy with the DR involved.

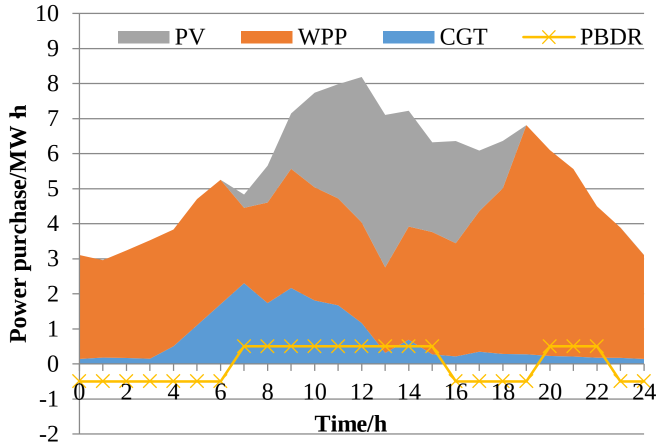


**Fig. 10 Power purchase strategy with the DR involved**

According to Fig. 10, after the DR was involved, power purchase in peak periods decreased while power purchase in valley periods increased, which made the load demand curve smoother. The retailer provided negative output in valley periods, i.e. employing energy storage system to charge, while positive output in peak periods, i.e. discharging, which established the optimal power purchase strategy.

### 5.2.3 Scenario 3 where the RDR is taken into consideration

In this scenario, retailers who are considered as DR implementers, set TOU price and controllable load price to encourage users to participate in DR and adjust their power demands. According to Tables 1 and 2, the load demands of users before and after the PBDR are calculated, as shown in Fig. 11.

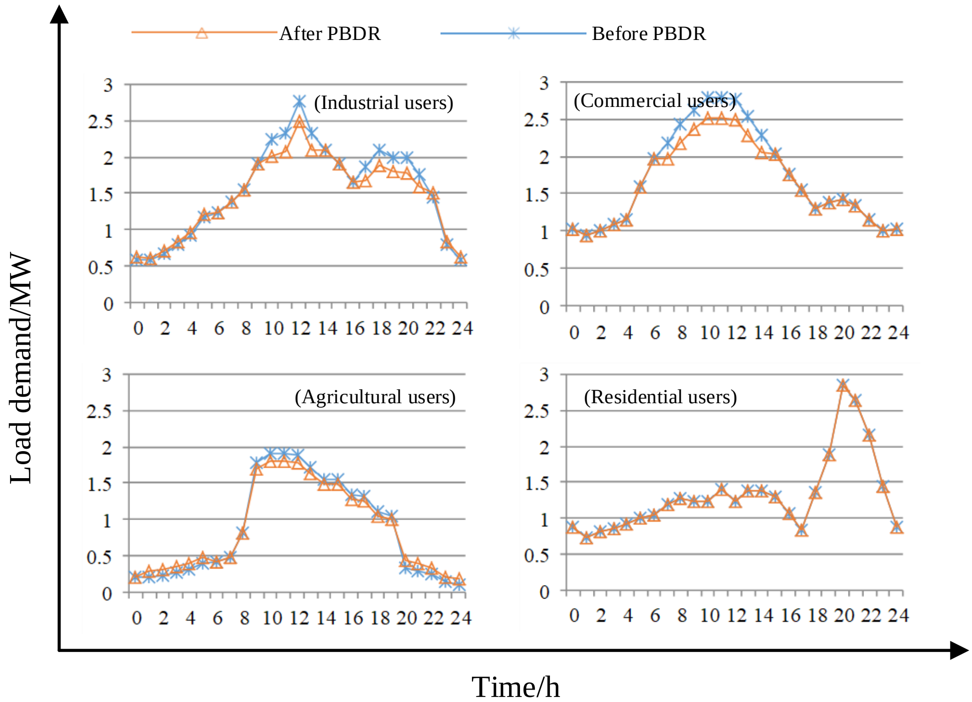


**Fig. 11 load demands of users before and after the PBDR**

According to Fig. 11, the load demand of IU is flexible and can be transferred or increased/decreased, so the maximum load demand decreases by 0.27MW, the maximum load demand in valley periods increases by 0.06MW, and the peak-valley ratio decreases from 4.73 to 3.87. The load demand of CU is barely able to be transferred, so some load demand in peak periods reduces. The maximum load demand of CU decreases from 2.79MW to 2.51MW, and its peak-valley ratio decreases from 2.98 to 2.69. The load demand of AU can be transferred mostly in daytime, so the peak-valley ratio significantly decreases, from 18.97 to 10.13. The load demand of RU is inevitable and difficult to be transferred, so it remains unchanged after PBDR. Fig. 12 shows the IBDR strategies for different types of users.

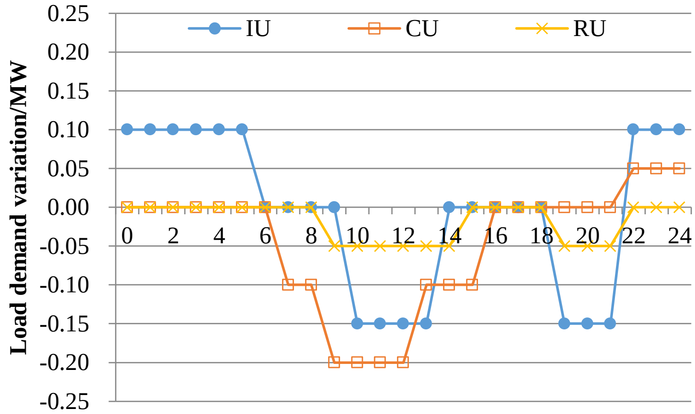


**Fig. 12 IBDR strategies of different types of users**

According to Fig. 12, considering that the agricultural power consumption is an inevitable part in production, it cannot be reduced but can be transferred. Thus, this AU cannot participate in IBDR. The industrial power consumption was flexible, which can increase at night (valley periods) for positive regulation and decrease in daytime (peak periods) for negative regulation. CU mostly work in daytime, so they can participate in IBDR by reducing temporary power consumption. Table 5 shows the optimal power retail strategy of the ESS-ER after DR.

**Table 5 The optimal power retail strategy of the ESS-ER after DR**

| | Power consumption cost/¥ | | | | DR revenue/¥ | | | | Revenue of the ESS-ER/¥ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IU | CU | AU | RU | IU | CU | AU | RU | IBDR cost | purchase cost | retail revenue | regulation revenue | Net revenue |
| Before DR | 28520 | 50549 | 12813 | 11235 | - | - | - | - | - | 58414 | 103117 | - | 44703 |
| After DR | 24349 | 48821 | 11966 | 11235 | 5731 | 3439 | 847 | 243 | 3513 | 57421 | 96371 | 12711 | 48148 |

According to Table 5, the power consumption costs of IU, CU and AU all decreases after the PBDR. Among them, AU gain the least DR revenue among the three types of users. For the ESS-ER, though the cost of IBDR increases, the power saved from PBDR and IBDR can be sold to the utility grid, thus gaining peak regulation revenue, so the net revenue of the ESS-ER increases by 3445¥. Therefore, for the ESS-ERs, implementing DR can not only reduce users' costs, but also bring more revenue, thus achieving the win-win between the retailers and users.

### 5.2.4 Scenario 4 where the PRDR is taken into consideration

In this scenario, the optimal power purchase and retail strategy for ESS-ERs considering PRDR is discussed. Different from Scenarios 2 and 3, DR in purchase side and DR in retail side are connected, and the lower retail model is transformed to the KKT conditions of the upper purchase model by using Eqs. (37) to (55), achieving coordinated optimization of power purchase and retail. Fig. 13 shows the optimal power purchase and retail strategy of the ESS-ER with the PSDR involved.

According to Fig. 13, the load demand in valley periods significantly increases and that in peak periods decreases via energy storage and DR, making the power purchase demand curve much smoother, which shows a better effect of "peak shaving and valley filling" than other scenarios. Correspondingly, the generation of WPP and PV increase and that of CGT reduces than Scenario 2, which indicated a cleaner and more low-carbon strategy. Table 6 shows the optimal strategies in different scenarios.

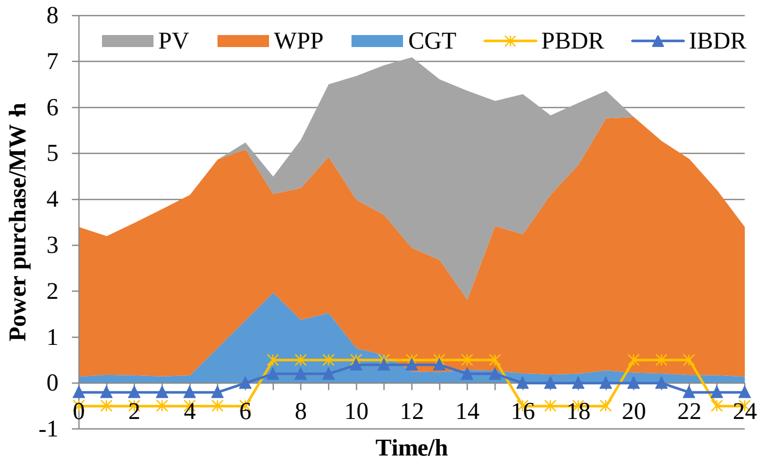


**Fig.13 The optimal power purchase and retail strategy of the ESS-ER with the PSDR involved**

Compared with Scenario 1, Scenarios 2 considers the impact of the PDR and Scenario 4 considers the impact of the PRDR. According to Table 6, after DR, power retailers purchase more power from WPP and PV due to the participating of ESS, which allowed the retailers to purchase more power with lower price in the valley periods for storage and sell it in peak periods. Although there were IBDR dispatch costs in Scenarios 3 and 4, peak regulation revenue was gained from trading with the utility grid. Finally, the net revenue of Scenario 3 or 4 is higher than that of Scenario 1 or 2, and Scenario 4 was the highest. Therefore, the retailers can use energy storage to participate in the PRDR, thus achieving the maximum net revenue.

**Table 6 The optimal strategies in different scenarios**

| | Power purchase/MW·h | | | | Power retail/MW·h | | | | Objective function results/¥ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CGT | WPP | PV | DR | IU | CU | AU | RU | Purchase cost | IBDR cost | Retail revenue | Regulation revenue | Net revenue |
| Scenario 1 | 26.2 | 82.41 | 26.28 | - | 38.03 | 42.12 | 21.36 | 32.1 | 58414 | - | 103117 | - | 44703 |
| Scenario 2 | 24.98 | 87.18 | 29.33 | ±6 | 36.66 | 40.09 | 21.36 | 32.1 | 57421 | - | 103117 | - | 45696 |
| Scenario 3 | 26.2 | 82.41 | 26.28 | - | 36.41 | 38.94 | 21.36 | 31.65 | 58414 | 3513 | 96371 | 12711 | 48148 |
| Scenario 4 | 20.85 | 85.82 | 31.21 | ±6 | 35.7 | 38.54 | 21.36 | 30.85 | 54552 | 5478 | 95824 | 14311 | 50105 |

## 5.3 Results analysis

Power generation of WPP and PV has a contradiction between lower cost and higher risk of power shortage, so the way to balance the cost of power purchase and the risk is the key issue in power purchase and retail for the ESS-ERs. The CVaR method and robust stochastic optimization theory are used to represent the uncertainty of the objective functions and constraints respectively. Different parameter settings also affect the power purchase strategy. In addition, the PDR quantity mainly depends on the energy storage capacity. The reasonable energy storage capacity is also important for optimal operation of the retailers. Therefore, the sensitivity analyses of risk cost coefficient, confidence level, robust coefficient and energy storage capacity are conducted.

(1) Impact of risk cost coefficient

The setting of the risk cost coefficient reflects the risk attitude of the retailer directly. When the risk cost coefficient is high, the retailers are sensitive to the uncertainty of wind/PV power generation and unwilling to bear the risk caused by the actual output of wind/photovoltaic power generating less than expected. When the risk cost coefficient is low, the retailers prefer low-priced wind/photovoltaic power generation to gain excess returns in the purchase and retail transactions. Fig. 14 shows the total cost of the retailer under different risk cost coefficients.

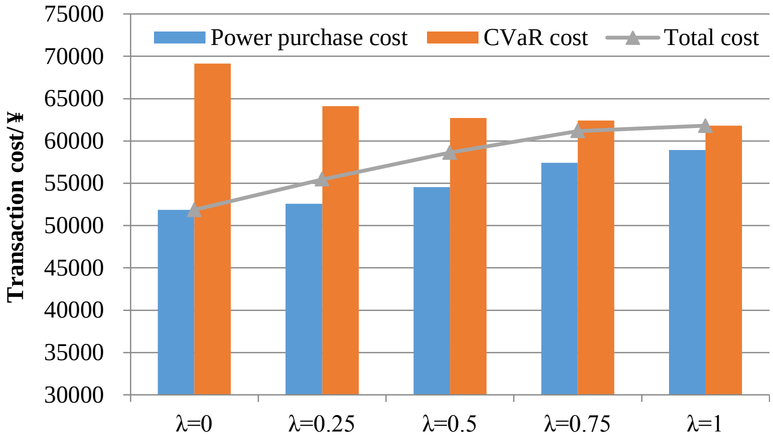


**Fig. 14 Total cost of the retailer under different risk cost coefficients**

According to Fig. 14, with the increase of risk cost coefficient, the power retailers gradually increase the power share of CGT, and the power purchase cost also gradually increases. Due to the high cost coefficient, the retailers faced higher risk cost, thus resulting in the increase of the total cost. With respect to total cost curve, when the risk cost coefficient is higher than 0.75, the curve started to go higher more slowly, which indicated that the purchase strategy was getting closer to the most conservative state. In general, the retailers can choose a reasonable risk cost coefficient between 0.25 and 0.75 based on their risk attitude.

(2) Impacts of confidence level and robust coefficient

Due to the strong uncertainty of wind power and PV generation, when different confidence levels and robust coefficients are set, the power purchase strategy of the retailer will change greatly, which is similar to the risk cost coefficient. When the values of confidence level and robust coefficient are high, the retailers are more sensitive and refuse to bear the power purchase risk. On the contrary, when the values are low, the retailers are willing to take some risks to pursue excess economic returns. Fig. 15 shows the optimal power purchase strategy of the retailers under different confidence levels and robust coefficients.

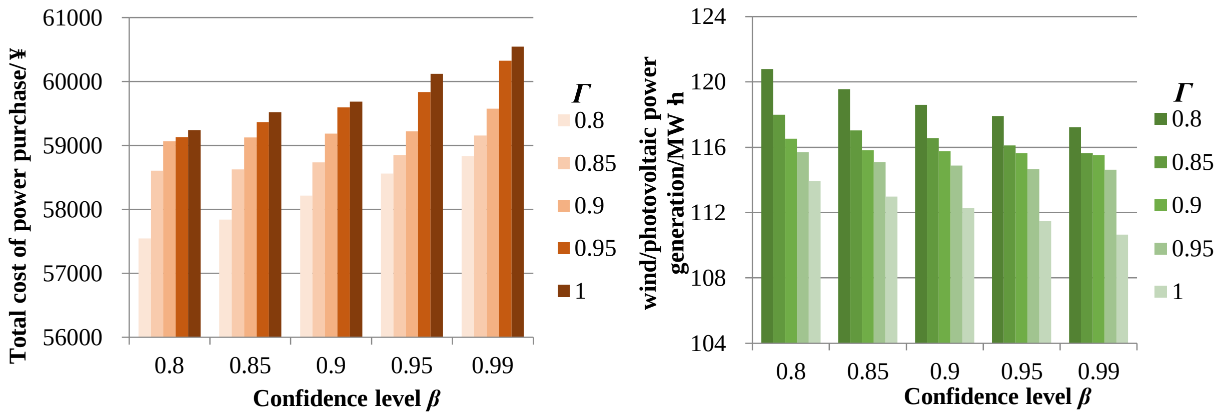


**Fig. 15 The optimal power purchase strategy under different confidence levels and robust coefficients**

According to Fig. 15, with respect to power purchase cost, the increase of confidence level and robust coefficient will bring higher costs for power purchase. When the confidence level is higher than 0.9, the power purchase cost increased sharply, showing that the CVaR method can effectively reflect the risk of power purchase strategies. When the robust coefficient increases from 0.8 to 0.9, the power purchase cost increased greatly, while when the robust coefficient is higher than 0.9, the power purchase cost increases slightly, indicating that the power purchase strategy basically reaches the most conservative state. With respect to the wind/PV power generation, when the robust coefficient increases from 0.8 to 0.85, the wind/PV power generation decreases dramatically. Meanwhile, the retailers also pay attention to the risk of power purchasing. When the robust coefficient is higher than 0.95, the wind power generation decreases substantially. At this point, the retailers are in a state of extreme risk aversion, where although the increase of confidence level may lead to reduced the wind/photovoltaic power generation, the strategy was basically close to the most conservative state, thus the curtailment of wind/photovoltaic power is not large.

(3) Impact of the capacity and mode of energy storage capacity

The capacity and mode of energy storage especially for electricity is very important and sensitive for the obtainable revenue of retailers. According to Eqs. (18)-(19) and Eqs. (20)-(22), the longest life cycle (LCC) mode and the optimum economic efficiency (OEE) mode are defined. Table 7 is the power purchase and sale transaction results under different operation modes.

**Table 7 Power purchase and sale transaction results under different operation mode**

| Mode | Power purchase/MW ħ | | | | Power purchase cost/$10^3$¥ | | Power sale benefit/$10^3$¥ | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CGT | WPP | PV | DR | Cost | CVaR | IBDR cost | Retail revenue | Regulation revenue | Net benefit |
| LCC | 30.84 | 78.95 | 28.09 | ±4.5 | 57.87 | 43.38 | 4.274 | 95.824 | 14.311 | 47.99 |
| OEE | 20.85 | 85.82 | 31.21 | ±6 | 54.55 | 47.53 | 5.478 | 95.824 | 14.311 | 50.105 |

According to Table 7, when the ESS operates in the LCC mode, the purchase and sale power of power retailers will be close to the rated discharging-charging power of the ESS, and the total output of the ESS is less than that in the OEE mode. Correspondingly, the grid-connected power of WPP and PV is also less than that in the OEE mode, namely, 6.87MW • h and 3.12 MW • h, resulting in that the power purchased cost increased by 6.1% and the CVaR cost decreased by 8.7%. The net benefits of power purchase and sale transaction decreases by 4.2%, which means the total power purchased from WPP and PV decreases in the LCC mode, and this will decrease the power purchase risk and increase the power purchase cost. Meanwhile, the net benefits will also decrease. That’s to say, in order to gain more operation life, the power retailers should sacrifice some net benefits. For gaining the maximum benefit, the OEE mode is better. Then, because the PDR mainly depends on energy storage system. In general, the larger the storage capacity is, the more the PDR will be. Therefore, it is necessary to analyze the purchase and retail strategies of the retailer under different kinds of storage capacity, and establish the optimal one. Table 8 shows the purchase and sale strategies of the retailer under different kinds of storage capacity.

**Table 8 Purchase and sale strategies of the retailer under different kinds of storage capacity**

| | Power purchase/MW ħ | | | | Objective function results/¥ | | |
|---|---|---|---|---|---|---|---|
| | CGT | WPP | PV | DR | Power purchase cost | IBDR cost | Net revenue |
| 0MW ħ | 26.2 | 82.41 | 26.28 | 0 | 58414 | 3513 | 48148 |
| 1MW ħ | 24.12 | 83.26 | 27.51 | ±2 | 57124 | 4079 | 48932 |
| 2MW ħ | 22.03 | 84.12 | 28.75 | ±4 | 55842 | 4716 | 49577 |
| 3MW ħ | 20.85 | 85.82 | 31.21 | ±6 | 54552 | 5478 | 50105 |
| 4MW ħ | 19.43 | 86.45 | 32.25 | ±7 | 53408 | 6315 | 50411 |
| 5MW ħ | 18.95 | 87.14 | 32.15 | ±8 | 53209 | 6246 | 50681 |

According to Table 8, when the storage capacity is 0, the retailers are unable to participate in the PDR, and cope with the uncertainty risk of wind power and PV generation, so the CGT contributes the most, which reaches 26.2MW ħ. When the storage capacity increasea from 1MW ħ to 3MW ħ, the retailers’ DR capacity grows rapidly, so does the share of wind power and PV generation. When the energy storage capacity exceeds 3 MW ħ, the growth of DR capacity slows down, as well as the share growth of wind power and PV power purchase. Especially, 4:1 is the best purchase ratio of wind/photovoltaic power and energy storage, which can realize the best utilization of DR capacity of the retailers and achieve the optimal power purchase. From the perspective of the RDR, the retailers have greater adjustment ability and can provide more powerful supports for the RDR after employing the ESS. Thus, the IBDR dispatching capacity and cost increase gradually. When the remaining capacity is sold to the utility grid, the net revenue of the retailers increase accordingly.

(4) Impact of power selling price and reserve purchase power coefficients

Based on the uncertainty of wind power and PV generation, the uncertainty of the electricity and the price are considered in this section. Firstly, the price of segmented electric power for residential users is discussed, and the segmented interval setting is key for residential users. Table 9 is the power purchasing and selling benefits under different segmented number.

**Table 9 Power retail and sale benefit under different segmented number**

| Segmented number | Power retail/MW h | | | | Power purchase and sale transaction benefit/ ¥ | | |
|---|---|---|---|---|---|---|---|
| | IU | CU | AU | RU | Cost | Revenue | Net benefit |
| 1 | 35.70 | 38.54 | 21.36 | 30.85 | 54552 | 104657 | 50105 |
| 2 | 35.70 | 40.50 | 21.85 | 28.40 | 54552 | 105704 | 51152 |
| 3 | 35.70 | 41.70 | 22.15 | 26.90 | 54552 | 106232 | 51680 |
| 4 | 35.70 | 43.20 | 22.25 | 25.30 | 54552 | 106763 | 52211 |

According to Table 9, if the price of segmented electricity for residential users is considered, the power proportio for RU decreases, and the power proportion for CU and AU increase since the power prices of CU and AU are higher. When more power is used by CU and AU, the power selling revenue increase and the net benefits also increase obviously. Overall, the price of segmented power is important for improving power selling incomes. For power retailers, the price of segmented power should be implemented for different types of users, which could bring more benefits. Except for the price fluctuation, the power consumption growth rates of China in 2016, 2017 and 2018 are about 4.9%、6.6% and 8.5%, respectively. The power retailers should also consider the power consumption growth rate as described in Eq.(10), Fig.16 is the power transaction results under different reserve purchase power coefficients.

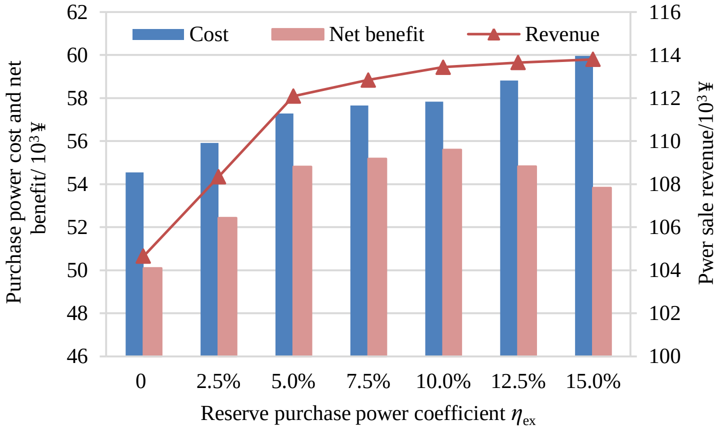


**Fig.16 Power transaction results under different reserve purchase power coefficients**

According to Fig.16, the reserve purchase power coefficients from 0 to 15% are discussed for the power purchase and sale transaction. It can be seen, when the reserve purchase power coefficients belong to [5%, 10%], the growth rate of the net benefits is relatively stable, which means the increased power purchase cost is able to offset risk costs, that's to say, to reach the optimal power transaction. However, when the reserve purchase power coefficients are bigger than 10%, the power sale revenue will reach the upper limit because the power demand reaches the top. When the reserve purchase power coefficients are less than 5%, the increased power purchase cost is less than the risk cost caused by renewable energy generation, so the power purchased cost and the net benefits of power transaction increase. Overall, reasonable reserve purchase power coefficients should be set according to the power consumption growth rate for power retailers to gain the optimal power transaction benefits.

## 6 Conclusions

As China's electric power market reformation developing constantly, more types of power sellers will come up in the future, among which, retailers with energy storage system will become a special kind that can realize optimal dispatch with their own charge/discharge systemin power generation side. In this paper, the electric power retailer with energy storage system was selected as the research object, and a two-stage demand response framework for power purchase and sale transactions both considering price-based demand response and incentive-based demand response was built. Correspondingly, a two-stage coordinated optimal model for power purchase and sale transactions of electric power retailers was proposed. Moreover, the model was solved by introducing the Karush-Kuhn-Tucker optimality conditions for establishing the optimal power purchase and sale strategy. Through case study, this paper concluded as follows.

(1) The two-stage demand response could smooth the curves of power purchasing and terminal load, which could bring more space for power transaction. On one hand, by adjusting the charging-discharging behaviors to response to the power source , the electricity retailers could purchase more power from wind power and PV power to decrease the cost of power purchasing. On the other hand, the electricity retailers could implement demand response to terminal customers, which will bring the controllable loads for the retailers to gain more revenue from the public power grid. Overall, the transaction space for electricity purchase and sale will be widen.

(2) The proposed two-stage transaction model could balance the cost and risk of power purchasing, and increase the transaction share from wind and PV power, thus decreasing power consumption cost of users as well as increasing the retailers' revenue. In the upper layer model, the uncertainty of wind and PV power is considered, and the influence degree of uncertainty variables in the objective function and constraint conditions are measured through the conditional value at risk method and robust stochastic optimization theory respectively. Meanwhile, the retailers participate in demand response in the power purchase side by making use of the energy storage system in order to reduce power purchase cost and risk cost. In the lower layer model, considering the complementarity and economy of different types of demand response, how to introduce demand response to achieve the optimal electricity allocation among different types of users is analyzed, so as to obtain the maximum power retail revenue.

(3) The results of sensitivity analysis show that introducing risk cost coefficient, confidence level and robust coefficient is an effective way for decision makers (i.e. retailers) to adjust the purchase and sale of electricity flexibly, and higher energy storage capacity, within an appropriate range, can drive a greater demand response effect. On the one hand, when the risk cost coefficient is set to be 0.75 or more, the increase of the total cost slows down, which indicates that the strategy of power purchase basically reaches the most conservative state. When the confidence is between 0.85 and 0.95, and the robust coefficient is between 0.8 and 0.9, both the power purchase cost and wind/photovoltaic power volume drop by a large margin, which indicates that the decision-maker balance the power purchase cost and power purchase risk according to the actual situation. When the ratio of wind/photovoltaic power purchase and energy storage capacity is over 4:1, the same increase of energy storage capacity will slow down the increase of demand response capacity of the retailer. When the reserve purchase power coefficients belong to [5%, 10%], the growth rate of the net benefits is relatively stable, which means the increased power purchase cost is able to offset risk costs, that's to say, the power transaction result is optimal.

(4) This paper focuses on the uncertainty of wind power and photovoltaic power generation when analyzing the uncertainty of power purchase cost, and proposes a decision-making model based on conditional value at risk method and robust stochastic optimization theory. As the current spot market in China is still in the pilot construction stage, the price volatility of power purchase and sale is not involved. In the future, with the development of the spot market, the price volatility will also become a key factor affecting retailers making decisions, which makes it a future research point. Although the price of segmented electricity is implemented for the residential users (RU), however, the price fluctuation of the other types of the electricity users should be researched further. In addition, the electricity consumption growth rate of China will be also a key issue, how to accurately deal with the problems based on the sensitivity analysis should also be studied further.

## Acknowledgments

This work was partially supported by the National Natural Science Foundation of China (Grant Nos.

71874053, 71573084), the Beijing Social Science Fund(18GLC058),the Project funded by China Postdoctoral Science Foundation (2019M650024) and the 2018 Key Projects of Philosophy and Social Science Research, Ministry of Education, China (18JZD032).

## References

[1] Bhattacharyya S.C. Reform of the energy industry. 2011.

[2] Meng M., Mander S., Zhao X., Niu D. Have market-oriented reforms improved the electricity generation efficiency of China's thermal power industry? An empirical analysis[J]. Energy, 2016,114:734e41.

[3] She Z.Y., Meng G., Xie B.C., O'Neill E. The effectiveness of the unbundling reform in China's power system from a dynamic efficiency perspective [J]. Applied Energy, 2020, 264: 1147174

[4] Peng X., Tao X.M. Cooperative game of electricity retailers in China's spot electricity market [J]. Energy, 2018, 145: 152-170

[5] Abbas Ihsan, Matthew Jeppesen, Michael J. Brear. Impact of demand response on the optimal, techno-economic performance of a hybrid, renewable energy power plant [J]. Applied Energy, 2019, 238: 972-984

[6] Muireann Á.L., Sheila N., Mel T. Devine, Mark O'Malley. The impacts of demand response participation in capacity markets [J].Applied Energy, 2019, 250:444-451.

[7] Huang P., Fan C., Zhang X.G., Wang J.Y. A hierarchical coordinated demand response control for buildings with improved performances at building group [J]. Applied Energy, 2019, 242: 684-694

[8] Luo Z., Hong S.H., Ding Y.M. A data mining-driven incentive-based demand response scheme for a virtual power plant [J]. Applied Energy, 2019, 239: 549-559

[9] Eissa M.M. First time real time incentive demand response program in smart grid with "i-Energy" management system with different resources[J]. Applied Energy, 2018, 212: 607-621.

[10] Athanasios S.D., Michael L.P. An integrated model for assessing electricity retailer's profitability with demand response [J]. Applied Energy, 2017, 198: 49-64

[11] Yoon A.Y., Kim Y.J., Zakula T., Moon S.I. Retail electricity pricing via online-learning of data-driven demand response of HVAC systems [J]. Applied Energy, 2020, 265: 114771

[12] Mohammad A.G., Jo ão S., Nuno H., Rui N., Rui C., ZitaV. A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers [J].Applied Energy, 2015, 151: 102-118

[13] Ben A.S., Boubaker H., Belkacem L. Price risk and hedging strategies in Nord Pool electricity market evidence with sector indexes[J]. Energy Economics, 2019, 80: 635-655

[14] Tom N., Dan M., Riccardo S. Consumer switching in retail electricity markets: Is price all that matters? [J]. Energy Economics, 2019, 83:88-103

[15] Boroumand R.H., Goutte S., Guesmi K., Porcher T. Potential benefits of optimal intra-day electricity hedging for the environment: The perspective of electricity retailers [J]. Energy Policy, 2019, 132: 1120-1129

[16] Sayyad N., Ramin N., Hamed P.D., Kazem Z. Uncertainty-based electricity procurement by retailer using robust optimization approach in the presence of demand response exchange [J]. International Journal of Electrical Power & Energy Systems, 2019, 105: 237-248.

[17] Maharjan S., Zhu Q., Zhang Y. Demand response management in the smart grid in a large population regime[J]. IEEE Transactions on Smart Grid, 2016, 7(1): 189-199

[18] Guo Y.M., Shao P., Wang J., Dou X., Zhao W.H. Purchase Strategies for Power Retailers Considering Load Deviation and CVaR [J]. Energy Procedia,2019,158:6658-6663

[19] Algarvio H., Lopes F., Sousa J., Lagarto J. Multi-agent electricity markets: Retailer portfolio optimization using Markowitz theory[J]. Electric Power Systems Research, 2017, 148: 282-294

[20] Ottesen S., Tomasgard A., Fleten S. Prosumer bidding and scheduling in electricity markets [J]. Energy 2016,94:828-843.

[21] Dai Y.M., Gao Y., Gao H.W., Zhu H.B. Real-time pricing scheme based on Stackelberg game in smart grid

with multiple power retailers [J]. I Neurocomputing, 2017, 260: 149-156
[22] Ren Y., Zhou M., Li G.Y. Bi-level model of electricity procurement and sale strategies for electricity retailers considering users' demand response[J]. Automation of Electric Power Systems, 2017, 41(14): 30-36
[23] Chen Y., Jiang X.Y., Yu Z.T. Coalition trading mode design and analysis for distributed generators and loads in regional distribution network[J]. Automation of Electric Power Systems, 2017, 41(14): 78-86
[24] Fotouhi M.A., Faria P., Ramos S., Morais H., Vale Z. Incentive-based demand response programs designed by asset-light retail electricity providers for the day-ahead market [J]. Energy 2015, 82:786-799
[25] Sekizaki S., Nishizaki I., Hayashida T. Electricity retail market model with flexible price settings and elastic price-based demand responses by consumers in distribution network[J]. International Journal of Electrical Power & Energy System, 2016, 81: 371-386.
[26] Mansour C., Mohsen G., Pierluigi S. A new active portfolio risk management for an electricity retailer based on a drawdown risk preference[J]. Energy, 2017: 118:387-398
[27] Sayyad N., Kazem Z. Optimal energy pricing for consumers by electricity retailer [J]. Applied Energy, 2018, 102: 401-412
[28] Ju LW., Tan Z.F., Yuan J.Y., Tan Q.K., Li H.H., Dong F.G. A bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind–photovoltaic–energy storage system considering the uncertainty and demand response [J]. Applied Energy,2016, 171:184-199
[29] Sebastian M., Alexandre S., Ken M. Risk-averse portfolio selection of renewable electricity generator investments in Brazil: An optimized multi-market commercialization strategy[J].Energy, 2016,115: 1331-1343
[30] Lin B.Q., Wang Y. Inconsistency of economic growth and electricity consumption in China: A panel VAR approach [J]. Journal of Cleaner Production, 2020, 229: 144-156
[31] Shinya Sekizaki, Ichiro Nishizaki, Tomohiro hayashid. Decision making of electricity retailer with multiple channels of purchase based on fractile criterion with rational responses of consumers [J]. International journal of Electrical power and energy systems, 2019,105:877-893
[32] Tan ZF, Wang G, Ju LW, et al. Application of CVaR risk aversion approach in the dynamical scheduling optimization model for virtual power plant connected with wind-photovoltaic-energy storage system with uncertainties and demand response [J]. Energy, 2017, 124:198-213