Bi-level Multi-leader Multi-follower Stackelberg Game Model for Multi-energy Retail Package Optimization

Hongjun Gao, Hongjin Pan, Rui An, Hao Xiao, Yanhong Yang, Shuaijia He, and Junyong Liu

***Abstract*—In the competitive energy market, energy retailers are facing the uncertainties of both energy price and demand, which requires them to formulate reasonable energy purchasing and selling strategies for improving their competitiveness in this market. Particularly, the attractive multi-energy retail packages are the key for retailers to increase their benefit. Therefore, combined with incentive means and price signals, five types of multi-energy retail packages such as peak-valley time-of-use (TOU) price package and day-night bundled price package are designed in this paper for retailers. The iterative interactions between retailers and end-users are modeled using a bi-level model of stochastic optimization based on multi-leader multi-follower (MLMF) Stackelberg game, in which retailers are leaders and end-users are followers. Retailers make decisions to maximize the profit considering the conditional value at risk (CVaR) while end-users optimize the satisfaction of both energy comfort and economy. Besides, a distributed algorithm is proposed to obtain the Nash equilibrium of above MLMF Stackelberg game model while the particle swarm optimization (PSO) algorithm and CPLEX solver are applied to solve the optimization model for each participant (retailer or end-user). Numeral results show that the designed retail packages can increase the overall profit of retailers, and the overall satisfaction of industrial users is the highest while that of residential users is the lowest after game interaction.**

***Index Terms*—Conditional value at risk (CVaR), energy retailer, multi-energy retail package design, multi-leader multi-follower (MLMF) Stackelberg game, satisfaction.**

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NOMENCLATURE

A. Set and Indices

Ω_{W}	Set of market clearing price (MCP) scenario
k, ω	Indexes of contracts and scenarios
m, n	Indexes of package types and end-user types
t, i, j	Indexes of time periods, retailers, and end-users

B. Parameters

$\omega_j^{\mathrm{E,com}}$, $\omega_j^{\mathrm{E,eco}}$	Electricity comfort and economy satisfaction weights of end-user j
$\omega_j^{\mathrm{G,com}}$, $\omega_j^{\mathrm{G,eco}}$	Natural gas comfort and economy satisfaction weights of end-user j
$\lambda_{k,t}^{\mathrm{B}}$	Usage proportion of bilateral contract k signed by the retailer during period t
λ_i, β_i	Risk factor weight and confidence levels of retailer i
π_ω	Probability of scenario ω
ε_0	Boundary parameter of peak-valley excess coefficient in package 3
$\varphi^{\mathrm{bundle}}$	Bundled sale proportion in package 2
$G_k^{\mathrm{B,R,max}}$, $G_k^{\mathrm{B,U,max}}$	The maximum natural gas signed by bilateral contract k for retailers and end-users
$G_n^{\max}$, $G_n^{\min}$	The maximum and minimum natural gas demands of type n end-user
G_n^{quota}	Natural gas quota value of type n end-user in package 4
N_{U}, N_{R}	Numbers of end-users and retailers
$N_{\mathrm{E,B}}$	Number of electricity bilateral contract
$N_{\mathrm{G,B,R}}$, $N_{\mathrm{G,B,U}}$	Numbers of natural gas bilateral contract for retailers and end-users
$p_{t,\omega}^{\mathrm{MCP}}$	MCP in scenario ω during period t
$p_k^{\mathrm{E,B}}$	Price of electricity by bilateral contract k
$p_k^{\mathrm{G,B,R}}$, $p_k^{\mathrm{G,B,U}}$	Prices of natural gas sold to retailers and end-users by bilateral contract k
$p_1^{\mathrm{peak,max}}$, $p_1^{\mathrm{peak,min}}$	The maximum and minimum electricity prices of residential end-user during peak period in package 1
Q^{1st}, Q^{2nd}	The first- and second-level electricity demand limits in package 4

$Q_k^{\mathrm{B,max}}$ The maximum electricity signed by bilateral contract k

$Q^{\mathrm{DA,max}}$ The maximum electricity purchased from day-ahead market during each period

$Q_n^{\max}$, $Q_n^{\min}$ The maximum and minimum electricity demands of type n end-user

$Q^{\mathrm{N,lim}}$ Limiting value of night-time electricity demand in package 2

$Q^{\mathrm{K,lim}}$, $Q^{\mathrm{V,lim}}$ Limiting values of electricity demand during peak and valley periods in package 3

T_{P}, T_{F}, T_{V}, T_{D}, T_{N}, T_{M} Peak, flat, valley, day, night, and month periods

C. Optimization Variables

$G_{i,k}^{\mathrm{B,R}}$ Natural gas purchased from bilateral contract k of retailer i

$G_{t,j,k,n}^{\mathrm{B,user}}$ Natural gas purchased by type n end-user j from bilateral contract k during period t

p_n^{peak}, p_n^{flat}, p_n^{valley} Electricity prices of type n end-user during peak, flat, and valley periods in package 1

$p_{t,n}^{\mathrm{E,1}}$, $p_{t,n}^{\mathrm{G,1}}$ Electricity and natural gas prices of type n end-user in package 1 during period t

p_n^{day}, p_n^{night} Electricity prices of type n end-user in package 2 during day and night-time periods

$p_{t,n}^{\mathrm{E,2}}$ Electricity price of type n end-user in package 2 during period t

$p_n^{\mathrm{E,basic}}$, $p_n^{\mathrm{E,reward}}$, $p_n^{\mathrm{E,penalty}}$ Basic, reward, and penalty electricity prices of type n end-user in package 3

$p_n^{\mathrm{E,4}}$ Electricity price of type n end-user in package 4

p_n^{1st}, p_n^{2nd}, p_n^{3rd} Electricity prices of type n end-user at the first, second, and third levels in package 4

$p_n^{\mathrm{G,basic}}$, $p_n^{\mathrm{G,reward}}$, $p_n^{\mathrm{G,penalty}}$ Basic, reward, and penalty natural gas prices of type n end-user in package 4

$p_n^{\mathrm{E,fixed}}$, $p_n^{\mathrm{G,fixed}}$ Electricity and natural gas prices of type n end-user in package 5

$Q_{i,k}^{\mathrm{B}}$ Electricity purchased from bilateral contract k of retailer i

$Q_{t,i,\omega}^{\mathrm{DA}}$ Electricity purchased from day-ahead market of retailer i in scenario ω during period t

$Q_{t,i,j,n}^{\mathrm{user}}$, $G_{t,i,j,n}^{\mathrm{user}}$ Electricity and natural gas purchased by type n end-user j from retailer i during period t

D. Other Variables

$C_{i,j}^{\mathrm{E,U},m}$, $C_{i,j}^{\mathrm{G,U},m}$ Costs of purchasing electricity and natural gas from retailer i in package m for end-user j

$C_j^{\mathrm{G,U,B}}$ Cost of purchasing natural gas by bilateral contracts for end-user j

$G_{i,j,n}^{\mathrm{month}}$, $Q_{i,j,n}^{\mathrm{month}}$ Monthly natural gas and electricity purchased of type n end-user j from retailer i

$G_{t,j,n}^{\mathrm{total}}$, $Q_{t,j,n}^{\mathrm{total}}$ Total natural gas and electricity demands of type n end-user j during period t

$p_{\mathrm{1st},n}^{\mathrm{E,4}}$, $p_{\mathrm{2nd},n}^{\mathrm{E,4}}$, $p_{\mathrm{3rd},n}^{\mathrm{E,4}}$ Electricity prices at the first, second, and third levels of type n in package 4

$Q_{\mathrm{1st}}^{\mathrm{E,4}}$, $Q_{\mathrm{2nd}}^{\mathrm{E,4}}$ The first- and second-level electricity consumptions in package 4

I. Introduction

WITH the rapid development of the energy retailing market, electricity retailers have gradually changed into energy retailers by providing both electricity and gas [1]-[4]. The options of end-users become further liberalized in the completely competitive energy retailing market. But most of small- and medium-size end-users only purchase energy from retailers since purchasing electricity directly from the wholesale market may result in expensive trading costs. In this situation, retailers purchase electricity on behalf of end-users in the wholesale market as the intermediary between energy suppliers and end-users. It brings the uncertainties of both energy price and end-user demand to retailers [5]-[7]. Meanwhile, the competition among retailers becomes more intense because of the increasing number of retailers. Thus, for retailers, it is important to design suitable multi-energy retail packages for end-users with different energy demand and behaviors to effectively address the above issues and improve the satisfaction of end-users.

In order to hedge against the risk caused by frequent market price fluctuations and end-user demand uncertainty, energy retailers need to determine optimal energy procurement portfolio and energy sale prices. In [8] and [9], a short-term planning model is developed to determine the day-ahead (DA) market bidding strategies for retailers, which aims to maximize the short-term profit. Reference [10] presents a stochastic model for an electricity retailer with flexible demands under the short-term market trading mechanism. Especially, providing abundant retail packages can improve the end-user stickiness of retailers when participating in market trading. In recent years, according to the Administrative Measures for Zhejiang Electric Power Retail Market (Trial), the existing retail electricity price package mainly includes fixed electricity price package, proportional share electricity price packages, and market price linkage package in China. For the fixed electricity price package, retailers and users agree on a fixed transaction settlement price. For the proportional share electricity price package, retailers and users agree on the sharing benchmark price and sharing proportion. They share the profits and risks based on the average monthly trading price. For the market price linkage package, retailer and users agree on an up or down fluctuation fee as the trading settlement price based on the average monthly trading price. Furthermore, some scholars have also carried out some studies on retail packages. Reference [11] designs electricity retail packages for different groups of residential consumers by using the quantile regression method. By investigating the electricity price change and load peak-valley ratio, time-of-use (TOU) discount based on peak energy usage is also designed in [11]. Reference [12] proposes an accurate applicability evaluation model for the electricity retail package, where data envelopment analysis and the cloud model are combined. A hybrid electricity retail package is proposed in [13] based on the characteristics of end-users and the multi-attribute utility of package. The above studies focus on designing the electricity retail package with price mechanism for retailers, which pay little attention to the multi-energy retail package. However, the modern power systems are evolving into integrated multi-energy system because of the low carbon economy and tight interdependence among multi-energy. As a result, it is obviously vital to formulate multi-energy retail packages for retailers to improve overall operation benefits.

At present, price-based demand response (DR) such as the fixed, TOUs and ladder prices are mainly applied into the energy selling for retailers [14], [15]. Reference [16] provides an adaptive and adjustable DR model for reducing the risk of the retailer by simulating the impact of price signal on each user's load curve. In [17], a new two-stage DR is designed for electricity retailers with the energy storage system. Especially, the energy storage system could adjust the charging/discharging behaviors according to the bidding power price. However, the incentive-based DR is still not introduced into the multi-energy retail packages. Therefore, this paper designs the day-night bundled electricity price package, which involves the bundled and gift method. Meanwhile, peak-valley reward-penalty electricity price and quota natural gas price packages are also designed by innovative reward and penalty programs.

In the competitive energy market, there are two relations including alliance and game among different retailers [18]. The Stackelberg game based on the bi-level stochastic optimization is used to model the interaction between retailer and end-user [19]. In [20], the TOU price optimization for users is modeled as a bi-level Stackelberg game between the retailer and users. In [21], a Stackelberg game model with one leader and multiple followers between the retailers and the users is established to study the real-time pricing scheme in a smart community. In [22], a one-leader and multi-follower game is developed to characterize the interactions between the demand-side management (DSM) center and users. In [23], the transaction between the retailer and end-users with elastic price-based DRs is modeled as a bi-level Stackelberg game. However, the above studies mainly focus on the game between one retailer and multiple end-users. In the practice, many retailers would appear in the deregulated energy market. Therefore, the trading between energy retailers and end-users is gradually described as a multi-leader and multi-follower (MLMF) Stackelberg game [24], [25]. A two-leader two-follower Nash-Stackelberg game is applied to formulate transaction problem considering consumer satisfaction and integrated DR among retailers and users in [26]. A Stackelberg game based DR method considering retailer incentive mechanism is set in [27] for multiple retailers and multiple users. Reference [28] generalizes the interactions between prosumers and end-users as a bi-level MLMF game where prosumers are leaders and end-users are followers. Reference [29] formulates an MLMF Stackelberg game model to describe the multilateral contract transactions between integrated energy service providers and load aggregators. Thus, a bi-level MLMF Stackelberg game model is adopted based on stochastic optimization in this paper to formulate the interaction between retailers and end-users in deregulated energy retailing market.

It is essential for retailers to effectively manage the financial risk caused by uncertainties when formulating the energy purchasing and selling strategies. Compared with value at risk (VaR) method, the conditional value at risk (CVaR) method considers the risk under the extreme condition and psychological preference. In [30]-[32], risk is considered and measured by CVaR method for retailers. In [33]-[36], the implications of demand uncertainty and the level of the players' risk aversion on market equilibrium are studied, and the players' risk is also measured by CVaR. The management of electricity retailer's contract portfolio subjected to risk preferences is analyzed in [37], [38]. Based on those studies, the risk aversion of retailers is considered in this paper, which measures the risk by CVaR when participating in the MLMF Stackelberg game.

Motivated by the aforementioned analysis, this paper proposes a bi-level MLMF Stackelberg game model to optimize multi-energy retail packages. Firstly, the integrated electricity and natural gas retailing market is described, which includes not only the trading between retailers and energy suppliers but also the trading between retailers and multi-energy end-users. Secondly, five types of multi-energy retail energy packages such as peak-valley penalty-compensation price package, day-night bundled price package, etc., are designed. Thirdly, a bi-level MLMF Stackelberg game model based on stochastic optimization is presented, where energy retailers are modeled as the leaders while multi-energy end-users are regarded as the followers. The retailers decide optimal energy purchasing and package pricing strategies considering profit maximization and risk integration at the upper level while end-users aim to maximize the satisfaction of energy comfort and economy at the lower level. Then, the particle swarm optimization (PSO) combined with CPLEX solver is used to solve the proposed bi-level stochastic optimization model. Finally, case studies are performed to verify the effectiveness of multi-energy retail packages.

The rest of this paper is organized as follows. In Section II, the integrated electricity and natural gas retailing market framework is presented. In Section III, the multi-energy retail packages are fully designed. In Section IV, a bi-level MLMF Stackelberg game model is formulated. In Section V, the solution method is described. In Section VI, case studies are performed and the results are discussed. Finally, the conclusions are presented in Section VII.

II. Integrated Electricity and Natural gas Retailing Market Framework

The trading framework for the integrated electricity and natural gas retailing market is illustrated in Fig. 1. As can be observed, market participants are composed of energy suppliers, energy retailers, and multi-energy end-users. Energy retailers purchase electricity from the upper electricity DA market and power generation companies, and natural gas from the upper natural gas companies. At the same time, they should sell energy to different kinds of end-users including residential, commercial, and industrial end-users.

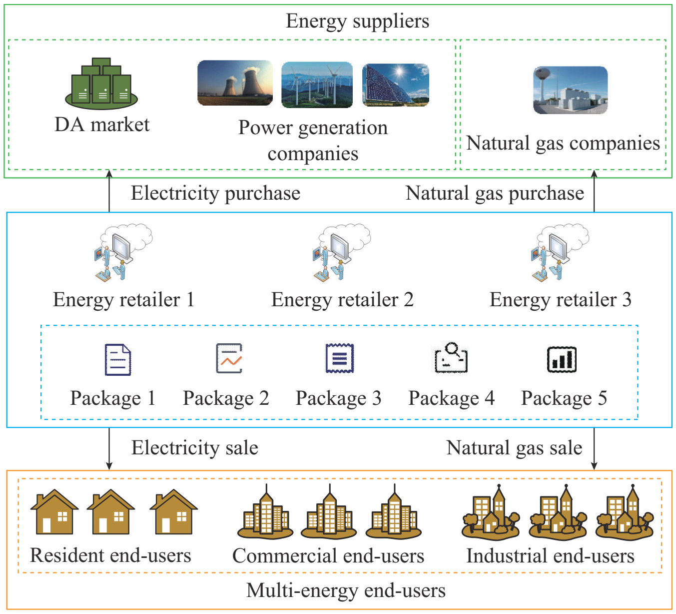

Fig. 1. Trading framework for integrated electricity and natural gas retailing market.

A. Trading Between Energy Retailers and Energy Suppliers

Energy retailers often sign monthly bilateral contracts with some power generation companies to ensure the majorities of the supplied electricity. Besides, retailers would participate in the electricity DA market so as to avoid the imbalance caused by the uncertain demand of end-users. The Monte Carlo method is used to generate the 24-hour marginal clearing price of multiple scenarios as the DA market electricity price scenario set Ω_{W} based on the stochastic planning theory. Then, the scenario reduction process is conducted by the K-means algorithm. The electricity purchasing cost for each retailer in scenario ω is shown as:

$$C_{i,\omega}^{\mathrm{E,R}}=\sum_{k=1}^{N_{\mathrm{E,B}}}p_k^{\mathrm{E,B}}Q_{i,k}^{\mathrm{B}}+\sum_{t=1}^{T_{\mathrm{M}}}p_{t,\omega}^{\mathrm{MCP}}Q_{t,i,\omega}^{\mathrm{DA}} \tag{1}$$

Some retailers may sign monthly bilateral contracts with the natural gas companies, which is depicted as:

$$C_i^{\mathrm{G,R}}=\sum_{k=1}^{N_{\mathrm{G,B,R}}}p_k^{\mathrm{G,B,R}}G_{i,k}^{\mathrm{B,R}} \tag{2}$$

B. Trading Between Retailers and Multi-energy End-users

Different kinds of end-users such as residential, commercial, and industrial end-users are included in this paper. The electricity and natural gas demands for different end-users vary a lot. Thus, it is important for energy retailers to design multi-energy retail packages to meet the diversified energy consumption. It should be noted that not all retailers provide both electricity and natural gas packages, i.e., some retailers may only provide electricity or natural gas retail packages. Relatively, end-users can choose more than one retailer to purchase the energy. Details of the designed retail packages are described in Section III. In this paper, the attractive design of multi-energy retail packages is paid more attention to for maximizing retailers' benefit and competitiveness in the market.

In order to reflect the diversity of retail packages in the competitive energy market, this paper designs five types of packages. Packages 1, 4, and 5 include both electricity and natural gas while only electricity is included in packages 2 and 3. In addition, all retail packages are settled monthly. Especially, various prices of energy sold to residential ($n=1$), commercial ($n=2$), and industrial ($n=3$) end-users are different in each package.

It should be noted that due to the difference in energy demand characteristics of end-users, more factors need to be considered when selecting the package. Therefore, the five types of packages designed in this paper are only applicable to the following end-users:

1) End-users with high price sensitivity: end-users with high price elasticity of demand can rapidly change their energy demand and behaviors when the price changes.

2) End-users with high energy consumption cost in the total cost and with flexible energy demand behavior.

III. Multi-energy Retail Package Design

A. Package 1: Peak-valley TOU Price

In this peak-valley TOU package, different electricity and natural gas prices are both set during different time periods. The load peak periods are 08:00-12:00 and 17:00-21:00. The load flat periods are 12:00-17:00 and 21:00-24:00. The load valley period is 00:00-08:00. $p_{t,n}^{\mathrm{E},1}$ during each period can be described as:

$$p_{t,n}^{\mathrm{E},1}=\begin{cases}p_n^{\mathrm{peak}} & t\in T_{\mathrm{P}}\\ p_n^{\mathrm{flat}} & t\in T_{\mathrm{F}}\\ p_n^{\mathrm{valley}} & t\in T_{\mathrm{V}}\end{cases}\quad \forall n=1,2,3 \tag{3}$$

The designed natural gas price is like the electricity price. The retailer's income from this package can be expressed as:

$$B_i^1=\sum_{j=1}^{N_{\mathrm{U}}}C_{i,j}^{\mathrm{E,U},1}+C_{i,j}^{\mathrm{G,U},1}=\sum_{t=1}^{T_{\mathrm{M}}}\sum_{j=1}^{N_{\mathrm{U}}}p_{t,n}^{\mathrm{E},1}Q_{t,i,j,n}^{\mathrm{user}}+p_{t,n}^{\mathrm{G},1}G_{t,i,j,n}^{\mathrm{user}} \tag{4}$$

B. Package 2: Day-night Bundled Price

In this day-night bundled package, different electricity prices are set during day-time and night-time periods. The night-time periods are from 21:00 to 06:00 while the day-time periods are from 06:00 to 21:00. Meanwhile, this package introduces the bundled sale concept during the day-time and night-time periods. When the night-time electricity demand is higher than the stated limiting value in the package, a few day-time electricity rewards can be given to end-users. Specifically, the complimentary day-time electricity demand depends on the excess quantity of night-time electricity demand. The bundled sale proportion is stated in the given package. The price of electricity sold to end-users during each period and the excess quantity of night-time electricity demand are respectively described as:

$$p_{t,n}^{\mathrm{E},2}=\begin{cases}p_n^{\mathrm{day}} & t\in T_{\mathrm{D}}\\ p_n^{\mathrm{night}} & t\in T_{\mathrm{N}}\end{cases}\quad \forall n=1,2,3 \tag{5}$$

$$Q_{i,j,n}^{\text{excess}}=\begin{cases}\sum\limits_{t\in T_{\text{N}}}Q_{t,i,j,n}^{\text{user}}-Q^{\text{N,lim}} & \sum\limits_{t\in T_{\text{N}}}Q_{t,i,j,n}^{\text{user}}>Q^{\text{N,lim}}\\ 0 & \sum\limits_{t\in T_{\text{N}}}Q_{t,i,j,n}^{\text{user}}\le Q^{\text{N,lim}}\end{cases}\tag{6}$$

The retailer's income from this package can be expressed as:

$$B_i^2=\sum_{j=1}^{N_{\text{U}}}C_{i,j}^{\text{E,U,2}}=\sum_{t=1}^{T_{\text{M}}}\sum_{j=1}^{N_{\text{U}}}\left(p_{t,n}^{\text{E,2}}Q_{t,i,j,n}^{\text{user}}-\varphi^{\text{bundle}}p_n^{\text{day}}Q_{t,i,j,n}^{\text{excess}}\right)\tag{7}$$

C. Package 3: Peak-valley Reward-penalty Price

The peak-valley excess coefficient is defined in this package to measure the peak-to-valley difference of end-users as:

$$\varepsilon_{i,j,n}=\left(\sum_{t=1}^{T_{\text{P}}}Q_{t,i,j,n}^{\text{user}}-Q^{\text{K,lim}}\right)-\left(\sum_{t=1}^{T_{\text{V}}}Q_{t,i,j,n}^{\text{user}}-Q^{\text{V,lim}}\right)\tag{8}$$

In this package, the electricity charge consists of basic charge and reward-penalty fees. It should be noted that the reward-penalty fee is charged according to the peak-valley excess coefficient, and reward or penalty price. To be specific, when $\varepsilon_{i,j,n}$ is positive and greater than the parameter ε_3, end-users need to pay the penalty fee. In this situation, the larger $\varepsilon_{i,j,n}$ is, the more the penalty fee is. When $\varepsilon_{i,j,n}$ is negative and less than the parameter $-\varepsilon_3$, end-users get the reward fee. In this situation, the smaller $\varepsilon_{i,j,n}$ is, the more the reward fee is. However, when $\varepsilon_{i,j,n}$ is between $-\varepsilon_3$ and ε_3, there is no penalty or reward, as shown in Fig. 2.

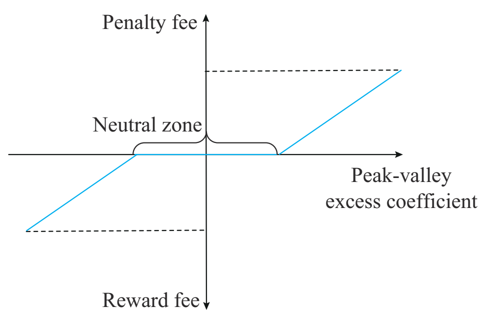

Fig. 2. Peak-valley reward-penalty mechanism.

The retailer's income from this package can be expressed as:

$$B_i^3=\begin{cases}\sum\limits_{j=1}^{N_{\text{U}}}C_{i,j}^{\text{E,U,3}}=\sum\limits_{t=1}^{T_{\text{M}}}\sum\limits_{j=1}^{N_{\text{U}}}p_n^{\text{E, basic}}Q_{t,i,j,n}^{\text{user}}+p_n^{\text{E, penalty}}\left|\varepsilon_{i,j,n}-\varepsilon_0\right| \\ \qquad\qquad\qquad\qquad \varepsilon_0<\varepsilon_{i,j,n}\\ \sum\limits_{j=1}^{N_{\text{U}}}C_{i,j}^{\text{E,U,3}}=\sum\limits_{t=1}^{T_{\text{M}}}\sum\limits_{j=1}^{N_{\text{U}}}p_n^{\text{E, basic}}Q_{t,i,j,n}^{\text{user}} \quad -\varepsilon_0<\varepsilon_{i,j,n}<\varepsilon_0\\ \sum\limits_{j=1}^{N_{\text{U}}}C_{i,j}^{\text{E,U,3}}=\sum\limits_{t=1}^{T_{\text{M}}}\sum\limits_{j=1}^{N_{\text{U}}}p_n^{\text{E, basic}}Q_{t,i,j,n}^{\text{user}}-p_n^{\text{E, reward}}\left|\varepsilon_{i,j,n}+\varepsilon_0\right| \\ \qquad\qquad\qquad\qquad \varepsilon_{i,j,n}<-\varepsilon_0\end{cases}\tag{9}$$

D. Package 4: Quota Natural Gas Price and Ladder Electricity Price

In this package, the monthly electricity demand of end-users is divided into several levels. Especially, different electricity prices are set at each level of ladder price, as shown in Fig. 3.

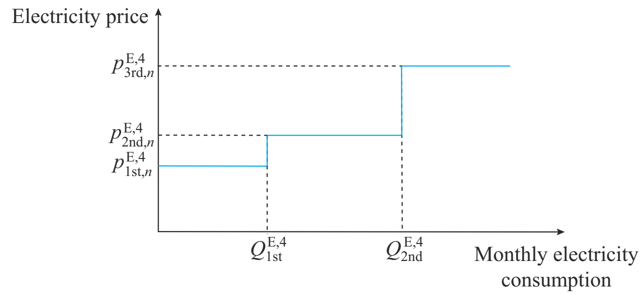

Fig. 3. Electricity price at each level of ladder price.

The electricity price at each level of ladder price is described as:

$$p_n^{\text{E,4}}=\begin{cases}p_n^{\text{1st}} & Q_{i,j,n}^{\text{month}}\in\left[0,Q_n^{\text{1st}}\right)\\ p_n^{\text{2nd}} & Q_{i,j,n}^{\text{month}}\in\left[Q_n^{\text{1st}},Q_n^{\text{2nd}}\right)\\ p_n^{\text{3rd}} & Q_{i,j,n}^{\text{month}}\in\left[Q_n^{\text{2nd}},\infty\right)\end{cases}\quad\forall n=1,2,3\tag{10}$$

$$\begin{cases}Q_{i,j,n}^{\text{month}}=\sum\limits_{t=1}^{T_{\text{M}}}Q_{t,i,j,n}^{\text{user}} & \forall n=1,2,3\\ G_{i,j,n}^{\text{month}}=\sum\limits_{t=1}^{T_{\text{M}}}G_{t,i,j,n}^{\text{user}} & \forall n=1,2,3\end{cases}\tag{11}$$

This package also proposes the natural gas quota, which requires that the monthly natural gas demand of end-users is not less than the quota value G_4. Otherwise, end-users would pay the penalty fee based on the natural gas demand and penalty price. Similarly, if the natural gas demand of end-users is higher than the specified value, end-users will get reward. The retailer's income from this package can be expressed as:

$$C_{i,j}^{\text{E,U,4}}=\begin{cases}p_n^{\text{1st}}Q_{i,j,n}^{\text{month}} & Q_{i,j,n}^{\text{month}}\in\left[0,Q_n^{\text{1st}}\right)\\ p_n^{\text{1st}}Q_n^{\text{1st}}+p_n^{\text{2nd}}\left(Q_{i,j,n}^{\text{month}}-Q_n^{\text{1st}}\right) & Q_{i,j,n}^{\text{month}}\in\left[Q_n^{\text{1st}},Q_n^{\text{2nd}}\right)\\ p_n^{\text{1st}}Q_n^{\text{1st}}+p_n^{\text{2nd}}\left(Q_n^{\text{2nd}}-Q_n^{\text{1st}}\right)+p_n^{\text{3rd}}\left(Q_{i,j,n}^{\text{month}}-Q_n^{\text{2nd}}\right) & \\ & Q_{i,j,n}^{\text{month}}\in\left[Q_n^{\text{2nd}},\infty\right)\end{cases}\tag{12}$$

$$C_{i,j}^{\text{G,U,4}}=\begin{cases}p_n^{\text{G, basic}}G_{i,j,n}^{\text{month}}-p_n^{\text{G, reward}}\left|G_{i,j,n}^{\text{month}}-G_n^{\text{quota}}\right| & G_{i,j,n}^{\text{month}}>G_n^{\text{quota}}\\ p_n^{\text{G, basic}}G_{i,j,n}^{\text{month}} & G_{i,j,n}^{\text{month}}=G_n^{\text{quota}}\\ p_n^{\text{G, basic}}G_{i,j,n}^{\text{month}}+p_n^{\text{G, penalty}}\left|G_{i,j,n}^{\text{month}}-G_n^{\text{quota}}\right| & G_{i,j,n}^{\text{month}}<G_n^{\text{quota}}\end{cases}\tag{13}$$

$$B_i^4=\sum_{j=1}^{N_{\text{U}}}\left(C_{i,j}^{\text{E,U,4}}+C_{i,j}^{\text{G,U,4}}\right)\tag{14}$$

E. Package 5: Fixed Electricity and Natural Gas Price

Package 5 provides end-users with the fixed electricity and natural gas price. It is simple and suitable for risk-averse end-users. The retailer's income from this package can be expressed as:

$$B_i^5=\sum_{j=1}^{N_\mathrm{U}} C_{i,j}^{\mathrm{E,U},5}=\sum_{t=1}^{T_\mathrm{M}}\sum_{j=1}^{N_\mathrm{U}}\left(p_n^{\mathrm{E,fixed}}Q_{t,i,j,n}^{\mathrm{user}}+p_n^{\mathrm{G,fixed}}G_{t,i,j,n}^{\mathrm{user}}\right) \tag{15}$$

IV. Bi-level MLMF Stackelberg Game Model

A. *Bi-Level MLMF Stackelberg Game Framework*

The interaction between energy retailers and multi-energy end-users is modeled by using a bi-level MLMF Stackelberg game model combined with stochastic optimization. The retailers act as leaders and end-users act as followers. As can be observed from Fig. 4, by considering both profit and risk factors, retailers decide the electricity and natural gas purchasing quantities from the upper market or companies, and the prices of multi-energy retail packages at the upper level. Then, after the prices of five packages are decided, end-users aim at maximizing the satisfaction of energy comfort and economy by choosing appropriate packages and retailers at the lower level. The iterative interaction among retailers and end-users would stop when the optimal game decision (namely Nash equilibrium solution) is obtained. With regard to the bi-level MLMF Stackelberg game, the game between retailers is assumed to be a non-cooperative static game while the game between retailers and end-users is assumed to be a non-cooperative dynamic game.

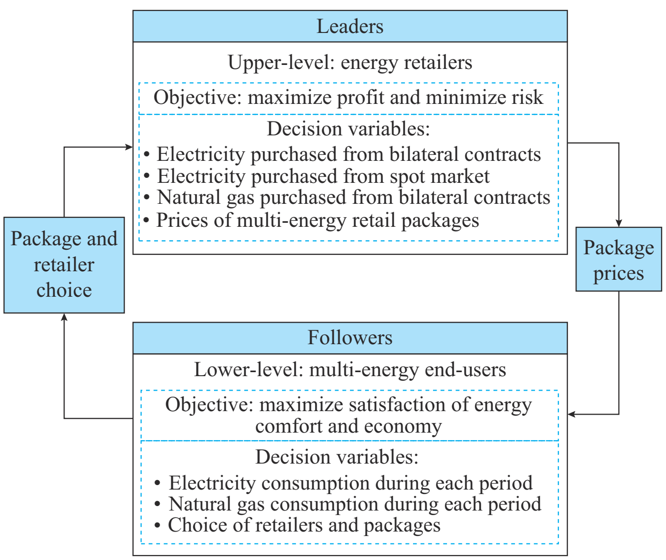

Fig. 4. Bi-level MLMF Stackelberg game framework.

B. *Upper-level Problem*

1) *Objective Function*

Due to the fluctuation of both MCP and demand of end-users during each period, energy retailers may face the financial risk [39]. CVaR is used for minimizing the expected value of regret over a set of worst scenarios [40]. Therefore, the potential risk is evaluated by CVaR to obtain high profit and low risk for retailers. The objective function in upper-level problem consists of three parts (retailer's income, cost, and risk) as can be expressed as:

$$\max PR_i^\mathrm{R}=\left(1-\lambda_i\right)\pi_\omega\left(B_i^\mathrm{R}-C_{i,\omega}^\mathrm{R}\right)-\lambda_i R_i^\mathrm{CVaR}\quad i=1,2,\ldots,N_\mathrm{R} \tag{16}$$

$$\begin{cases} B_i^\mathrm{R}=\sum\limits_{m=1}^{5}B_i^m \\ C_{i,\omega}^\mathrm{R}=C_{i,\omega}^\mathrm{E,R}+C_i^\mathrm{G,R} \end{cases} \tag{17}$$

The mathematical model of risk evaluation based on CVaR is expressed as:

$$\begin{cases} prob\left\{F_i(y,\omega)\le R_i^\mathrm{VaR}\right\}=\beta_i \\ \left[F_i(y,\omega)-R_i^\mathrm{VaR}\right]^+=\max\left[0,F_i(y,\omega)-R_i^\mathrm{VaR}\right] \\ R_i^\mathrm{CVaR}=R_i^\mathrm{VaR}+\dfrac{1}{1-\beta_i}\sum\limits_{\omega\in\Omega_\mathrm{W}}\pi_\omega\left[F_i(y,\omega)-R_i^\mathrm{VaR}\right]^+ \end{cases} \tag{18}$$

where the undefined variables in (16)-(18) are explained in [41].

In order to simplify the model, the auxiliary variables δ_i and $x_{i,\omega}$ are introduced. The above equation is transformed as:

$$R_i^\mathrm{CVaR}=\delta_i+\frac{1}{1-\beta_i}\sum_{\omega\in\Omega_\mathrm{W}}\pi_\omega x_{i,\omega} \tag{19}$$

2) *Constraints*

1) Energy balance constraints: (20) and (21) determine the energy balance for electricity and natural gas, respectively.

$$Q_{i,k}^\mathrm{B}\lambda_{k,t}^\mathrm{B}+Q_{t,i,\omega}^\mathrm{DA}=\sum_{j=1}^{N_\mathrm{U}}Q_{t,i,j,n}^\mathrm{user}\quad \forall n=1,2,3 \tag{20}$$

$$\sum_{k=1}^{N_\mathrm{G,B,R}}G_{i,k}^\mathrm{B,R}=\sum_{t=1}^{T_\mathrm{M}}\sum_{j=1}^{N_\mathrm{U}}G_{t,i,j,n}^\mathrm{user}\quad \forall n=1,2,3 \tag{21}$$

2) Energy purchasing constraints: the purchased electricity and natural gas are limited within the following ranges:

$$\begin{cases} 0\le Q_{i,k}^\mathrm{B}\le Q_k^\mathrm{B,max} \\ 0\le G_{i,k}^\mathrm{B,R}\le G_k^\mathrm{B,R,max} \\ 0\le Q_{t,i,\omega}^\mathrm{DA}\le Q^\mathrm{DA,max} \end{cases} \tag{22}$$

3) Package price constraints: the price relationship in each package is constructed by the following constraints:

$$\begin{cases} p_n^\mathrm{valley}<p_n^\mathrm{flat}<p_n^\mathrm{peak} \\ p_n^\mathrm{night}<p_n^\mathrm{day} \\ p_n^\mathrm{E,reward}<p_n^\mathrm{E,basic} \\ p_n^\mathrm{E,penalty}<p_n^\mathrm{E,basic} \\ p_n^\mathrm{G,reward}<p_n^\mathrm{G,basic} \\ p_n^\mathrm{G,penalty}<p_n^\mathrm{G,basic} \\ p_n^\mathrm{1st}<p_n^\mathrm{2nd}<p_n^\mathrm{3rd} \end{cases} \tag{23}$$

Meanwhile, the prices of energy sold to residential, commercial, and industrial end-users in each package are related. Taking package 1 as an example, it is shown as follows (other packages are similar):

$$\begin{cases} p_{t,1}^\mathrm{E,1}<p_{t,3}^\mathrm{E,1}<p_{t,2}^\mathrm{E,1} \\ p_{t,1}^\mathrm{G,1}<p_{t,3}^\mathrm{G,1}<p_{t,2}^\mathrm{G,1} \end{cases} \tag{24}$$

Also, there are upper and lower limits for prices in each package. Take the electricity price sold to residential end-users during peak periods in package 1 as an example:

$$p_1^{\text{peak,min}} \le p_1^{\text{peak}} \le p_1^{\text{peak,max}} \tag{25}$$

4) CVaR constraints: the relationship between the auxiliary variables used to evaluate the risk is expressed by the following constraints:

$$\begin{cases} -\delta_i - (B_i^{\text{R}} - C_{i,\omega}^{\text{R}}) \le x_{i,\omega} \\ x_{i,\omega} \ge 0 \end{cases} \tag{26}$$

C. Lower-level Problem

1) Objective Function

In the MLMF Stackelberg game, end-users accept prices of multi-energy retail packages passively. But the decisions of end-users are also a crucial part of the game since the strategies of end-users would affect prices of packages in turn. In this paper, the objective function in lower-level problem consists of four parts (the satisfaction of end-user of electricity comfort $S_j^{\text{E,com}}$, natural gas comfort $S_j^{\text{G,com}}$, electricity economy $S_j^{\text{E,eco}}$, and natural gas economy $S_j^{\text{G,eco}}$) as can be expressed in (27). At the same time, different weights of these satisfaction should be considered when end-users formulate energy demand strategies.

$$\max S_j = \omega_j^{\text{E,com}} S_j^{\text{E,com}} + \omega_j^{\text{E,eco}} S_j^{\text{E,eco}} + \omega_j^{\text{G,com}} S_j^{\text{G,com}} + \omega_j^{\text{G,eco}} S_j^{\text{G,eco}} \tag{27}$$

$$S_j^{\text{E,eco}} = \left(C_j^{\text{E,initial}} - \sum_{i=1}^{N_{\text{R}}} \sum_{m=1}^{5} C_{i,j}^{\text{E,U},m} \right) \Big/ C_j^{\text{E,initial}} \tag{28}$$

$$S_j^{\text{G,eco}} = \left(C_j^{\text{G,initial}} - \sum_{i=1}^{N_{\text{R}}} \sum_{m=1}^{5} C_{i,j}^{\text{G,U},m} - C_j^{\text{G,U,B}} \right) \Big/ C_j^{\text{G,initial}} \tag{29}$$

$$S_j^{\text{E,com}} = 1 - \left(\sum_{t=1}^{T_{\text{M}}} \left| \sum_{i=1}^{N_{\text{R}}} Q_{t,i,j,n}^{\text{user}} - Q_{t,j,n}^{\text{initial}} \right| \right) \Big/ \sum_{t=1}^{T_{\text{M}}} Q_{t,j,n}^{\text{initial}} \tag{30}$$

$$S_j^{\text{G,com}} = 1 - \left(\sum_{t=1}^{T_{\text{M}}} \left| \sum_{i=1}^{N_{\text{R}}} G_{t,i,j,n}^{\text{user}} - G_{t,j,n}^{\text{initial}} \right| \right) \Big/ \sum_{t=1}^{T_{\text{M}}} G_{t,j,n}^{\text{initial}} \tag{31}$$

It should be noted that the initial electricity cost $C_j^{\text{E,initial}}$ and natural gas cost $C_j^{\text{G,initial}}$ are calculated according to the fixed single price. Except for purchasing natural gas from retailers, end-users can also trade with natural gas companies directly by monthly bilateral contracts. This cost is expressed as:

$$C_j^{\text{G,U,B}} = \sum_{t=1}^{T_{\text{M}}} \sum_{k=1}^{N_{\text{G,B,U}}} G_{t,j,k,n}^{\text{B,user}} p_k^{\text{G,B,U}} \tag{32}$$

The price that natural gas companies provide to end-users is often higher than that to retailers because of the amount difference of purchased natural gas.

2) Constraints

1) Energy demand constraints: the limits of energy demand for end-users during each period are constructed by the following constraints:

$$\begin{cases} Q_n^{\min} \le Q_{t,j,n}^{\text{total}} \le Q_n^{\max} \\ G_n^{\min} \le G_{t,j,n}^{\text{total}} \le G_n^{\max} \end{cases} \tag{33}$$

2) Energy balance constraints: energy balance constraints of end-users are similarly modeled compared with retailers. Equation (34) shows the corresponding constraints.

$$\begin{cases} Q_{t,j,n}^{\text{total}} = \sum_{i=1}^{N_{\text{R}}} Q_{t,i,j,n}^{\text{user}} \\ G_{t,j,n}^{\text{total}} = \sum_{k=1}^{N_{\text{G,B,U}}} G_{t,j,k,n}^{\text{B,user}} + \sum_{i=1}^{N_{\text{R}}} G_{t,i,j,n}^{\text{user}} \end{cases} \tag{34}$$

3) Natural gas purchase constraint: the purchased natural gas of end-users by bilateral contracts should be lower than their maximum levels.

$$0 \le G_{t,j,k,n}^{\text{B,user}} \le G_k^{\text{B,U,max}} \tag{35}$$

V. Solution Method

To verify the effectiveness of the designed multi-energy retail packages for retailers, a distributed algorithm is proposed to solve the bi-level MLMF Stackelberg game problem, which consists of 4 steps.

Step 1: define the iterative number variable and the iterativetolerance φ_1; initialize energy demand of end-users and package prices, as represented by (3)-(15). Furthermore, generate MCP scenario and set prices of bilateral contracts, as represented by (1) and (2).

Step 2: according to Section IV-C, each end-user decides on its optimal trading strategy during each period. Then, its energy demand behavior is updated.

Step 3: with the updated energy demand of end-users, each retailer determines its optimal trading strategy which includes package prices and purchased energy by solving the optimization problems shown in Section IV-B. The optimization of each retailer is shown as follows.

Step 3.1: set the parameters of PSO, including the numbers of particles and iterations, iterative tolerance φ_2, etc.

Step 3.2: initialize the position and velocity of each particle.

Step 3.3: get the fitness values of initial particles and determine the initial individual and global optimal position.

Step *3.4*: update the position and velocity of particles.

Step 3.5: get the fitness values of initial particles again and update the individual and global optimal position.

Step 3.6: if the solution satisfies the given tolerance φ_2, output the optimal solution; otherwise, go to *Step* 3.4.

Step 4: the updated package prices determined by *Step 3.6* are broadcasted to the end-users. If the difference between optimal profit of retailers in the k^{th} iteration and $(k-1)^{\text{th}}$ iteration is not less than φ_1, go back to *Step* 2. Then, end-users adjust their strategies and offers to retailers again based on the updated package prices. Otherwise, the iteration terminates, which means that the bi-level MLMF Stackelberg game reaches the Nash equilibrium.

VI. Case Study

A. System and Data Specifications

The integrated electricity and natural gas retailing market is assumed to consist of three energy retailers and five end-users (including three residential end-users, one commercial end-user, and one industrial end-user). The packages provided by three energy retailers are shown in Table I, and the satisfaction weights of end-users for natural gas comfort and economy are 0.1 and 0.4, respectively.

TABLE I
PACKAGES PROVIDED BY THREE ENERGY RETAILERS

Energy retailer	Package 1	Package 2	Package 3	Package 4	Package 5
1	×	×	×	√	×
2	√	×	√	×	×
3	×	√	×	×	√

Note: √ indicates that the energy retailer provides this package, and × indicates that the energy retailer does not provide this package.

Due to the limited space, the quotation parameters of power generation companies and natural gas companies, package parameters, and other parameters involved in solving the model can be found in [41]. Based on a typical 24-hour MCP in [1], 1000000 MCP scenarios are generated by the Monte Carlo method. Then, the generated 1000000 MCP scenarios are reduced to 5 typical scenarios by the *K*-means algorithm [41]. The initial electricity and natural gas demands of end-users in a day are also shown in [41]. Assume that the electricity and natural gas demand curves of each day of the month are the same. All the algorithms are executed on a personal computer with an Intel Core (i7 1.80 GHz) and 16 GB of memory. The proposed bi-level stochastic optimization model is solved by PSO and CPLEX 12.6.0 using MATLAB R2016b.

B. Game Equilibrium Analysis

The energy comfort and economy satisfaction of end-users are listed in Table II. The iterative interaction curves between retailers and end-users are shown in Figs. 5 and 6, where the profit of retailers and economy satisfaction of end-users fluctuate violently with the change of each other's strategy in the first 30 iterations. The slope of iteration curves gradually decreases from the 30th to 60th iterations, which implies that the competition between MLMF Stackelberg game players becomes less intense. In the 63rd iteration, the retailers and end-users get the Nash equilibrium solution.

TABLE II
ENERGY COMFORT AND ECONOMY SATISFACTION OF END-USERS

End-user	$S_j^{E,Com}$	$S_j^{E,Eco}$	$S_j^{G,Com}$	$S_j^{G,Eco}$
Residential end-user 1	0.805	0.253	0.880	–0.721
Residential end-user 2	0.669	–0.043		
Residential end-user 3			0.946	–0.089
Commercial end-user 1	0.886	0.114	0.818	–0.265
Industrial end-user 1	0.906	0.247	0.850	0.147

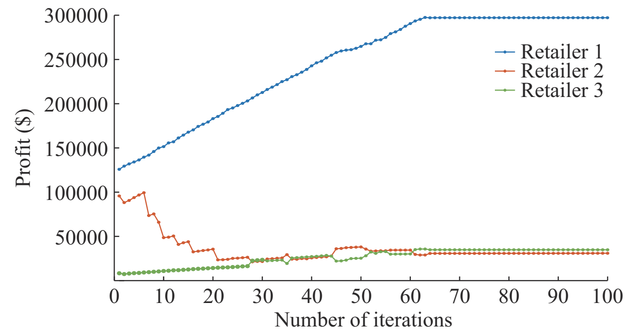

Fig. 5. Iterative curves of retailers.

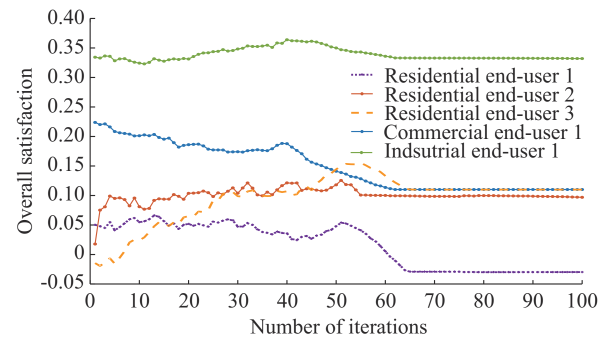

Fig. 6. Iterative curves of end-users.

In Fig. 6, the order of overall satisfaction from the highest to the lowest is the industrial, commercial, and residential end-users, respectively. The reason could be found from Table II. To be specific, residential end-users have the lowest energy demand, which results in the lowest price elasticity and range reduction of energy demand. Then, it further leads to the lowest overall satisfaction. Meanwhile, the commercial end-user has no night-time energy demand, resulting in the higher satisfaction of energy economy compared with residential end-users. Similarly, the industrial end-user has the highest energy demand, resulting in the highest overall satisfaction. The above detailed analysis demonstrates that the industrial end-user has an advantage in the game. Moreover, Fig. 6 also shows that the overall satisfaction of both resident end-user 1 and commercial end-user 1 decreases after the game. However, the overall satisfaction of residential end-users 2 and 3 increases, and that of industrial end-user 1 remains almost unchanged.

C. Analysis of Package Choice of End-users

Figure 7(a) shows that the residential end-user 1 reduces electricity demand as a whole in order to improve the economy satisfaction of electricity. On the contrary, the residential end-user 2 increases electricity demand in Fig. 7(b). This is because the electricity demand of residential end-user 2 is low during peak and flat periods and high during valley periods. It can reduce the electricity cost by choosing package 3 during valley periods to get a high reward fee. The optimal solution indicates that the exact amount of the reward fee is $\$6.5725\times10^3$ within a month. Thus, even if the electricity demand of the end-user increases, the cost is almost unchanged.

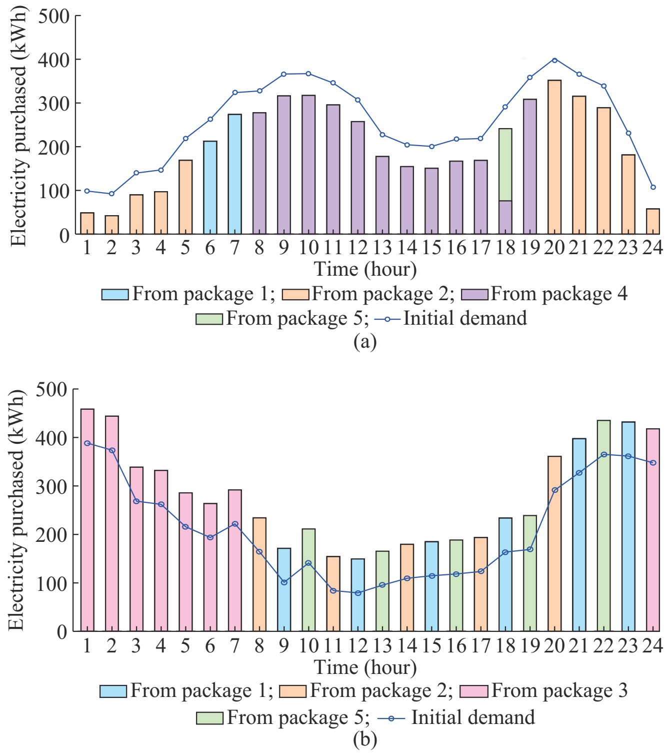

Fig. 7. Purchased electricity of residential end-users. (a) Residential end-user 1. (b) Residential end-user 2.

Figure 8 shows the purchased electricity of commercial end-user 1 and industrial end-user 1. In Fig. 8(a), during the night-time period 21: 00-23: 00, commercial end-user 1 purchases electricity from package 2 because of the low night-time price. Furthermore, during the peak period 17:00-19:00, the end-user purchases 870 kWh electricity at the basic price of package 3. It indicates that the peak-valley excess coefficient of the end-user is between $-\varepsilon_3$ and ε_3, so there is no penalty or reward. The monthly electricity purchased by the end-user from package 4 is 76350 kWh, which does not exceed the first level of electricity demand limit in package 4. Hence, the end-user is charged by the price at the first level in package 4, which reduces the cost effectively.

Figure 8(b) shows that industrial end-user 1 purchases 92400 kWh electricity during the valley period and 19500 kWh during the flat period from package 3 within a month, resulting in a reward fee of \$$7.9534\times10^3$. In addition, the end-user purchases 1180 kWh electricity from package 2 during the night-time period 21: 00-24: 00, which exceeds the limit of night-time electricity demand in package 2. Thus, the end-user gets 190 kWh electricity reward from package 2 during day-time periods 17:00-18:00 and 20:00-21:00. Similarly, the 66000 kWh electricity is purchased from package 4 at the first-level price within a month because it is lower than the second-level price.

According to Figs. 7 and 8, when formulating electricity demand strategies to maximize overall satisfaction, they all have selected multiple retail packages instead of a single retail package. This shows that choosing multiple packages is more conducive to reducing the electricity cost of end-users with little change in electricity demand behavior. This is because end-users can use electricity by different packages during different periods, so as to improve the efficiency. Besides, it can also be concluded from Figs. 7 and 8 that for end-users whose electricity demand is high during the peak period and low during the valley period, reducing overall electricity demand is the main measure to improve their economy. However, for end-users with opposite electricity demand characteristics, they can increase electricity demand as a whole while ensuring the cost almost unchanged.

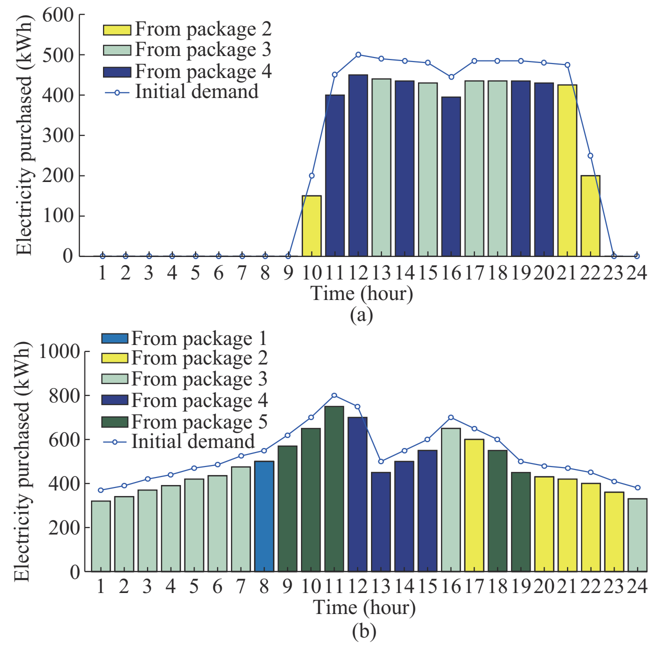

Fig. 8. Purchased electricity of commercial end-user 1 and industrial end-user 1. (a) Commercial end-user 1. (b) Industrial end-user 1.

Figure 9 presents the purchased natural gas of end-users. As shown in Fig. 9, end-users prefer to trade with the natural gas company because of the lowest price of the bilateral contract.

It can be found that all end-users purchase 10000 m^3 natural gas from package 4 within a month. It slightly exceeds the natural gas quota value in package 4 and results in a reward fee. The reason why end-users do not choose package 1 is that it is not beneficial to the economy satisfaction since all end-users have large natural gas demand during peak periods where the price is the highest. Moreover, package 5 is also not chosen by end-users. This is because the retailer providing package 5 always increases the fixed natural gas price to ensure income. These demonstrate that it is necessary for retailers to provide suitable packages for end-users with different natural gas demand behaviors such as the quota natural gas price package. Otherwise, end-users will choose to trade more with natural gas companies that provide lower prices than retailers.

D. Analysis of Electricity Income and Cost of Retailers

The electricity income of retailers from end-users in packages is shown in Fig. 10, where end-user 1 represents residential end-user 1; end-user 2 represents residential end-user 2; end-user 3 represents commercial end-user 1; and end-user 4 represents industrial end-user 1. It can be oberserved that among all packages, only package 2 is chosen by each end-user with electricity demand. This is because all end-users have a number of night-time electricity demand. It leads to a few day-time electricity reward by choosing package 2 which contributes to reducing the cost. Moreover, the type of packages chosen by commercial end-user 3 is the least because of the shortest period with electricity demand. Meanwhile, except for residential end-user 2 with opposite electricity demand behaviors, the electricity income of retailer 1 from other end-users in package 4 is nearly the same. It can be found that 70% of the electricity income of retailer 2 comes from package 3, but packages 2 and 5 bring similar electricity income to retailer 3. The above comparison shows that retailer 2 needs to adjust the prices of package 1 to improve the market share.

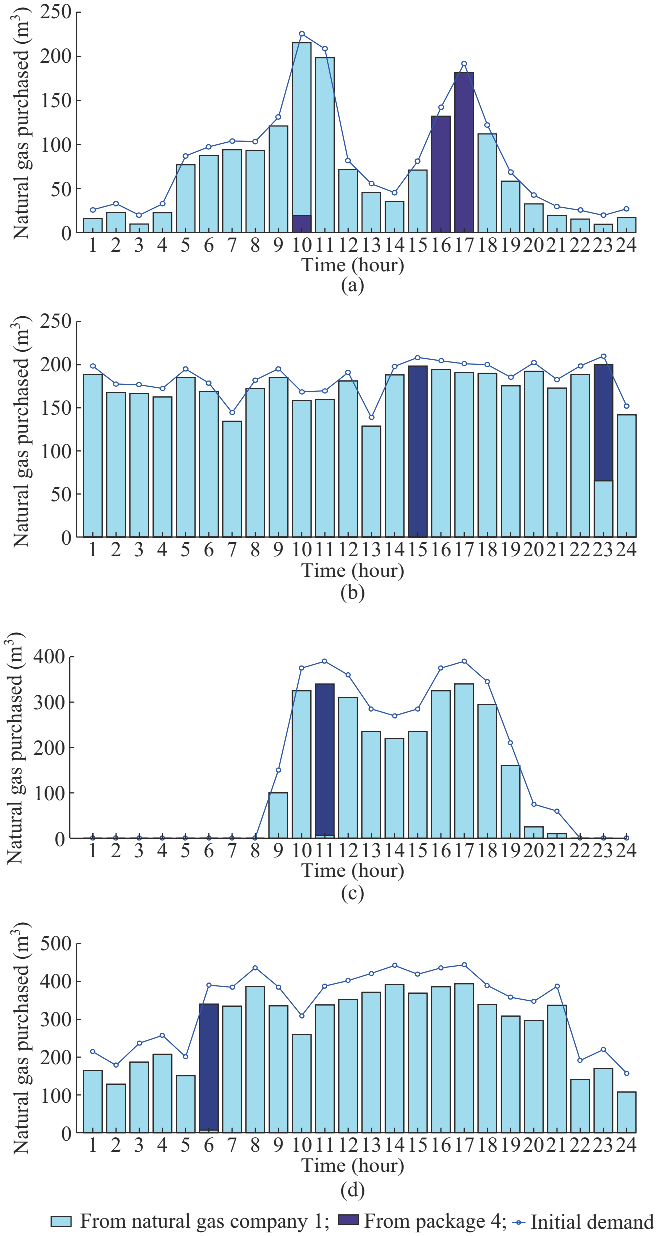

Fig. 9. Purchased natural gas of end-users. (a) Residential end-user 1. (b) Residential end-user 3. (c) Commercial end-user 1. (d) Industrial end-user 1.

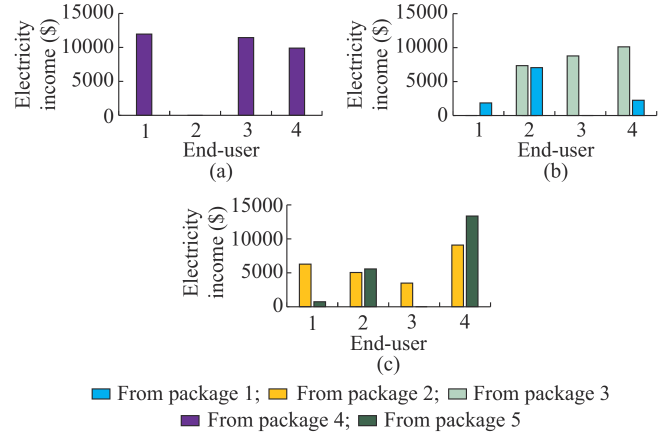

Fig. 10. Electricity income of retailers. (a) Retailer 1. (b) Retailer 2. (c) Retailer 3.

The optimal solution shows that the package prices tend to rise firstly and then stabilize during the iteration. It implies that the increasing prices are the main measure to improve the electricity income for retailers in the MLMF Stackelberg game. By taking the penalty electricity price in package 3 and the reward natural gas price in package 4 as examples, their iterative curves are shown in Fig. 11.

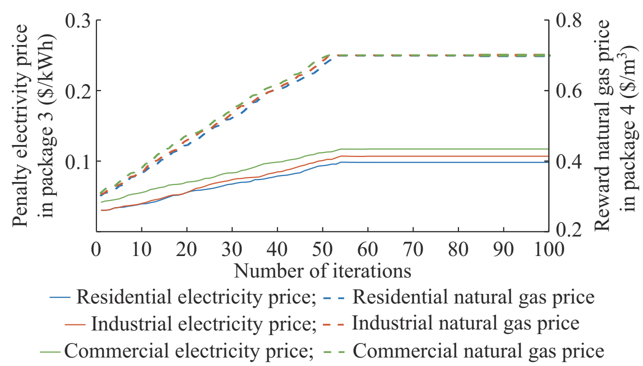

Fig. 11. Iterative curves of penalty electricity price in package 3 and reward natural gas price in package 4.

Figure 12 depicts the profit, risk, cost, income of electricity and natural gas, and total traded electricity of retailers. It should be noted that the profit and cost take the expectations of all scenarios. Meanwhile, costs of retailers 2 and 3 before and after the game in five scenarios in the spot market are shown in Fig. 13.

It can be observed from Fig. 12(a) that after the game, the profits of retailers 1 and 3 greatly increase while those of retailer 2 decrease. The reason may be that before the game, many end-users purchase natural gas from retailer 2 in package 1, as shown in Fig. 12(e). However, after the game, end-users prefer to trade with natural gas company 1 because of the increased natural gas price of package 1. This reduces the natural gas income of retailer 2 significantly. Therefore, the profit and cost of retailer 2 are lower than those before the game. In addition, as the only retailer with natural gas income, retailer 1 has the highest profit. Figure 12(a) and (b) shows that the higher the profit of retailer is, the greater risk it would face. In Fig. 12(d), retailer 3 has the highest electricity income with retailer 2 ranking the second, while retailer 1 has the lowest. This proves that it is more beneficial to retailers than a single type by providing multi-type packages. It also means that the adaptability of packages to end-users is the key to determine the retailers' income. In Fig. 12(f), the total traded electricity of retailers 1 and 3 increases after the game while that of retailer 2 decreases. It implies that retailer 2 is at a disadvantage in the game, and its package design cannot completely satisfy end-users. In contrast, packages 2 and 4 are more favored by end-users in this paper.

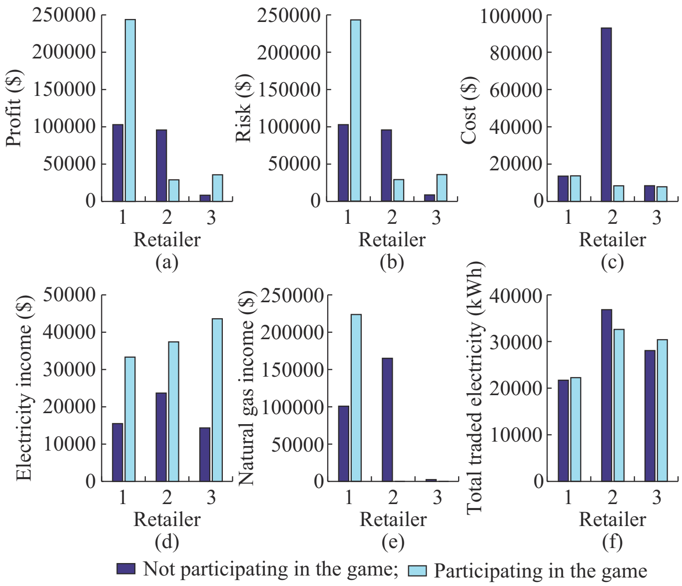

Fig. 12. Profit, risk, cost, income of electricity and natural gas, and total traded electricity of retailers. (a) Profit. (b) Risk. (c) Cost. (d) Electricity income. (e) Natural gas income. (f) Total traded electricity.

The above results demonstrate that retailers still dominate in the MLMF Stackelberg game although end-users have the right to trade with multiple retailers and determine the quantity of energy demand during each period. Therefore, the market manager should control the rise of prices provided by retailers for the fairness of energy retailing market.

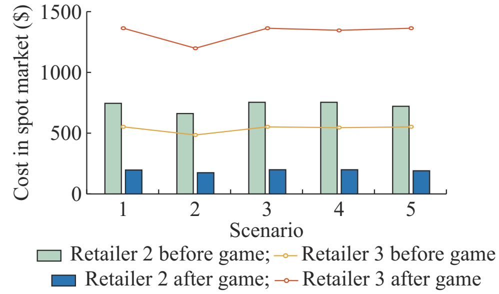

Fig. 13. Costs of retailers 2 and 3 before and after game in five scenarios in spot market.

E. Analysis of Energy Purchase and Sale of Retailers

The sold electricity of retailers before and after participating in the game is shown in Figs. 14 and 15. It can be observed from Fig. 14 that before the game, the sold electricity of retailer 1 is concentrated during the peak period. However, it is concentrated during the peak and flat periods after the game. Moreover, after the game, the main electricity package sold by retailer 2 changes from package 1 to package 3 because of the rise of prices in package 1. And the main selling electricity period distribution of retailer 2 also transfers from flat periods to valley periods. The sold electricity of retailer 3 in package 5 increases slightly after the game, which is mainly during the peak period. The reason is that the second-level price of package 4 is gradually equal to the fixed price of package 5. This results in the reduction of electricity from package 4 and the increase of electricity from package 5. Comparing Fig. 14(c) with Fig. 15(c), we can find the sold electricity in package 2 decreases significantly during the valley period. This is because that the increase of the reward electricity price in package 3 makes end-users who originally chooses package 2 turn to choose package 3.

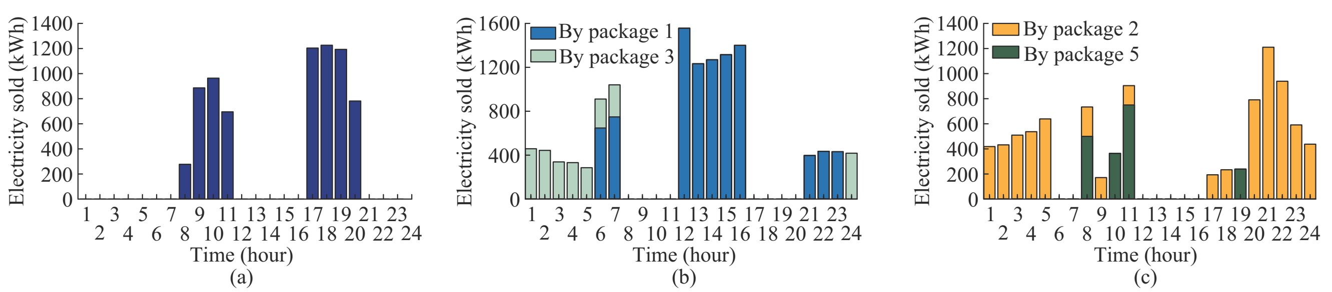

Fig. 14. Sold electricity of retailers before participating in game. (a) Retailer 1. (b) Retailer 2. (c) Retailer 3.

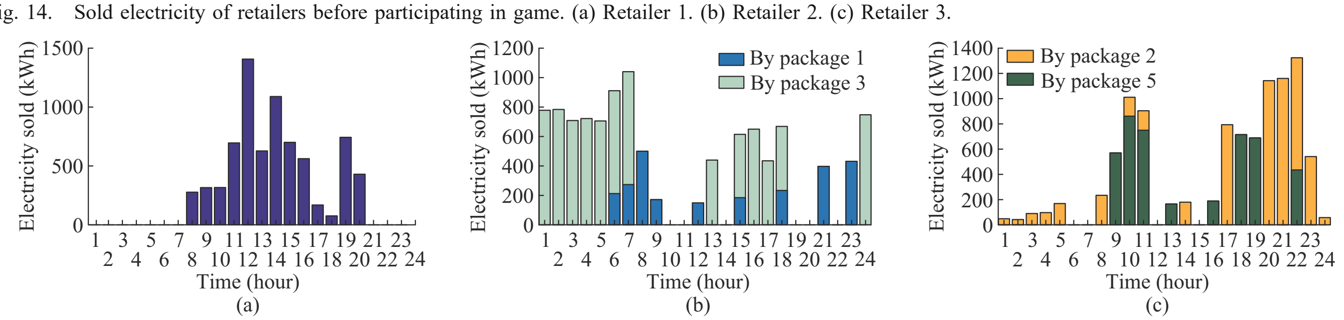

Fig. 15. Sold electricity of retailers after participating in game. (a) Retailer 1. (b) Retailer 2. (c) Retailer 3.

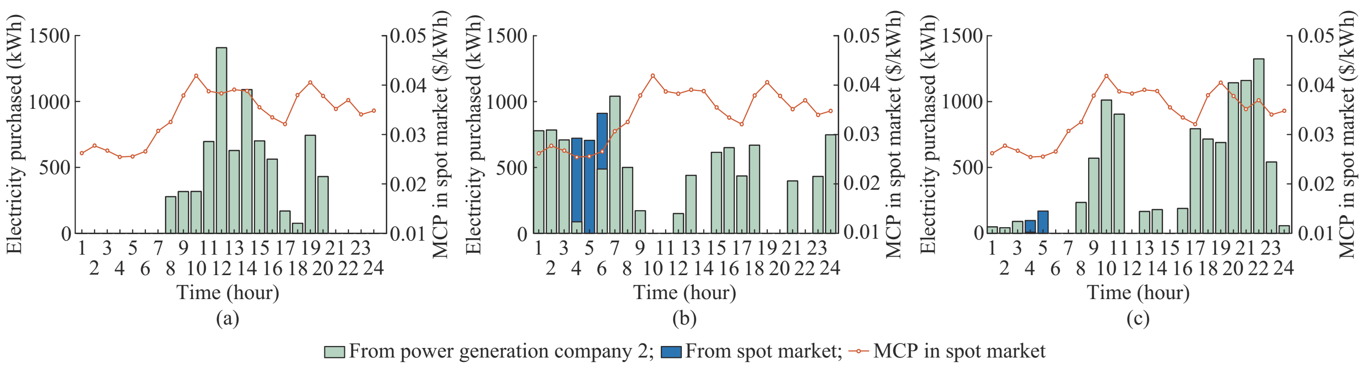

Fig. 16. Purchased electricity of retailers after participating in game. (a) Retailer 1. (b) Retailer 2. (c) Retailer 3.

The purchased electricity of retailers after the game and the MCP curve in the spot market in a typical scenario are shown in Fig. 16. Retailers only trade with power generation company 2 since the bilateral contract price is low. Besides, the electricity in the spot market is mainly purchased from 04:00 to 07:00 when MCP is lower than the bilateral contract price. In summary, after the MLMF Stackelberg game, end-users prefer to choose package 3 during the valley period 00:00-08:00, package 5 during the peak period 08:00-12:00, package 4 during the flat period 12:00-17:00, and package 2 during the flat period 21:00-24:00. In addition, all packages are appropriate for end-users during the peak period 17:00-21:00.

VII. Conclusion

This paper designs five types of multi-energy retail packages for energy retailers, including peak-valley TOU price, day-night bundled price, peak-valley reward-penalty price, quota natural gas price and tiered electricity price, and fixed single price. A bi-level stochastic optimization model is constructed based on MLMF Stackelberg game between energy retailers and end-users. The case is solved by the combination of PSO and CPLEX solver. The simulation results verify the applicability of the designed retail packages to multi-energy end-users. The main conclusions are as follows.

In addition, the design of electricity package and natural-gas package in this paper is independent, but with the development of Energy Internet, the possibility of electrical energy replacement is becoming greater and greater. How to design the package bundled with electricity and natural gas will help retailers face a more complex market environment.

1) In the 63rd iteration, retailers and end-users reach Nash equilibrium. According to the Nash equilibrium solution, the overall satisfaction of the industrial end-user is the highest, followed by the overall satisfaction of commercial end-user and the residential end-user is the lowest.

2) For end-users whose electricity demand is high during load peak periods and low during load valley periods, reducing overall electricity demand is the main measure to improve their economy. However, for end-users with opposite electricity demand characteristics, they can increase electricity demand as a whole while ensuring the cost almost unchanged.

3) The profits of retailers 1 and 3 greatly increase while the profit of retailer 2 decreases after the MLMF Stackelberg game because the end-users choose to purchase natural gas from the natural gas company 1 instead of the original retailer 2. This demonstrates that the advantage in the game for those retailers depends on whether their packages are favored by end-users.

In addition, the design of electricity package and natural gas package in this paper is independent, but with the development of Energy Internet, the possibility of electrical energy replacement is becoming greater and greater. How to design the package bundled with electricity and natural gas will help retailers face a more complex market environment.

References

[1] W. Wei, F. Liu, S. Mei *et al*., "Energy pricing and dispatch for smart grid retailers under demand response and market price uncertainty," *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1364-1374, May 2015.

[2] L. Chen, Q. Xu, Y. Yang *et al*., "Community integrated energy system trading: a comprehensive review," *Journal of Modern Power Systems and Clean Energy*, vol. 10, no. 6, pp. 1445-1458, Nov. 2022.

[3] L. Yang, J. Jian, Y. Xu *et al*., "Multiple perspective-cuts outer approximation method for risk-averse operational planning of regional energy service providers," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2606-2619, Oct. 2017.

[4] M. Z. Oskouei, M. A. Mirzaei, B. Mohammadi-Ivatloo *et al*., "A hybrid robust-stochastic approach to evaluate the profit of a multi-energy retailer in tri-layer energy markets," *Energy*, vol. 214, p. 118948, Jan. 2021.

[5] Y. Liu, D. Zhang, and H. B. Gooi, "Data-driven decision-making strategies for electricity retailers: a deep reinforcement learning approach," *CSEE Journal of Power and Energy Systems*, vol. 7, no. 2, pp. 358-367, Mar. 2021.

[6] J. Yang, J. Zhao, F. Luo *et al*., "Decision-making for electricity retailers: a brief survey," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4140-4153, Sept. 2018.

[7] H. Golmohamadi and R. Keypour, "Stochastic optimization for retailers with distributed wind generation considering demand response," *Journal of Modern Power Systems and Clean Energy*, vol. 6, no. 4, pp. 733-748, Jul. 2018.

[8] M. Song and M. Amelin, "Purchase bidding strategy for a retailer with flexible demands in day-ahead electricity market," *IEEE Transactions on Power Systems*, vol. 32, no. 3, pp. 1839-1850, May 2017.

[9] M. Song and M. Amelin, "Price-maker bidding in day-ahead electricity market for a retailer with flexible demands," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1948-1958, Mar. 2018.

[10] S. M. Mousavi, T. Barforoushi, and F. H. Moghimi, "A decision-making model for a retailer considering a new short-term contract and flexible demands," *Electric Power Systems Research*, vol. 192, p. 106960, Mar. 2021.

[11] Q. Yan, C. Qin, and M. Nie, "Designing household retail electricity packages based on a quantile regression approach," *Energy Strategy Reviews*, vol. 25, pp. 1-10, Aug. 2019.

[12] Y. He, M. Wang, and F. Guang, "Applicability evaluation of China's retail electricity price package combining data envelopment analysis and a cloud model," *Energies*, vol. 13, no. 1, p. 6, Jan. 2020.

[13] Y. He, M. Wang, J. Yu *et al*., "Research on the hybrid recommendation method of retail electricity price package based on power user characteristics and multi-attribute utility in China," *Energies*, vol. 13, no. 11, p. 2693, Jun. 2020.

[14] S. Nojavan and K. Zare, "Optimal energy pricing for consumers by electricity retailer," *International Journal of Electrical Power & Energy Systems*, vol. 102, pp. 401-412, Nov. 2018.

[15] X. Wu, W. Cao, D. Wang *et al*., "Demand response model based on improved pareto optimum considering seasonal electricity prices for dongfushan island," *Renewable Energy*, vol. 164, pp. 926-936, Feb. 2021.

[16] R. Sharifi, A. Anvari-Moghaddam, S. H. Fathi *et al*., "A bi-level model for strategic bidding of a price-maker retailer with flexible demands in day-ahead electricity market," *International Journal of Electrical Power & Energy Systems*, vol. 121, pp. 1-10, Oct. 2020.

[17] L. Ju, J. Wu, H. Lin *et al*., "Robust purchase and sale transactions optimization strategy for electricity retailers with energy storage system considering two-stage demand response," *Applied Energy*, vol. 271, p. 115155, Aug. 2020.

[18] Z. Zhang, Y. Jiang, Z. Lin *et al*., "Optimal alliance strategies among retailers under energy deviation settlement mechanism in China's forward electricity market," *IEEE Transactions on Power Systems*, vol. 35, no. 3, pp. 2059-2071, May 2020.

[19] L. Jia and L. Tong, "Dynamic pricing and distributed energy management for demand response," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1128-1136, Mar. 2016.

[20] S. Sekizaki and I. Nishizaki, "Decision making of electricity retailer with multiple channels of purchase based on fractile criterion with rational responses of consumers," *International Journal of Electrical Power & Energy Systems*, vol. 105, pp. 877-893, Feb. 2019.

[21] Y. Dai, L. Li, P. Zhao *et al*., "Real-time pricing in smart community with constraint from the perspective of advertising game," *International Transactions on Electrical Energy Systems*, vol. 29, no. 9, p. 12043, Sept. 2019.

[22] Y. Dai, X. Sun, Y. Qi *et al*., "A real-time, personalized consumption-based pricing scheme for the consumptions of traditional and renewable energies," *Renewable Energy*, vol 180, pp. 452-466, Dec. 2021.

[23] S. Sekizaki, I. Nishizaki, and T. Hayashida, "Electricity retail market model with flexible price settings and elastic price-based demand responses by consumers in distribution network," *International Journal of Electrical Power & Energy Systems*, vol. 81, pp. 371-386, Oct. 2016.

[24] X. Liu, Q. Wang, and C. Wu, "A stackelberg game approach for heterogeneous energy market in integrated energy system," *International Journal of Energy Research*, vol. 45, no. 1, pp. 1038-1054, Jan. 2021.

[25] S. Khazeni and A. Sheikhi, "Retail market equilibrium in multicarrier energy systems: a game theoretical approach," *IEEE Systems Journal*, vol. 13, no. 1, pp. 738-747, Mar. 2019.

[26] Q. Lu, S. Lv, and Y. Leng, "A Nash-Stackelberg game approach in regional energy market considering users' integrated demand response," *Energy*, vol. 175, pp. 456-470, May 2019.

[27] Y. Dai, Y. Gao, H. Gao *et al*., "A demand response approach considering retailer incentive mechanism based on Stackelberg game in smart grid with multi retailers," *International Transactions on Electrical Energy Systems*, vol 28, no. 9, p. 2590 Sept. 2018.

[28] Y. Xiao, X. Wang, P. Pinson *et al*., "Transactive energy based aggregation of prosumers as a retailer," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3302-3312, Jul. 2020.

[29] L. Wang, W. Gu, Z. Wu *et al*., "Non-cooperative game-based multilateral contract transactions in power-heating integrated systems," *Applied Energy*, vol. 268, p. 114930, Jun. 2020.

[30] A. R. Hatami, H. Seifi, and M. K. Sheikh-El-Eslami, "Optimal selling price and energy procurement strategies for a retailer in an electricity market," *Electric Power Systems Research*, vol. 79, no. 1, pp. 246-254, Jan. 2009.

[31] M. Carrion, J. M. Arroyo, and A. J. Conejo, "A bilevel stochastic programming approach for retailer futures market trading," *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1446-1456, Aug. 2009.

[32] S. Yau, R. H. Kwon, R. J. Scott *et al*., "Financial and operational decisions in the electricity sector: contract portfolio optimization with the conditional value-at-risk criterion," *International Journal of Production Economics*, vol. 134, no. 1, pp. 67-77, Nov. 2011.

[33] F. S. Oliveira and C. Ruiz, "Analysis of futures and spot electricity markets under risk aversion," *European Journal of Operational Research*, vol. 291, no. 3, pp. 1132-1148, Jun. 2021.

[34] R. Freitas and E. P. Vogel, "Stochastic model to aid decision making on investments in renewable energy generation: portfolio diffusion and investor risk aversion," *Renewable Energy*, vol. 162, pp. 1161-1176, Dec. 2020.

[35] I. G. Moghaddam, M. Nick, F. Fallahi *et al*., "Risk-averse profit-based optimal operation strategy of a combined wind farm – cascade hydro system in an electricity market," *Renewable Energy*, vol. 55, pp. 252-259, Jul. 2013.

[36] I. Gomes and R. Melicio, "Decision making for sustainable aggregation of clean energy in day-ahead market: uncertainty and risk," *Renewable Energy*, vol. 133, pp. 692-702, Apr. 2019.

[37] B. Sun, F. Wang, J. Xie *et al*., "Electricity retailer trading portfolio optimization considering risk assessment in Chinese electricity market," *Electric Power Systems Research*, vol. 190, pp. 1-12, Jan. 2021.

[38] A. Hatami, H. Seifi, M. Sheikh-El-Eslami, "A stochastic-based decision-making framework for an electricity retailer: time-of-use pricing and electricity portfolio optimization," *IEEE Transactions on Power System*, vol. 26, no. 4, pp. 1808-1816, Nov. 2011.

[39] T. S. A. Loi and J. L. Ng, "Anticipating electricity prices for future needs – implications for liberalised retail markets," *Applied Energy*, vol. 212, pp. 244-264, Feb. 2018.

[40] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-khah *et al*., "A regret-based stochastic bi-level framework for scheduling of dr aggregator under uncertainties," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3171-3184, Jul. 2020.

[41] H. Gao. (2023, Mar.). Supplementary materialo. [Online]. Available https://github.com/ShuaijiaHe/

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