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# A bilevel game-theoretic decision-making framework for strategic retailers in both local and wholesale electricity markets

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## ABSTRACT

This paper proposes a bilevel game-theoretic model for multiple strategic retailers participating in both wholesale and local electricity markets while considering customers' switching behaviors. At the upper level, each retailer maximizes its own profit by making optimal pricing decisions in the retail market and bidding decisions in the day-ahead wholesale (DAW) and local power exchange (LPE) markets. The interaction among multiple strategic retailers is formulated using the Bertrand competition model. For the lower level, there are three optimization problems. First, the welfare maximization problem is formulated for customers to model their switching behaviors among different retailers. Second, a market-clearing problem is formulated for the independent system operator (ISO) in the DAW market. Third, a novel LPE market is developed for retailers to facilitate their power balancing. In addition, the bilevel multi-leader multi-follower Stackelberg game forms an equilibrium problem with equilibrium constraints (EPEC) problem, which is solved by the diagonalization algorithm. Numerical results demonstrate the feasibility and effectiveness of the EPEC model and the importance of modeling customers' switching behaviors. We corroborate that incentivizing customers' switching behaviors and increasing the number of retailers facilitates retail competition, which results in reducing strategic retailers' retail prices and profits. Moreover, the relationship between customers' switching behaviors and welfare is reflected by a balance between the electricity purchasing cost (i.e., electricity price) and the electricity consumption level.

## 1. Introduction

### 1.1. Background

Strategic bidding and offering are important research problems for both wholesale and local electricity markets where market participants attempt to maximize their own profits or minimize their costs by choosing optimal strategies. Many existing studies address along the direction, but mainly focus on the decision-making problem of electricity producers (e.g., generators). This is due to the fact that previously only electricity producers typically act as price-makers in the wholesale electricity markets [1–3]. However, with the development of smart grids and demand response (DR) management, the role of market players such as energy retailers has been changing. Traditionally, energy retailers act as price-takers in the wholesale market while offering fixed retail prices to their customers. With the increasing demand-side flexibility empowered by the penetration of distributed energy resources (DERs) such as electric vehicles, energy storage systems (ESS), photovoltaic,

and DR programs [4,5], energy retailers are now better positioned to make strategic bidding in the wholesale and local electricity markets and offer more flexible retail pricing decisions such as dynamic pricing to end customers [6,7].

### 1.2. Literature review

The decision-making of participants in hierarchical systems (e.g., electricity markets) is often modeled as a bilevel optimization problem or Stackelberg game [8,9]. In bilevel models for electricity markets, strategic participants (e.g., electricity generators and retailers) either maximize their profits or minimize their costs at the upper level. The lower level usually consists of a market-clearing problem solved by ISO or a customer-side energy management problem. The standard approach to solving the bilevel models is reformulating it as a single-level mixed-integer program by applying Karush–Kuhn–Tucker (KKT) conditions to the lower level problem. There are numerous existing

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## Nomenclature

### Abbreviations and Indices

DAW	Day-ahead Wholesale.
LPE	Local Power Exchange.
ISO	Independent System Operator.
ESS	Energy Storage System.
DR	Demand Response.
KKT	Karush–Kuhn–Tucker.
MPEC	Mathematical Programming with Equilibrium Constraints.
EPEC	Equilibrium Problems with Equilibrium Constraints.
MIQP	Mixed-Integer Quadratic Programming.
$k$	Index of the strategic retailer.
$n$	Index of all retailers.
$m$	Index of generators.
$t$	Index of time periods.

### Sets

$\mathcal{M}$	Set of generators in the grid.
$\mathcal{N}$	Set of retailers in the grid.
$\mathcal{T}$	Set of scheduling hours.

### Parameters

$\Delta t$	Duration of each time period.
$\epsilon_k$	Self loss of the ESS of the retailer $k$ .
$\eta_k^c, \eta_k^d$	Charging and discharging efficiencies of the ESS of the retailer $k$ .
$\omega_{n,j}, \forall j \neq n$	Switching coefficient among retailers.
$\omega_{n,n}^t$	Self-elasticity of the retailer $n$ at time $t$ .
$\pi_i^{bid,t}$	The electricity price the retailer $i$ bought from the DAW market at time $t$ .
$\pi_i^{LPE,t}$	The electricity price the retailer $i$ bought from the LPE market at time $t$ .
$\pi_i^{retail,t}$	The electricity price the retailer $i$ sold to customers at time $t$ .
$\pi_k^{bid,max}$	Maximum bid price of the retailer $k$ .
$\pi_k^{bid,min}$	Minimum bid price of the retailer $k$ .
$\pi_k^{retail,max}$	Maximum retail price of the retailer $k$ .
$\pi_k^{retail,min}$	Minimum retail price of the retailer $k$ .
$c_k$	Operation and maintenance cost of the retailer $k$ .
$c_m$	The production cost of the generator $m$ .
$E_k^{min}, E_k^{max}$	Minimum and maximum energy level of ESS of the retailer $k$ .
$p_k^{c,min}, p_k^{c,max}$	Minimum and maximum charging power of ESS of the retailer $k$ .
$p_k^{d,min}, p_k^{d,max}$	Minimum and maximum discharging power of ESS of the retailer $k$ .

$$q_m^{min}, q_m^{max}$$

Minimum and maximum electricity volume that the generator  $m$  sold to the DAW market.

$$q_{n,in}^{LPE,max,t}$$

Maximum electricity volume the retailer  $n$  bought from other retailers in LPE market.

$$q_{n,out}^{LPE,max,t}$$

Maximum electricity volume the retailer  $n$  sold to the other retailers in LPE market.

$$q_n^{bid,max,t}$$

Maximum electricity volume that the retailer  $n$  bought from the DAW market.

$$q_n^{bid,min,t}$$

Minimum electricity volume that the retailer  $n$  bought from the DAW market.

### Variables

$$\gamma_k^{c,t}, \gamma_k^{d,t}$$

Charging and discharging status of the ESS of the retailer  $k$ .

$$\lambda^{LPE,t}$$

LPE market-clearing price at time  $t$ .

$$\lambda^t$$

DAW market-clearing price at time  $t$ .

$$\pi_k^{bid,t}$$

Bid price of the retailer  $k$  at time  $t$ .

$$\pi_k^{retail,t}$$

Retail price of the retailer  $k$  at time  $t$ .

$$E_k^t$$

Energy level of the ESS of the retailer  $k$  at time  $t$ .

$$p_k^{c,t}, p_k^{d,t}$$

Charging and discharging power of the ESS of the retailer  $k$  at time  $t$ .

$$q_m^t$$

Electricity volume that the generator  $m$  sold to the DAW market at time  $t$ .

$$q_n^{bid,t}$$

Electricity volume that the retailer  $n$  bought from the DAW market at time  $t$ .

$$q_n^{LPE,t}$$

Electricity volume that retailer  $n$  bought from other retailers (if positive), or sold to other retailers (if negative) in the LPE market.

$$q_n^{retail,t}$$

Electricity volume the retailer  $n$  sold in the retail market at time  $t$ .

wholesale markets and compete for the market share. Although the bilevel models considering retailers, system operators, or generators are prevailing, there are increasing attentions paid to other market participants such as DR aggregators and microgrids. For instance, [12] introduces multi-energy players as aggregators to maximize their profits and mitigate their operational risks. The problem is modeled as a bilevel problem and interpreted as an MPEC problem. [13] focuses on the reserve management problem of the EV aggregator. The upper level of the bilevel model is formulated as the profit maximization problem of the EV aggregator. The lower level represents optimal charging/discharging decisions of EV owners. An exact and finite decomposition algorithm is proposed to solve the problem in an iterative manner. [14] proposes a bilevel program for EV aggregators from a different perspective. Instead of maximizing profit at the upper level, charging cost minimization is formulated. The lower level represents the DAW market-clearing problem. [15] develops a single-leader multi-follower game model where the market operator acts as the player at the upper level and smart grid entities at the lower level aim to optimally schedule their own renewable energy resources, energy storage, and DR resources. Likewise, [16] develops a bilevel model for microgrids to achieve optimal bidding strategy, in which the lower level is distributed energy market's clearing problem and the upper level represents the optimal scheduling problem for a microgrid. [17] constructs a bilevel Stackelberg competition model to investigate the interaction between regulated and merchant storage investment. A merchant profit maximization problem is modeled at the upper level, while an overall system cost minimization problem is formulated at the lower level. [18] proposes a stochastic bilevel framework to model the

studies along this direction. For instance, in [10], a scenario-based bilevel model has been applied to a large consumer's profit maximization problem where the wholesale market-clearing problem is considered at the lower level, and a heuristic method is introduced to solve one mathematical programming with equilibrium constraints (MPEC) per scenario. [11] proposes a customized pricing framework for retailers for different residential users. The pricing framework is modeled as bilevel program where retailers purchase electricity from

interactions between a wind power producer at the upper level, and EV and DR aggregators at the lower level. The wind power producer is also formulated to achieve optimal bidding decisions in the competitive wholesale markets.

From an economics point of view, existing studies on strategic bidding and offering problems can be classified based on whether the market participants are price-makers or price-takers [2]. If the market participants have relatively large-scale and flexible loads or supplies, they can be considered as price-makers. Along this direction, [6] develops a short-term planning model of a price-maker retailer with flexible power demand participating in the DAW electricity market. [19] develops a new scenario-based stochastic optimization model for price-maker economic bidding in both day-ahead and real-time markets where a DR program with time-shiftable load is adopted to create load flexibility. [14] proposes an optimal bidding strategy for a large-scale plug-in electric vehicle (PEV) aggregator. The upper level represents the charging cost minimization of the PEV aggregator, whereas the market-clearing problem is formulated at the lower level. In contrast, if the market participants are small-scale or have inelastic loads or supplies, they usually act as price-takers. Along this direction, [4] formulates a stochastic mixed-integer linear program to obtain an optimal bidding strategy for a DERs aggregator participating in the day-ahead market where the market-clearing prices are given by different scenarios. In [15], the lower level of the bilevel program represents multiple smart grids' optimal scheduling problems, whereas the ISO clears the day-ahead market at the upper level. [20] takes both price-maker and price-taker positions into consideration. Specifically, the DR aggregator acts as a price-taker and a price-maker in the day-ahead and real-time market, respectively.

Decision-making of multiple retailers has also been studied in the literature either through a single-level model or a bilevel model. For the former, [21] addresses the portfolio optimization model of retailers, which involves a risk-return optimization method based on the Markowitz theory. [22] proposes a multistage stochastic optimization approach to capture the uncertainties of electricity loads and prices for retailers' contract portfolios which account for their risk preferences. For the latter, [23] proposes a bilevel multi-leader multi-follower game to investigate the benefit of aggregation of prosumers to revenue generation in wholesale and retail markets in which aggregated prosumers act as retailers (leaders) and end-users act as followers. [24] considers strategic firms as leaders in the upper level problem, whereas electricity and natural gas market operators act as followers in the lower level. [25] presents a dynamic pricing framework for electricity and gas utility companies in the coupled retail electricity and natural gas markets by developing a two-leader multi-follower bilevel model. In particular, the electricity and gas utility companies acting as leaders serve energies to the integrated DR aggregators which are followers at the lower level. The competition among multi-energy retailers in the presence of integrated DR prosumers is formulated as a multi-leader–follower bilevel game in [26]. Lastly, [27] considers an EPEC framework to model the interaction among generation companies, microgrids, and load aggregators participating in the wholesale and distribution network electricity markets. In this paper, we study multiple strategic retailers as price-makers participating in both wholesale and local/regional energy markets within the bilevel decision making framework.

Existing studies can be further categorized based on whether market players participate in multiple levels of markets (e.g., wholesale vs. local/retail) simultaneously. Most studies, however, are often based on a single electricity market, such as day-ahead market [1,3,4,6,10,14,15,29] or retail market [2,7,28,33,36]. There are also a few studies focus on analyzing interactions among market participants in the wholesale (i.e., day-ahead and real-time) electricity markets [11,19,20]. Only a few studies in the literature consider multiple levels of markets simultaneously, such as wholesale and retail markets [12,27,34,37].

For instance, the aggregator in [12] participates in both the wholesale and local energy markets. [34] proposes a framework that can optimize the strategy of a distribution company owning DERs and ESS in the wholesale and retail energy markets. In this paper, we also consider multiple levels of electricity markets (i.e., wholesale and local markets). Apart from the conventional retail market, we develop a novel local/regional energy exchange market named the LPE market for retailers. In the literature, studying the local energy market typically focuses on modeling the operation of emerging market participants such as prosumers, DERs aggregators, and microgrids [30,31]. For instance, in [30], a local power exchange center is developed where a novel clustering algorithm is developed to cluster prosumers trading in the local energy market geographically. Another local energy exchange market design for energy trading among energy storage unit's owners is studied in [31], where a novel local energy exchange market-clearing approach is proposed based on double auctions. However, modeling the established and traditional role of energy retailers in the local market is much less studied. In this paper, we propose a LPE market for strategic retailers equipped with energy storage to manage their supply and demand deviation. Compared to the papers mentioned above, the uniqueness of our proposed LPE market lies in that: (1) The participants in the LPE market are strategic retailers equipped with energy storage and arbitrage opportunities; (2) retailers in the LPE market can buy/sell electricity from/to other retailers; (3) the LPE market provides a platform for retailers to balance their supply and demand deviation in a local level market. This new local market for energy retailers will complement existing local energy markets to better facilitate the management of local and distribution energy systems.

In addition to the strategic decision-making problem of multiple retailers in multiple levels of electricity markets, customers' switching behaviors are also modeled in this paper. There are only a few existing studies that address along this direction. For instance, [37] considers customers' switching behaviors in the retail market where a single-level model is proposed to maximize the profit of strategic retailers. [35] presents a decision-making framework for an electricity retailer considering the rational response of consumers under the competitive environment. The retailer is considered as a price-taker in the day-ahead market, and the rival retailers' selling prices are assumed to be given. The switching behaviors of consumers are modeled as the switching cost for the hesitation of consumers to switch contracts between retailers. [33] adopts utility functions to model three categories of DR customers based on their sensitivity to retail prices from low, semi, to high flexibility. It should be noted that modeling customers' switching behaviors for the strategic offering of multiple retailers is particularly crucial to capture the switching decisions of customers among different retailers, the implications and impacts on retailers' strategic decisions, and the market operations. To the best of our knowledge, there is no existing research tackles this problem while considering the hierarchical nature of multiple competitive price-maker retailers and customers.

The above reviewed literature is summarized in Table 1. To fill the research gap following the above analysis, we propose a bilevel game-theoretic framework to model the multiple retailers' (as price-makers) optimal decision-making problems when participating in both wholesale and local markets with customers' switching behaviors considered.

### 1.3. Contributions

The contributions of this paper are summarized as follows:

- We propose a novel bilevel model to formulate strategic behaviors of multiple retailers as price-makers participating in both DAW and local markets. The proposed bilevel model consisting of multiple retailers, multiple electricity markets, and customers' abilities to switch to different retailers is particularly important to model practical scenarios. To the best of our knowledge, this is the first work from the bilevel

**Table 1**  
Literature classification. ✓: Yes; ✗: No; – : Not applicable.

Literature	Bilevel model	Price maker	Multi-market	Multi-leader	Customer behavior
[23,25–27]	✓	✓	✓	✓	✗
[2,3,10,13,14,16,28]	✓	✓	✗	✗	✗
[1,24,29]	✓	✓	✗	✓	✗
[15]	✓	✗	✗	✗	✗
[4]	✗	✗	✗	–	✗
[6,22,30,31]	✗	✓	✗	–	✗
[21]	✗	✓	✓	–	✗
[12,32]	✓	✓	✓	✗	✗
[33]	✓	✓	✗	✗	✓
[7]	✗	✗	✗	–	✓
[11,20,34,35]	✓	✓	✓	✗	✓
[19,36]	✗	✓	✓	–	✓
[37]	✗	✓	✓	✓	✓

game-theoretic perspective to investigate the problem for multiple retailers considering customers' switching behaviors and market share.

- The bilevel problem with a single retailer is firstly reformulated into an MPEC problem by deriving KKT conditions from lower level problems. To overcome the non-convexity in the resulting MPEC problem introduced by the bilinear terms and complementarity slackness constraints, linearization methods are conducted, which leads to a tractable mixed-integer quadratic programming (MIQP) problem. In addition, the Bertrand competition model is adopted to model the interaction among strategic retailers, which is formulated as an EPEC problem and solved by the diagonalization algorithm.

- Comprehensive numerical results are provided to verify the feasibility and effectiveness of the proposed EPEC model and diagonalization algorithm. In addition, the effects of customers' switching behaviors and the number of retailers in the markets on the strategic retailers' optimal decisions are extensively studied. Specifically, increasing customers' switching behaviors and the number of retailers promotes retail competition, which negatively correlated to strategic retailers' equilibrium retail prices and profits. The relationship between customers' switching behaviors and their welfare is also elaborated.

#### 1.4. Paper organization

The remainder of this paper is organized as follows. The proposed bilevel model of a single retailer is developed in Section 2. Section 3 discusses the methodologies for reformulating the bilevel model into an MIQP model. Furthermore, the diagonalization algorithm for solving the EPEC problem with multiple retailers is also proposed in this section. Numerical results are presented and discussed in detail in Section 4. Section 5 concludes this paper.

## 2. Bilevel game-theoretic model

This section proposes a bilevel optimization problem for a strategic retailer who maximizes its profit. Specifically, the strategic retailer participates in DAW and local markets (i.e., retail and LPE markets). The detailed description of the proposed bilevel model is presented in Section 2.1. Furthermore, the upper and lower level problems of the bilevel model are introduced and analyzed in Sections 2.2 and 2.3, respectively. Consequently, the complete bilevel model is formulated in Section 2.4.

### 2.1. Model description

The proposed bilevel model with a single retailer can be interpreted as a single-leader multi-follower game where the strategic retailer acts as the leader, whereas customers, ISO, and the LPE market operator are followers. In particular, the strategic retailer optimizes the ESS management and pricing decisions (i.e., retail prices in the retail market, bid prices in the DAW market, and bid/offer prices in the LPE market) at the upper level. Subsequently, customers react to the optimal load

demand at the lower level based on their welfare. Market operators clear their corresponding markets (i.e., DAW and LPE markets) and send their cleared electricity volume back to the strategic retailer. The structure of the proposed bilevel model is shown in Fig. 1. Specifically, the strategic retailer  $k$  maximizes its profit at the upper level by setting its strategies when participating in all three electricity markets. These strategies include its retail prices  $\pi_k^{retail,t}$  in the retail market, its bid prices in the DAW market  $\pi_k^{bid,t}$ , its bid/offer prices in the LPE market  $\pi_k^{LPE,t}$  and its ESS charging/discharging volume  $p_e^{c,t}/p_e^{d,t}$ . Subsequently, there are three lower level problems. The first lower level problem describes customers' welfare maximization problem. The welfare function is formulated as the difference between customers' utility and their cost of purchasing electricity [38]. The market share function of the retailer  $k$ , as opposed to other retailers participating in the retail market, is derived after reformulating the problem, which can be embedded directly into the upper level problem as a constraint. The ISO's DAW market-clearing problem is constructed as the second lower level problem. The ISO receives the bid prices and electricity load demand from retailers, and offer prices and generation capacities from generators to clear the DAW market. As a result, generators receive the volume of electricity that needs to be produced in each time period, while retailers receive the volume of electricity allocated to each of them. The market-clearing price of the DAW market can also be obtained. The third lower level problem represents the LPE market-clearing problem, where the volume of electricity that each retailer needs to buy or sell is optimized. The market-clearing price of the LPE market can be derived simultaneously.

### 2.2. Upper level problem

The upper level problem aims to maximize the profit of the strategic retailer  $k$  participating in the retail, DAW, and LPE markets. We assume that all three markets are operated on an hourly basis and scheduled on the same time horizon  $\mathcal{T} = \{1, \dots, T\}$  [19,34]. It is also assumed that the retailer  $k$  owns the ESS, which aims to facilitate its energy operations. Mathematically, the upper level problem is modeled as follows:

$$\underset{\pi_{upper}}{\text{Maximize}} \sum_{t \in \mathcal{T}} \left\{ \pi_k^{retail,t} q_k^{retail,t} - \lambda^t q_k^{bid,t} - c_k(p_k^{c,t} + p_k^{d,t}) \Delta t - \lambda^{LPE,t} q_k^{LPE,t} \right\} \quad (1a)$$

Subject to:

$$\pi_k^{retail,min} \leq \pi_k^{retail,t} \leq \pi_k^{retail,max}, \forall t \in \mathcal{T} \quad (1b)$$

$$\pi_k^{bid,min} \leq \pi_k^{bid,t} \leq \pi_k^{bid,max}, \forall t \in \mathcal{T} \quad (1c)$$

$$\pi_k^{LPE,min} \leq \pi_k^{LPE,t} \leq \pi_k^{LPE,max}, \forall t \in \mathcal{T} \quad (1d)$$

$$E_k^{t+1} = E_k^t + \eta_k^c p_k^{c,t} \Delta t - \frac{1}{\eta_k^d} p_k^{d,t} \Delta t - c_k \Delta t, \forall t \in \mathcal{T} \quad (1e)$$

$$E_k^{min} \leq E_k^t \leq E_k^{max}, \forall t \in \mathcal{T} \quad (1f)$$

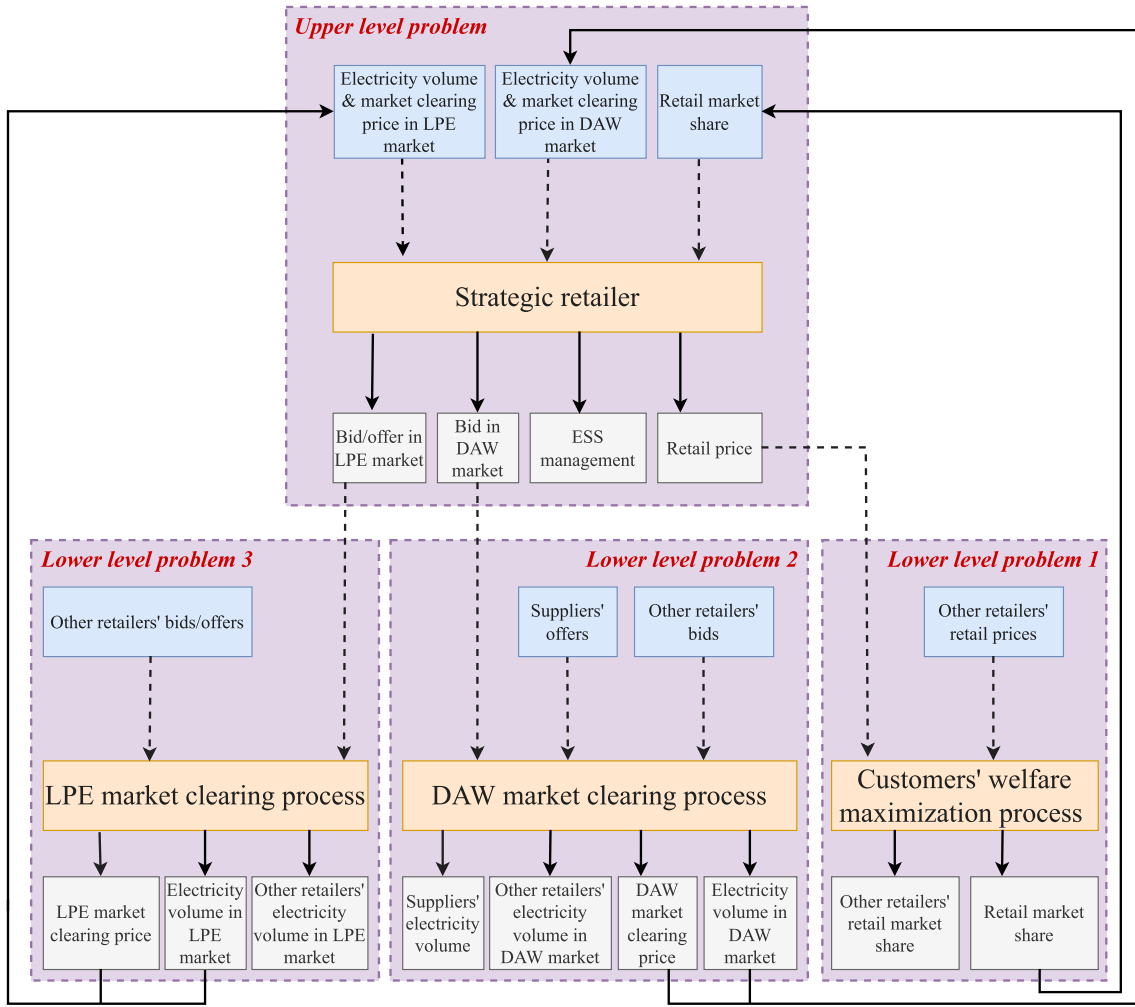


Fig. 1. Bilevel model structure.

$$E_k^1 = E_k^{T+1} \quad (1g)$$

$$\gamma_k^{c,t} p_k^{c,min} \leq p_k^{c,t} \leq \gamma_k^{c,t} p_k^{c,max}, \forall t \in \mathcal{T} \quad (1h)$$

$$\gamma_k^{d,t} p_k^{d,min} \leq p_k^{d,t} \leq \gamma_k^{d,t} p_k^{d,max}, \forall t \in \mathcal{T} \quad (1i)$$

$$\gamma_k^{c,t} + \gamma_k^{d,t} \leq 1, \forall t \in \mathcal{T} \quad (1j)$$

$$\gamma_k^{c,t}, \gamma_k^{d,t} \in \{0, 1\}, \forall t \in \mathcal{T} \quad (1k)$$

$$q_k^{bid,t} + p_k^{d,t} \Delta t + q_k^{LPE,t} = q_k^{retail,t} + p_k^{c,t} \Delta t, \forall t \in \mathcal{T} \quad (1l)$$

The decision variables of the upper level problem are  $\Xi_{upper} = \{p_k^{retail,t}, \pi_k^{bid,t}, \pi_k^{LPE,t}, p_k^{c,t}, p_k^{d,t}, E_k^t, \gamma_k^{c,t}, \gamma_k^{d,t}, \forall t \in \mathcal{T}\}$ .

The upper level objective function (1a) denotes the overall profit that the strategic retailer  $k$  can obtain. It consists of the revenue made in the retail market, the cost of purchasing electricity in the DAW market, the cost of operating the ESS, and the revenue or cost made in the LPE market. (1b)–(1d) constrain the pricing decisions of the retailer in the three markets, respectively. We define the operating constraints for the ESS following [39,40]. In particular, (1e) represents the time-varying energy level of ESS. (1f), (1h) and (1i) ensure the energy level, charging and discharging power of the ESS at each time period follow the operational limitations. (1g) makes sure that by the end of the scheduling hours, the energy level of the retailer is equivalent to the initial energy level. (1j) and (1k) ensure the ESS can only be in either charging or discharging state in a time period. (1l) represents the retailer's power balance constraint at each time period.

### 2.3. Lower level problems

The lower level of the proposed bilevel model consists of three different optimization problems: customers' welfare maximization problem and market-clearing problems of the DAW and LPE markets, respectively. It should be noted that we model aggregated customers' welfare and behavior from the perspective of retailers to reflect customers' switching behaviors among different retailers. In addition, we follow [3,12,35,41] in formulating the market-clearing problems by omitting the loss of direct current power flow and line congestion in transmission (i.e., DAW market) and distribution (i.e., LPE market) networks. Such a modeling choice will improve the computational tractability and also allow us to focus on studying the strategic behaviors of retailers in different electricity markets.

#### 2.3.1. Customers welfare maximization

In the first lower level problem, customers' satisfaction is considered and modeled as the utility function from microeconomics [42]. Following [37,43], the utility function can be formulated as follows:

$$U(q^{retail,t}) = \sum_{n \in \mathcal{N}} \alpha_n^t q_n^{retail,t} - \frac{1}{2} \left( \sum_{n \in \mathcal{N}} \beta_n^t q_n^{retail,t,2} + \sum_{n \in \mathcal{N}, i \in \mathcal{N} \setminus \{k\}} \beta_{n,i}^t q_n^{retail,t} q_i^{retail,t} \right) \quad (2a)$$

where  $\mathcal{N} = \{1, \dots, N\}$  represents a set of retailers in the markets.  $q^{retail,t} \in \mathcal{R}^N$  is a vector where each element denotes the electricity

demand of customers from each retailer at time  $t$ . Moreover, customers' welfare is defined as the difference between the utility of all customers and the electricity purchase cost [38], which is formulated below:

$$\text{Maximize}_{\Xi_{lower1}} \sum_{t \in \mathcal{T}} \left\{ U(q^{retail,t}) - \sum_{n \in \mathcal{N}} q_n^{retail,t} \pi_n^{retail,t} \right\} \quad (2b)$$

where the decision variables of the customer's welfare maximization problem are  $\Xi_{lower1} = \{q_n^{retail,t}, \forall n \in \mathcal{N}, \forall t \in \mathcal{T}\}$ .

After deriving KKT optimality conditions from (2b), the market share function of each retailer is obtained below, which can be directly embedded in the upper level optimization problem of the retailer as a constraint.

$$q_n^{retail,t}(\pi^{retail,t}) = \sum_{j \in \mathcal{N}} \omega'_{n,j} \alpha'_j - \omega'_{n,n} \pi_n^{retail,t} - \sum_{j \in \mathcal{N} \setminus \{n\}} \omega'_{n,j} \pi_j^{retail,t}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \quad (2c)$$

where  $\pi^{retail,t} \in \mathcal{R}^{\mathcal{N}}$  is a vector that each element denotes the electricity retail price of each retailer at time  $t$ . The details of the derivation of (2c) can be found in Appendix A. In particular, elements along the main diagonal of  $\Omega^t$  (taking into account the negative sign) could be used to indicate the self-elasticity of the corresponding retailer's pricing decisions on its own customers. For instance, when the magnitude of  $\omega'_{n,n}$  becomes larger, it causes the load of customers served by the retailer  $n$  to reduce given that the unit retail price  $\pi_n^{retail,t}$  increases. Furthermore, other off-diagonal elements of  $\Omega^t$  (taking into account the negative sign) could be used to indicate cross-impact effects among retail prices of different retailers, which can be interpreted as switching coefficients [37]. The switching coefficients indicate the impact on the retailer's market share when other retailers change their retail prices. A larger magnitude of the switching coefficient demonstrates a more significant impact on other retailers' retail price change to the retailer's market share. From the customers' perspective, (2c) implies that customers can switch among different retailers based on their offered retail prices. Specifically, customers prefer to switch to other retailers who offer lower retail prices when their subscribed retailer increases its retail price. Moreover,  $\sum_{j \in \mathcal{N}} \omega'_{n,j} \alpha'_j$  indicates the market share potential of the retailer  $n$ , which is not affected by the price changes. It is also worth noting that (2c) indicates customers switch energy retailers at each time period  $t$  (e.g. on hourly basis), which could be a viable business model in practice. This is because with the development of information and communication technology and smart meter analytics, technical barriers to automatic and smart switching among retailers will be ultimately removed [44,45]. In addition, the proposed agile customer switching model could be modified and utilized to provide much-needed demand flexibility in short notice to help with the demand and supply management (e.g. unexpected peak demand or excessive renewable generation in some hours due to forecast uncertainty).

### 2.3.2. DAW market-clearing problem

The ISO's DAW market-clearing problem is formulated to minimize the social cost among all generators and retailers participating in the DAW market [46]. Specifically, the bid prices  $\pi_k^{bid,t}$  of the strategic retailer  $k$  are treated as known parameters in the lower level problem. Furthermore, all generators are assumed to be non-strategic since we focus on the strategic behaviors of retailers in this paper. The optimization problem is therefore formulated below.

$$\text{Minimize}_{\Xi_{lower2}} \sum_{t \in \mathcal{T}} \left\{ \sum_{m \in \mathcal{M}} q_m^t c_m - \left( q_k^{bid,t} \pi_k^{bid,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{bid,t} \pi_i^{bid,t} \right) \right\} \quad (3a)$$

Subject to:

$$q_m^{min} \leq q_m^t \leq q_m^{max} : \underline{\mu}_m^t, \overline{\mu}_m^t, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (3b)$$

$$q_k^{bid,min,t} \leq q_k^{bid,t} \leq q_k^{bid,max,t} : \underline{\zeta}_k^t, \overline{\zeta}_k^t, \forall t \in \mathcal{T} \quad (3c)$$

$$q_i^{bid,min,t} \leq q_i^{bid,t} \leq q_i^{bid,max,t} : \underline{\zeta}_i^t, \overline{\zeta}_i^t, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (3d)$$

$$q_k^{bid,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{bid,t} - \sum_{m \in \mathcal{M}} q_m^t = 0 : \lambda^t, \forall t \in \mathcal{T} \quad (3e)$$

where  $\Xi_{lower2} = \{q_m^t, q_k^{bid,t}, q_i^{bid,t}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T}\}$  are the decision variables in this lower level problem.  $\Xi_{lower2}^{dual} = \{\underline{\mu}_m^t, \overline{\mu}_m^t, \underline{\zeta}_k^t, \overline{\zeta}_k^t, \underline{\zeta}_i^t, \overline{\zeta}_i^t, \lambda^t, \forall m \in \mathcal{M}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T}\}$  represents the set of dual variables of corresponding constraints.

The objective function (3a) minimizes the social cost of the DAW market. The production level of each generator is constrained in (3b). (3c) and (3d) constrain the demand level of strategic retailer  $k$  and other retailers, respectively. (3e) represents the electricity supply and demand balance. Furthermore, the dual variable  $\lambda^t$  in (3e) represents the market-clearing price of the DAW market.

### 2.3.3. LPE market-clearing problem

The LPE market facilitates each retailer's electricity supply and demand balance. The LPE market operator acts as a non-profit entity (the same role as the ISO) and clears the LPE market as the social welfare maximization problem. The mathematical formulation is shown as follows:

$$\text{Maximize}_{\Xi_{lower3}} \sum_{t \in \mathcal{T}} \left\{ \pi_k^{LPE,t} q_k^{LPE,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} \pi_i^{LPE,t} q_i^{LPE,t} \right\} \quad (4a)$$

Subject to:

$$-q_{k,out}^{LPE,max,t} \leq q_k^{LPE,t} \leq q_{k,in}^{LPE,max,t} : \psi_{k,out}^t, \psi_{k,in}^t, \forall t \in \mathcal{T} \quad (4b)$$

$$-q_{i,out}^{LPE,max,t} \leq q_i^{LPE,t} \leq q_{i,in}^{LPE,max,t} : \sigma_{i,out}^t, \sigma_{i,in}^t, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (4c)$$

$$\sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{LPE,t} + q_k^{LPE,t} = 0 : \lambda^{LPE,t}, \forall t \in \mathcal{T} \quad (4d)$$

where the decision variables are  $\Xi_{lower3} = \{q_k^{LPE,t}, q_i^{LPE,t}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T}\}$ . The dual variables of corresponding constraints are denoted as  $\Xi_{lower3}^{dual} = \{\psi_{k,out}^t, \psi_{k,in}^t, \sigma_{i,out}^t, \sigma_{i,in}^t, \lambda^{LPE,t}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T}\}$ .

The objective function (4a) maximizes the social welfare of the LPE market. (4b) and (4c) ensure the volume of electricity that each retailer buys or sells in the LPE market is bounded. Finally, (4d) represents the power balance constraint. The dual variable  $\lambda^{LPE,t}$  represents the market-clearing price of the LPE market.

### 2.4. Bilevel model

After formulating both the upper and lower level problems, the proposed bilevel model for the strategic retailer  $k$  can be summarized as follows.

$$\Xi_{upper} \in \arg \text{maximize}_{\Xi_{upper}} \quad (1a) \quad (5a)$$

Subject to:

$$\text{Constraints (1b)–(11)} \quad (5b)$$

$$\Xi_{lower1} \in \arg \text{maximize}_{\Xi_{lower1}} \quad (2b) \quad (5c)$$

$$\Xi_{lower2}, \underline{\mu}_m^t, \overline{\mu}_m^t, \underline{\zeta}_k^t, \overline{\zeta}_k^t, \underline{\zeta}_i^t, \overline{\zeta}_i^t, \lambda^t \in \arg \text{minimize}_{\Xi_{lower2}} \left\{ \quad (3a) \right. \quad (5d)$$

Subject to:

$$\text{Constraints (3b)–(3e)} \left. \right\}, \forall m \in \mathcal{M}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T}$$

$$\Xi_{lower3}, \psi_{k,out}^t, \psi_{k,in}^t, \sigma_{i,out}^t, \sigma_{i,in}^t, \lambda^{LPE,t} \in \arg \text{maximize}_{\Xi_{lower3}} \left\{ \quad (4a) \right. \quad (5e)$$

Subject to:

$$\text{Constraints (4b)–(4d)} \left. \right\}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T}$$

(5a) and (5b) denote the strategies of the retailer  $k$  at the upper level. Furthermore, (5c)–(5e) represent the reactions from the three electricity markets given by the upper level decisions, respectively. The bilevel model forms a single-leader–multiple-follower Stackelberg game which can also be interpreted as an MPEC program [47]. The methods to solve the MPEC problem are discussed in detail in the next section.

### 3. Solution methods

The section illustrates the solution methods for both MPEC and EPEC problems. It first details the treatment of the MPEC problem, which is linearized and reformulated to a MIQP problem. Furthermore, the single leader MPEC model is extended to the multi-leader EPEC model, which can be solved by the diagonalization algorithm.

#### 3.1. MPEC problem

The bilevel model can be transformed into a single-level MPEC problem by deriving KKT optimality conditions for the lower level problems into a system of equations and inequalities. The transformed MPEC problem is shown below:

$$\text{Maximize } \Xi_{MPEC} \quad (6a)$$

Subject to:

$$\text{Constraints (1b)–(1l), (2c)} \quad (6b)$$

$$c_m - \underline{\mu}_m^t + \overline{\mu}_m^t - \lambda^t = 0, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (6c)$$

$$-\pi_k^{bid,t} - \underline{\zeta}_k^t + \overline{\zeta}_k^t + \lambda^t = 0, \forall t \in \mathcal{T} \quad (6d)$$

$$-\pi_i^{bid,t} - \underline{\zeta}_i^t + \overline{\zeta}_i^t + \lambda^t = 0, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (6e)$$

$$q_k^{bid,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{bid,t} - \sum_{m \in \mathcal{M}} q_m^t = 0, \forall t \in \mathcal{T} \quad (6f)$$

$$0 \leq (q_m^t - q_m^{min}) \perp \underline{\mu}_m^t \geq 0, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (6g)$$

$$0 \leq (q_m^{max} - q_m^t) \perp \overline{\mu}_m^t \geq 0, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (6h)$$

$$0 \leq (q_n^{bid,t} - q_n^{bid,min,t}) \perp \underline{\zeta}_n^t \geq 0, \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \quad (6i)$$

$$0 \leq (q_n^{bid,max,t} - q_n^{bid,t}) \perp \overline{\zeta}_n^t \geq 0, \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \quad (6j)$$

$$-\pi_k^{LPE,t} - \psi_{k,out}^t + \psi_{k,in}^t + \lambda^{LPE,t} = 0, \forall t \in \mathcal{T} \quad (6k)$$

$$-\pi_i^{LPE,t} - \sigma_{i,out}^t + \sigma_{i,in}^t + \lambda^{LPE,t} = 0, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (6l)$$

$$\sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{LPE,t} + q_k^{LPE,t} = 0, \forall t \in \mathcal{T} \quad (6m)$$

$$0 \leq \psi_{k,out}^t \perp (q_k^{LPE,t} - q_{k,out}^{LPE,max,t}) \geq 0, \forall t \in \mathcal{T} \quad (6n)$$

$$0 \leq \psi_{k,in}^t \perp (q_{k,in}^{LPE,max,t} - q_k^{LPE,t}) \geq 0, \forall t \in \mathcal{T} \quad (6o)$$

$$0 \leq \sigma_{i,out}^t \perp (q_i^{LPE,t} - q_{i,out}^{LPE,max,t}) \geq 0, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (6p)$$

$$0 \leq \sigma_{i,in}^t \perp (q_{i,in}^{LPE,max,t} - q_i^{LPE,t}) \geq 0, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (6q)$$

where the decision variables of the MPEC problem are  $\Xi_{MPEC} = \left\{ \pi_k^{retail,t}, \pi_k^{bid,t}, q_k^{retail,t}, q_i^{retail,t}, q_k^{bid,t}, q_i^{bid,t}, p_k^{c,t}, p_k^{d,t}, E_k^t, \pi_k^{LPE,t}, q_k^{LPE,t}, q_i^{LPE,t}, q_m^t, \gamma_k^{c,t}, \gamma_k^{d,t}, \underline{\mu}_m^t, \overline{\mu}_m^t, \underline{\zeta}_j^t, \overline{\zeta}_j^t, \lambda^t, \psi_{k,out}^t, \psi_{k,in}^t, \sigma_{i,out}^t, \sigma_{i,in}^t, \forall t \in \mathcal{T}, \forall i \in \mathcal{N} \setminus \{k\}, \forall m \in \mathcal{M}, \forall j \in \mathcal{N} \right\}$ .

(6a) denotes the objective function of the MPEC model. In the following constraints, (6b) represents a collection of constraints from the upper level problem and retailers' market share function. Eqs. (6c)–(6f) and (6k)–(6m) are stationary conditions of the KKT optimality conditions. Moreover, (6g)–(6j) and (6n)–(6q) represent the complementarity slackness.

#### 3.2. Linearization of the MPEC problem

The MPEC model above is non-convex and difficult to solve due to the existence of bilinear terms in the objective function (6a) and complementarity slackness constraints (6g)–(6j) and (6n)–(6q). To overcome the difficulties, we firstly deal with the bilinear terms in the upper level objective function (6a) through the strong duality theorem [48]. Therefore, the objective function of the MPEC model becomes:

$$\begin{aligned} \Phi = & \sum_{i \in \mathcal{T}} \left\{ \sum_{m \in \mathcal{M}} \left( q_m^t c_m - \underline{\mu}_m^t q_m^{min} + \overline{\mu}_m^t q_m^{max} \right) \right. \\ & - \sum_{j \in \mathcal{N} \setminus \{k\}} \left( \pi_j^{bid,t} q_j^{bid,t} + \underline{\zeta}_j^t q_j^{bid,min} - \overline{\zeta}_j^t q_j^{bid,max} \right) + c_k \left( p_k^{c,t} + p_k^{d,t} \right) \Delta t \\ & - \pi_k^{retail,t} \sum_{j \in \mathcal{N}} \omega_{k,j}^t \alpha_j^t + \omega_k^t \pi_k^{retail,t^2} + \pi_k^{retail,t} \sum_{j \in \mathcal{N} \setminus \{k\}} \omega_{k,j}^t \pi_j^{retail,t} \\ & \left. + \sum_{i \in \mathcal{N} \setminus \{k\}} \left( \sigma_{i,out}^t q_{i,out}^{LPE,max,t} + \sigma_{i,in}^t q_{i,in}^{LPE,max,t} - \pi_i^{LPE,t} q_i^{LPE,t} \right) \right\} \end{aligned}$$

The details of the derivation of objective function  $\Phi$  are provided in the Appendix B. Furthermore, Fortuny-Amat transformation is used to linearize complementarity slackness by introducing additional binary variables and a relatively large integer constant  $M$  [49]. The resulting linearized constraints of (6g)–(6j) and (6n)–(6q) are shown in (7a)–(7j) and (7k)–(7v), respectively.

$$0 \leq \underline{\mu}_m^t \leq \overline{\mu}_m^t M, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (7a)$$

$$0 \leq q_m^t - q_m^{min} \leq (1 - \underline{\mu}_m^t) M, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (7b)$$

$$0 \leq \overline{\mu}_m^t \leq \overline{\mu}_m^t M, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (7c)$$

$$0 \leq q_m^{max} - q_m^t \leq (1 - \overline{\mu}_m^t) M, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (7d)$$

$$\underline{\zeta}_m^t, \overline{\zeta}_m^t \in \{0, 1\}, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \quad (7e)$$

$$0 \leq \underline{\zeta}_i^t \leq \overline{\zeta}_i^t M, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \quad (7f)$$

$$0 \leq q_i^{bid,t} - q_i^{bid,min,t} \leq (1 - \underline{\zeta}_i^t) M, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \quad (7g)$$

$$0 \leq \overline{\zeta}_i^t \leq \overline{\zeta}_i^t M, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \quad (7h)$$

$$0 \leq q_i^{bid,max,t} - q_i^{bid,t} \leq (1 - \overline{\zeta}_i^t) M, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \quad (7i)$$

$$\underline{\zeta}_m^t, \overline{\zeta}_m^t \in \{0, 1\}, \forall m \in \mathcal{N}, \forall t \in \mathcal{T} \quad (7j)$$

$$0 \leq \psi_{k,out}^t \leq \rho_{k,out}^t M, \forall t \in \mathcal{T} \quad (7k)$$

$$0 \leq q_k^{LPE,t} + q_{k,out}^{LPE,max,t} \leq (1 - \rho_{k,out}^t) M, \forall t \in \mathcal{T} \quad (7l)$$

$$0 \leq \psi_{k,in}^t \leq \rho_{k,in}^t M, \forall t \in \mathcal{T} \quad (7m)$$

$$0 \leq q_{k,in}^{LPE,max,t} - q_k^{LPE,t} \leq (1 - \rho_{k,in}^t) M, \forall t \in \mathcal{T} \quad (7n)$$

$$\rho_{k,out}^t, \rho_{k,in}^t \in \{0, 1\}, \forall t \in \mathcal{T} \quad (7o)$$

$$0 \leq \sigma_{i,out}^t \leq \delta_{i,out}^t M, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (7p)$$

$$0 \leq q_i^{LPE,t} + q_{i,out}^{LPE,max,t} \leq (1 - \delta_{i,out}^t) M, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (7q)$$

$$0 \leq \sigma_{i,in}^t \leq \delta_{i,in}^t M, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (7r)$$

$$0 \leq q_{i,in}^{LPE,max,t} - q_i^{LPE,t} \leq (1 - \delta_{i,in}^t) M, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (7s)$$

$$\delta_{i,out}^t, \delta_{i,in}^t \in \{0, 1\}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \quad (7t)$$

#### 3.3. MIQP problem

After the linearization, the MPEC model is reformulated into a MIQP problem and can be solved efficiently using off-the-shelf solvers. The complete MIQP model is formulated as follows.

$$\text{Minimize } \Phi_{MIQP} \quad (8a)$$



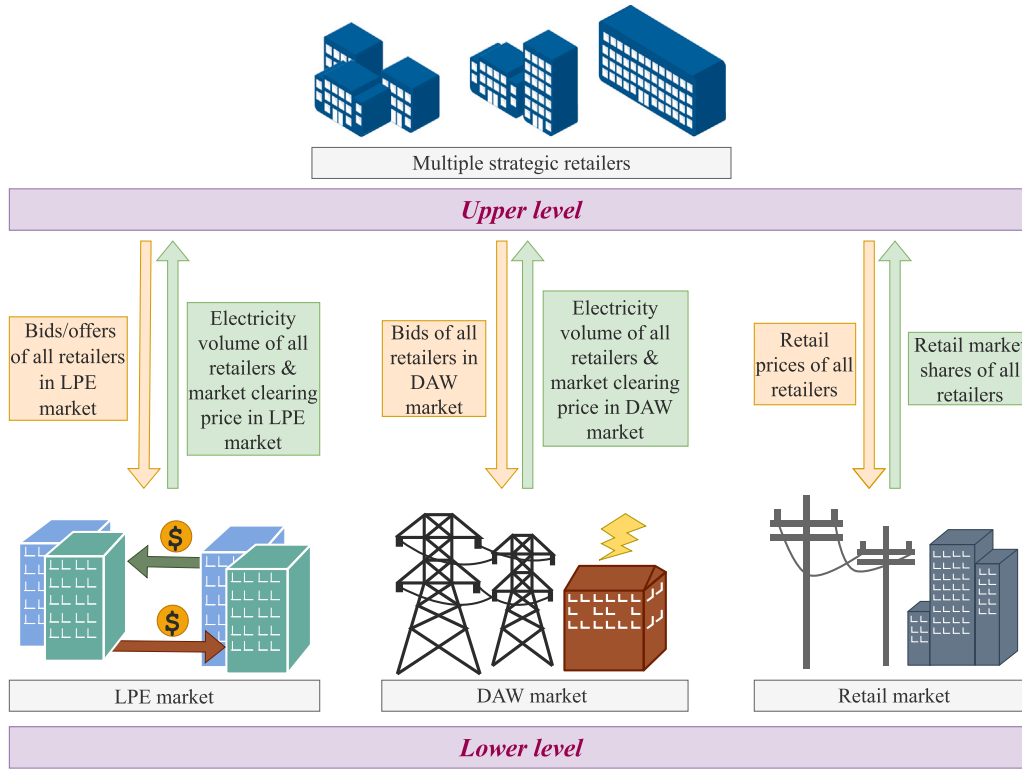


Fig. 2. EPEC problem structure.

Subject to:

$$\text{Constraints (1b)–(1l), (2c), (6c)–(6f), (6k)–(6m), (7a)–(7t)} \quad (8b)$$

where  $\Xi_{MIQP} = \{ \pi_k^{retail,t}, \pi_k^{bid,t}, q_k^{retail,t}, q_i^{retail,t}, q_k^{bid,t}, q_i^{bid,t}, p_k^{c,t}, p_k^{d,t}, E_k^t, \pi_k^{LPE,t}, q_k^{LPE,t}, q_i^{LPE,t}, q_m^t, \gamma_k^{c,t}, \gamma_k^{d,t}, \tau_{in}^t, \tau_{out}^t, \mu_m^t, \mu_m^t, \zeta_j^t, \zeta_j^t, \bar{t}_m^t, \bar{t}_m^t, \xi_j^t, \xi_j^t, \lambda^t, \psi_{k,out}^t, \psi_{k,in}^t, \sigma_{i,out}^t, \sigma_{i,in}^t, \rho_{k,out}^t, \rho_{k,in}^t, \delta_{i,out}^t, \delta_{i,in}^t, \forall t \in \mathcal{T}, \forall i \in \mathcal{N} \setminus \{k\}, \forall m \in \mathcal{M}, \forall j \in \mathcal{N} \}$  represents the set of decision variables of the MIQP model.

The objective function (8a) shapes a quadratic form with respect to  $\pi_k^{retail,t}$ . Constraint (8b) consists of all the constraints in the upper level problem, market share functions, KKT stationary conditions for the market-clearing problems of the DAW and LPE markets, and the linearized complementarity slackness constraints.

### 3.4. EPEC problem

The Bertrand competition model is utilized to extend the MIQP model from a single strategic retailer to multiple strategic retailers. This results into a multi-leader multi-follower Stackelberg game and can be reformulated as an EPEC problem [47], which is illustrated in Fig. 2. Although the retailers share complete information among themselves in the theoretic setting of the EPEC problem, in practice, an independent market agent (e.g. ISO for wholesale markets) can play such a role for sharing required information among retailers. We adopt the diagonalization algorithm in [50] to tackle our formulated EPEC problem where the converged strategies of strategic retailers represent a generalized Nash equilibrium. The diagonalization algorithm considered for solving our EPEC problem is outlined in Algorithm 1. In Step 1, the strategy set is initialized as  $S^0$ . The maximum iteration  $Y$  and convergence criterion  $\epsilon$  are also predefined. The main iteration procedure of the diagonalization algorithm is shown in Steps 2–13, which consists of an outer loop and an inner loop. In particular, the outer loop controls the iteration of the algorithm. For each iteration of the outer loop, Steps 3–6 define the inner loop and aim to solve the MIQP problem for each strategic retailer sequentially with the other retailers' strategies as

### Algorithm 1 Diagonalization algorithm

1: Initialization:

$$S^0 = \{ \pi_n^{retail,t}, \pi_n^{bid,t}, \pi_n^{LPE,t}, p_n^{c,t}, p_n^{d,t}, E_n^t, \gamma_n^{c,t}, \gamma_n^{d,t}, \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \};$$

maximum number of iterations  $Y$ ; convergence criterion  $\epsilon$ .

2: **for**  $y = 1$  to  $Y$  **do**

3: **for**  $i = 1$  to  $N$  **do**

4: Solve strategic retailer  $i$ 's MIQP model assuming other retailers' strategies as given parameters.

5: Update  $S_i^y$ ;

6: **end for**

7: **if**  $\|S_i^y - S_i^{y-1}\| \leq \epsilon, \forall i \in \mathcal{N}$  **then**

8: The algorithm converges and terminates.

9: **end if**

10: **if**  $y = Y$  **then**

11: The algorithm fails to converge and terminates.

12: **end if**

13: **end for**

given parameters. The convergence of the algorithm is checked in Steps 7–12 at each iteration of the outer loop. Specifically, in Steps 7–9, if the difference between the retailers' optimal decisions of two adjacent iterations is less than  $\epsilon$ , the algorithm converges and terminates with retailers' optimal decisions. However, in Steps 10–12, if the algorithm reaches the maximum iteration  $Y$  without convergence, it terminates and no optimal results are found.

### 4. Numerical results

Numerical results are illustrated in this section to demonstrate the feasibility and effectiveness of the EPEC model and the diagonalization algorithm. The effects of customers' switching behaviors and the number of strategic retailers on retail competition are discussed in detail.

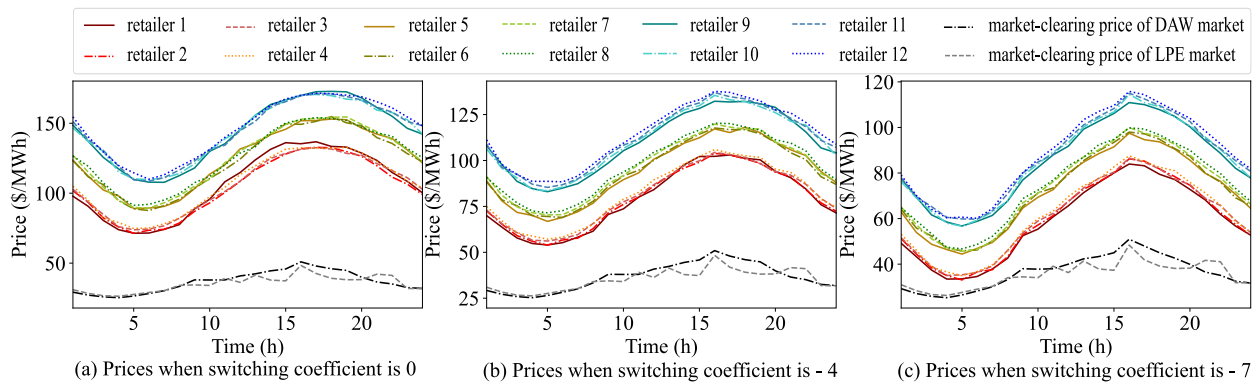


Fig. 3. Time-varying retail prices and market-clearing prices of LPE and DAW markets with different switching coefficients.

The proposed model is solved by Gurobi Optimizer (version 9.5.2) using the branch and bound algorithm under Pyomo [51] on Windows 10 Enterprise 64-bit with 4 cores CPU at 3.6 GHz and 16 GB of RAM.

#### 4.1. Experimental setup

Data used in this section comes mainly from the PJM datasets [52], such as the initial retail and DAW market bid prices for each retailer during the day. The initial LPE market bid/offer prices and the maximum of cleared electricity volume are based on PJM real-time market bid prices and cleared electricity for each retailer. We further calibrate the retailers' maximum cleared electricity volume in the LPE market to be 5% of the maximum bid load of retailers in the DAW market. The initial DAW market's maximum bid load of each retailer comes from the PJM DAW market bid load of different utility companies. In addition, the minimum and maximum retail, DAW market bid, and LPE market bid/offer prices are all set to be \$0/MWh and \$300/MWh respectively. The minimum bid load for the retailers in the DAW market is considered to be 0.1 MW following PJM day-ahead wholesale market [53]. The maximum iteration  $Y = 30$  and the termination criteria  $\epsilon = 1$  are chosen for the diagonalization algorithm. The ESS-related parameters are modified based on [40]. In particular, the initial ESS energy level is set to be 80 MWh. The maximum and minimum charging and discharging rates are 60 MW and 2 MW. The maximum and minimum ESS energy capacities are 200 MWh and 30 MWh. The charging and discharging efficiencies are set to be 0.9. Lastly, the self-discharge rate  $\epsilon_k = 0.002$  MW is considered.

In this paper, we consider 24 time periods for the day starting from midnight. That is, each time period represents an hour. In this case, 12 strategic retailers are considered in the proposed EPEC model. Furthermore, the strategic retailers are classified into 3 groups based on their market share potential which the self-elasticity coefficient  $\omega'_{n,n}$  and parameter  $\alpha'_n$  are assumed to be time-varying. Specifically, retailers 1–4 are classified into small market share group (group 1). Retailers 5–8 belong to the medium market share group (group 2). Lastly, retailers 9–12 are in the large market share group (group 3). The input data of electricity prices and volume, self-elasticity coefficient  $\omega'_{n,n}$ , and  $\alpha'_n$  for each retailer can be found in Appendix C.1. Additionally, we include 30 generators participating in the DAW market. The cost and maximum supply of each generator are shown in Appendix C.2.

#### 4.2. Illustrative examples

In this section, illustrative examples are given to discuss the results of the EPEC model when switching coefficients are set to be 0 MWh/\$, -4 MWh/\$, and -7 MWh/\$ respectively. The magnitude of the switching coefficient represents the ability of customers to switch to other retailers and thus the competition level in the retail market. A larger magnitude of the switching coefficient indicates more competition

in the retail market. Time-varying retail prices of each retailer and market-clearing prices of the LPE and DAW markets are shown in Fig. 3. It can be found that both the retail and market-clearing prices decrease from 1 am to around 5 am, then increase until around 5 pm and drop down again afterward, which follows customers' demand during the day.

Furthermore, the retail prices of all retailers are generally higher than the market-clearing prices of the LPE and DAW markets but become closer to the market-clearing prices with the increase of magnitude of the switching coefficient. This can be explained that with more competition in the retail market, it drives down the retail prices and retailers' profit margin becomes lower. In addition, the retail prices are typically higher when the retailers have a larger market share (bigger retailers). This could be due to that retailers with large market share have more flexibility in their pricing decisions without worrying losing customers.

It is also observed that the market-clearing prices of the LPE market are generally more volatile than the market-clearing prices of the DAW market. This could be explained by the fact that the market size (market-cleared electricity volume) of the LPE market is much smaller than the DAW market. Therefore, the unit difference in customers' demand has a more significant impact on the LPE market, which results in higher volatility of its market-clearing prices.

#### 4.3. Retail prices and profits

Fig. 4 presents the equilibrium retail prices among all strategic retailers given by different switching coefficients at 5 am, 12 pm, and 5 pm, respectively. It shows that when the magnitude of the switching coefficient becomes larger, the retail prices among all retailers decrease dramatically. This is because retailers would like to reduce their retail prices to prevent customer losses as customers are more capable of switching their electricity retailers.

Moreover, the percentage changes in average retail prices of different retailer groups at 5 am, 12 pm, and 5 pm are shown against different switching coefficients in Fig. 5. From the figure, we can find that with the increase of the magnitude of the switching coefficient, average retail prices of all retailer groups decrease consistently for different time periods. It should also be noted that when the magnitude is less than 4 MWh/\$, there is not much difference in price changes among three retailer groups at different time periods. However, following the continuing increase of the magnitude, the price changes differ in different retailer groups and different time periods. For instance, the price changes in all three retailer groups at 5 am are much higher than other time periods. In addition, the price change of small retailer group (e.g. group 1) is larger than large retailer group (e.g. group 3). The above two phenomena enforces our findings that the switching coefficients have a larger impact on prices of small retailers and low-demand time periods.

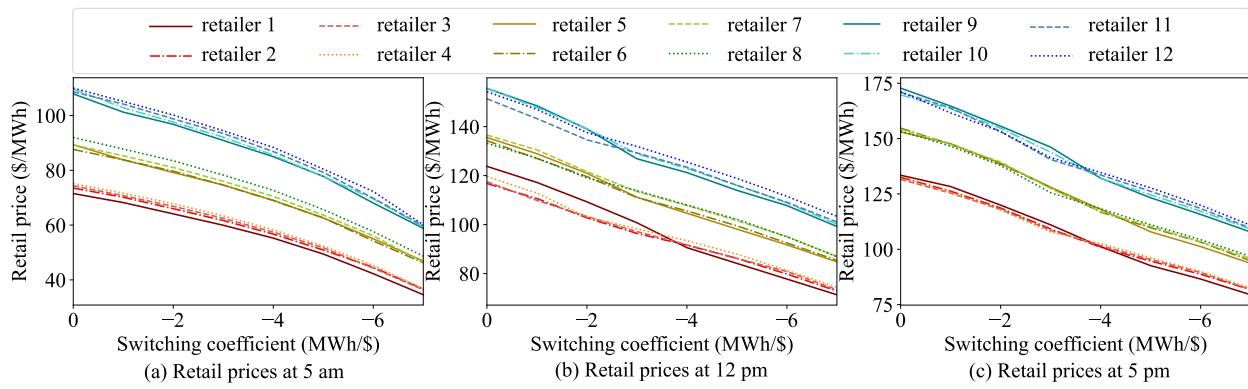


Fig. 4. Retail prices of retailers with different switching coefficients at different times of the day.

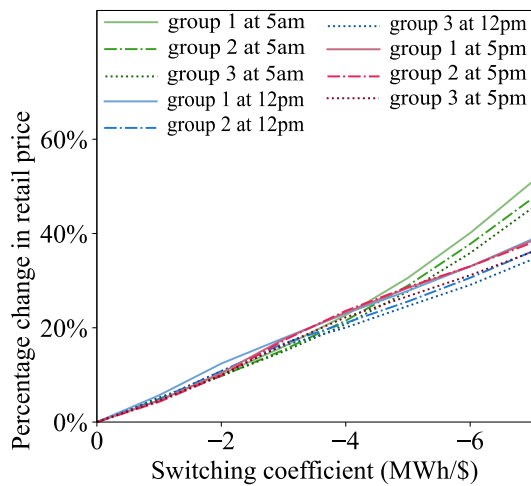


Fig. 5. Percentage change in retail prices with different switching coefficients.

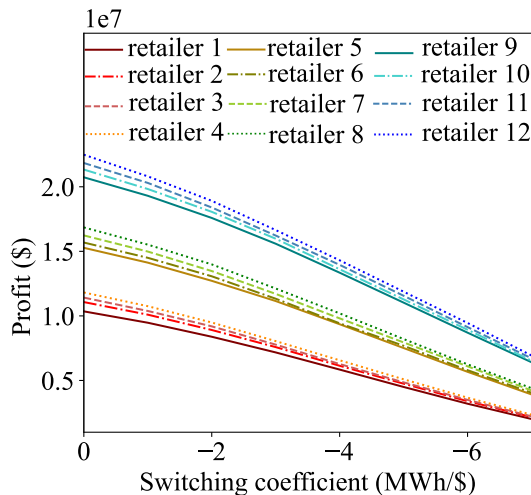


Fig. 6. Profit of retailers with different switching coefficients.

The impact of the switching coefficient on the profits of retailers is illustrated in Fig. 6. Not surprisingly, the retailers' profits reduce significantly when increasing the magnitude of the switching coefficient. In addition, although the profits of bigger retailers are usually higher, the profit difference among retailers tends to decrease when the magnitude of the switching coefficient becomes larger (higher competition in the

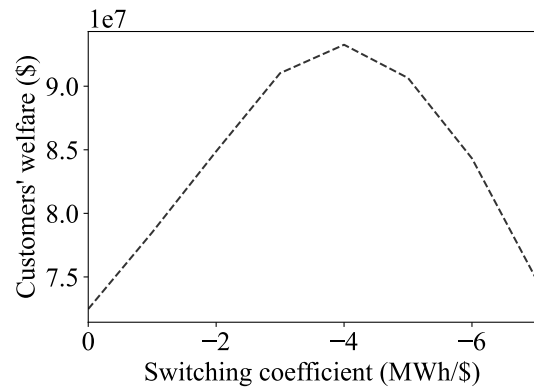


Fig. 7. Customers' welfare with different switching coefficients.

market). In other words, a market with higher competition provides a healthier environment for small players/entrants.

#### 4.4. Customers' welfare

The relationship between the switching coefficient and customers' welfare is displayed in Fig. 7, which reflects the balance between the customers' utility (the amount of electricity consumed) and the electricity purchase cost. In particular, there is a positive correlation between the magnitude of the switching coefficient and customers' welfare until it reaches the peak with the switching coefficient around  $-4$  MWh/\$. Thereafter, the customers' welfare decreases drastically. Namely, compared to the situation of no switching behaviors being considered, increasing the magnitude of the switching coefficient at a certain level can increase customers' welfare since it can cause the reduction of the retail price whilst keeping the retailers' load supply at an acceptable level. However, when the magnitude of the switching coefficient becomes sufficiently large, it discourages the retailers from offering electricity supply since the smaller profit margin in return. In this regard, the customers are provided less electricity by the retailers, which results in the reduction of the customers' utility. Therefore, it leads to the customers' welfare losses.

#### 4.5. ESS result

This section discusses the ESS operation in the EPEC problem. Figs. 8–10 show the ESS energy level, charging, and discharging power of each retailer in different retailers' market share groups, respectively. Particularly, Fig. 8(a) indicates the ESS result when there are no customers' switching behaviors. Fig. 8(b) and (c) show the ESS results when the switching coefficients are  $-4$  MWh/\$ and  $-7$  MWh/\$. Notice

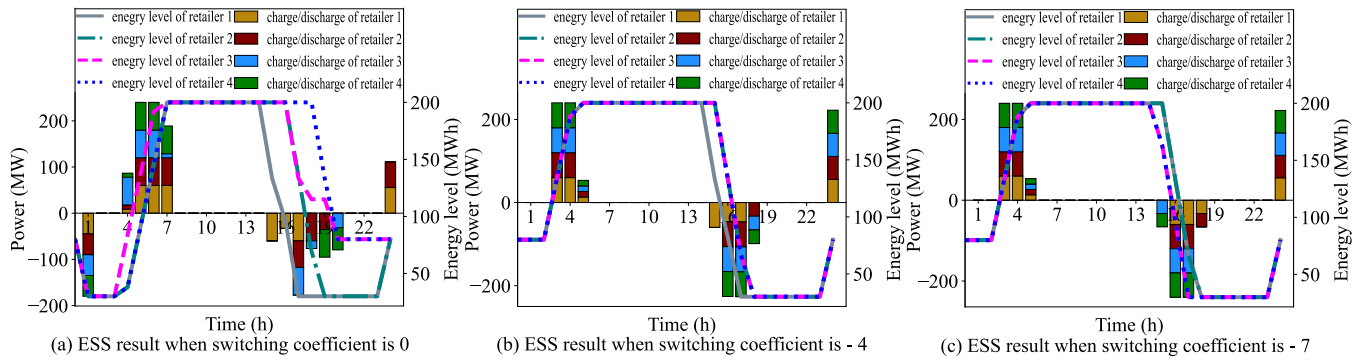


Fig. 8. ESS energy level, charging and discharging power of retailers in group 1.

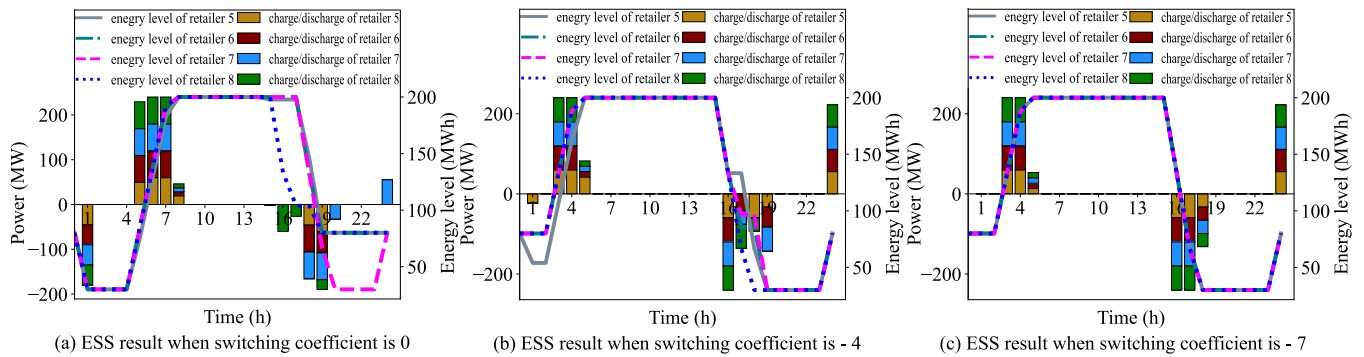


Fig. 9. ESS energy level, charging and discharging power of retailers in group 2.

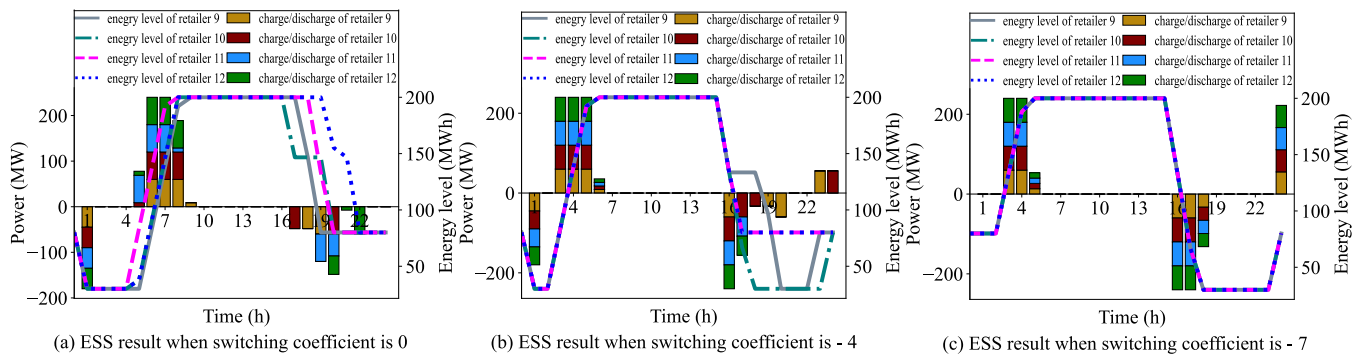


Fig. 10. ESS energy level, charging and discharging power of retailers in group 3.

that the line plot in each figure denotes the ESS energy level, while the bar plot indicates the charging power (if positive) and discharging power (if negative) of the ESS. We conclude that the retailers typically charge their ESS when the DAW market-clearing price is low and discharge the ESS when the DAW market-clearing price is high regardless of the corresponding market share and the value of the switching coefficient.

Moreover, by comparing the ESS results under different switching coefficients, we can find that each retailer's charging/discharging strategy within each market share group becomes similar when the magnitude of the switching coefficient increases. The reason is that increasing the ability of customers' switching behaviors causes the convergence of the retailers' optimal strategies, including the ESS operating decisions.

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#### 4.6. The number of retailers on the retail competition

This section discusses the effect of the number of strategic retailers on the retail competition where the results are shown in Table 2. We consider three different cases with different number of retailers. All cases have three retailer groups with different market share. To focus on the effect of the number of retailers, we do not consider switching behaviors in these three cases. The parameter setup for cases 2 and 3 can be found in Appendix C.3 and Appendix C.4, respectively. Compared to case 1, decreasing the number of retailers in cases 2 and 3 can significantly reduce the competition among retailers, resulting into much higher daily average retail prices in the larger market share group (e.g., group 3). Furthermore, the reduced retail competition surges the retail prices in each group consistently. For instance, the retailer's daily average retail price in group 3 of case 3 is \$299.86/MWh, which approaches the cap of the retail price (\$300/MWh). In addition, reducing retail competition causes the remarkable dilation of retailers' profit in each group and the total profit in each case. This is the result of the







**Table C.14**  
Maximum LPE market bid/offer electricity volume of retailers in case 2 (MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1002	962	924	929	929	937	959	1000	1062	1128	1183	1241	1286	1316	1325	1332	1325	1296	1260	1226	1196	1145	1068	1005
2	1007	970	945	944	949	959	982	1049	1136	1214	1274	1314	1368	1412	1443	1468	1476	1450	1414	1347	1307	1226	1128	1057
3	1010	973	951	953	971	967	994	1051	1136	1218	1291	1365	1399	1430	1449	1471	1478	1463	1416	1357	1308	1227	1128	1063
4	1013	983	962	963	975	1012	1059	1109	1161	1222	1292	1367	1428	1470	1488	1507	1504	1467	1416	1357	1319	1232	1139	1064
5	1046	1001	978	978	992	1040	1084	1138	1178	1252	1300	1376	1439	1472	1502	1529	1517	1474	1418	1358	1322	1246	1145	1065
6	1074	1028	996	981	1012	1049	1087	1138	1207	1277	1336	1396	1441	1496	1523	1530	1529	1506	1449	1395	1361	1284	1204	1129

**Table C.15**  
Maximum DAW market bid load of retailers in case 2 (MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	20735	19713	18956	18586	18582	18714	19464	20445	21350	22084	22668	23378	24225	25197	26409	27508	28154	27978	26977	26237	25408	23975	22428	20945
2	20764	19930	19306	19030	19027	19221	20328	22015	23826	25478	27038	28578	29760	30612	31288	31627	31690	30970	29928	29154	28280	26167	23929	22117
3	20881	19941	19483	19485	20149	20744	21486	22812	24443	26201	27528	28706	29939	30972	31646	32224	32397	31826	30555	29390	28304	26232	24117	22224
4	21773	20799	20186	20174	20645	21178	22604	23957	25069	26294	28027	29167	30166	31041	31986	32779	33161	32492	31067	29541	28428	26642	24360	22290
5	22442	21586	20957	20597	20750	21864	23409	24698	25765	26959	28247	30049	31744	33082	33690	33693	33333	32643	31872	30364	28811	27002	25310	23251
6	23484	22613	22068	22098	22769	23978	25807	27412	28722	30014	31350	32432	33278	33655	34252	34642	34585	33991	32191	31208	30000	27710	25336	23684

**Table C.16**  
Alpha values of retailers in case 2.

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	242	230	222	216	212	210	215	221	230	240	250	261	269	275	281	284	287	284	281	274	266	260	251	239
2	252	238	231	224	222	222	224	231	239	248	260	270	279	286	290	294	294	292	289	287	278	269	259	251
3	293	284	274	269	264	264	269	276	284	295	304	314	322	329	334	337	340	338	333	330	322	314	305	295
4	307	294	287	279	275	276	279	287	294	307	316	324	335	343	347	349	350	351	346	342	334	326	316	306
5	354	346	335	329	327	323	327	336	343	356	364	373	384	391	397	399	398	400	395	390	383	374	365	355
6	367	355	348	342	337	337	340	349	357	367	376	387	394	402	407	411	412	410	408	401	393	387	377	367

**Table C.17**  
Self-elasticity values of retailers in case 2.

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	128	120	115	111	111	108	114	115	121	126	131	131	136	138	142	140	142	141	140	139	135	134	130	127
2	123	116	111	107	106	107	107	111	116	121	125	129	131	135	138	138	138	137	135	136	132	128	126	124
3	112	107	102	98	95	96	98	102	107	113	116	120	121	126	127	127	128	128	128	126	124	118	114	111
4	108	103	98	92	92	93	94	98	102	108	112	115	118	121	122	124	124	125	124	121	118	114	112	108
5	98	93	88	86	83	84	85	89	92	99	103	105	109	111	112	115	116	114	114	110	109	104	103	99
6	95	89	86	83	77	80	83	85	88	96	98	101	104	108	110	110	112	109	110	108	105	102	99	96

**Table C.18**  
Initial retail prices of retailers in case 3 (\$/MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	37.88	38.19	40.09	37.17	34.99	37.28	34.05	34.14	33.48	33.64	32.13	32.95	32.13	33.79	30.90	31.77	35.11	36.70	32.63	34.65	35.19	36.34	35.52	35.89
2	39.28	38.80	38.02	37.70	35.47	35.19	36.09	34.68	33.75	33.53	33.71	33.91	33.18	34.19	32.95	34.43	34.29	33.95	34.69	34.79	37.20	38.00	37.89	37.22
3	37.95	37.26	38.46	38.22	34.23	33.98	33.79	36.38	33.84	35.32	33.43	33.72	32.75	33.29	31.79	31.99	35.34	33.89	34.74	34.34	34.11	36.94	33.92	38.20

**Table C.19**  
Initial DAW market bid prices of retailers in case 3 (\$/MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	28.80	29.63	28.97	28.79	26.83	27.46	26.89	26.72	25.61	26.13	25.63	25.50	24.99	25.53	25.05	24.98	26.12	26.80	26.26	26.16	27.82	28.61	27.99	27.93
2	29.45	29.30	29.20	29.28	27.28	27.15	27.15	27.16	25.97	25.87	25.97	25.89	25.37	25.27	25.41	25.28	26.61	26.48	26.61	26.49	28.41	28.24	28.27	28.25
3	29.45	28.74	28.50	29.23	27.34	26.67	26.44	27.10	26.11	25.43	25.21	25.84	25.53	24.86	24.64	25.24	26.75	26.06	25.81	26.47	28.44	27.81	27.54	28.20



**Table C.20**  
Initial LPE market bid/offer prices of retailers in case 3 (\$/MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	30.63	31.52	30.67	30.24	28.06	28.77	28.07	27.74	26.38	27.03	26.42	26.13	25.95	26.61	26.02	25.79	27.23	27.96	27.30	27.06	28.75	29.47	28.71	28.33
2	31.24	30.97	31.01	31.00	28.55	28.35	28.38	28.39	26.84	26.69	26.67	26.75	26.43	26.33	26.26	26.37	27.74	27.64	27.60	27.68	29.17	29.03	29.14	29.08
3	31.19	30.26	30.06	31.00	28.53	27.71	27.57	28.40	26.81	26.09	25.95	26.76	26.39	25.72	25.58	26.38	27.73	27.01	26.84	27.70	29.26	28.42	28.23	29.09

**Table C.21**  
Maximum LPE market bid/offer electricity volume of retailers in case 3 (MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	6260	6012	5777	5806	5806	5855	5995	6248	6639	7052	7392	7758	8038	8222	8282	8324	8282	8097	7876	7661	7472	7156	6674	6284
2	6296	6064	5905	5902	5928	5994	6140	6558	7098	7590	7960	8214	8547	8827	9018	9173	9228	9060	8837	8418	8170	7662	7050	6606
3	6314	6080	5946	5959	6072	6042	6215	6568	7102	7614	8070	8534	8744	8937	9056	9193	9239	9141	8848	8480	8174	7668	7052	6642

**Table C.22**  
Maximum DAW market bid load of retailers in case 3 (MWh).

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	129595	123205	118475	116160	116135	116960	121650	127780	133440	138025	141675	146115	151405	157480	165055	171925	175965	174865	168605	163980	158800	149845	140175	130905
2	129775	124565	120665	118940	118920	120130	127050	137595	148910	159240	168990	178615	186000	191325	195550	197670	198065	193565	187050	182210	176750	163545	149555	138230
3	130505	124630	121770	121780	125930	129650	134285	142575	152770	163755	172050	179415	187120	193575	197790	201400	202480	198915	190970	183690	176900	163950	150730	138900

**Table C.23**  
Alpha values of retailers in case 3.

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	411	399	391	385	381	379	384	390	399	409	419	430	438	444	450	453	456	453	450	443	435	429	420	408
2	503	489	481	474	472	472	474	481	489	498	510	520	530	537	540	544	544	543	539	537	528	519	509	501
3	599	590	580	575	570	569	574	581	590	601	610	619	628	635	640	642	645	644	639	636	627	620	611	600

**Table C.24**  
Self-elasticity values of retailers in case 3.

Retailer	Time																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	123	116	111	107	107	104	110	111	117	122	127	127	131	134	137	136	138	137	136	135	131	130	126	122
2	109	102	98	93	92	93	93	97	102	107	111	115	117	121	124	124	124	123	122	122	118	114	112	110
3	95	90	85	81	78	79	81	85	90	96	99	103	104	109	110	110	111	111	111	109	107	101	97	94

worth investigating. Moreover, the proposed bilevel strategic model could consider multi-energy scenarios involving electricity, natural gas, and heat energy. Lastly, data-driven approaches can be employed to improve the modeling process. For instance, customers' switching behaviors can be learned from historical data through machine learning methods.

**CRedit authorship contribution statement**

**Qiuyi Hong:** Conceptualization, Methodology, Validation, Writing – original draft. **Fanlin Meng:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Jian Liu:** Methodology, Writing – review & editing. **Rui Bo:** Methodology, Writing – review & editing.

**Declaration of competing interest**

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

**Data availability**

Data will be made available on request.

**Appendix A. Derivation of the market share function**

The combination of (2a) and (2b) can derive an unconstrained minimization problem as follows:

$$\text{Minimize}_{\Xi_{lower1}} \sum_{i \in \mathcal{I}} \left\{ \frac{1}{2} \left( \sum_{n \in \mathcal{N}} \beta_n^t q_n^{retail,t^2} + \sum_{n \in \mathcal{N}, i \in \mathcal{N} \setminus \{k\}} \beta_{n,i}^t q_n^{retail,t} q_i^{retail,t} \right) + \sum_{n \in \mathcal{N}} q_n^{retail,t} \pi_n^{retail,t} - \sum_{n \in \mathcal{N}} \alpha_n^t q_n^{retail,t} \right\} \quad (9a)$$

The first order conditions of the objective function (9a) can be derived as:

$$\beta_n^t q_n^{retail,t} + \sum_{n \in \mathcal{N}, i \in \mathcal{N} \setminus \{n\}} + \beta_{n,i}^t q_i^{retail,t} + \pi_n^{retail,t} - \alpha_n^t = 0, \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \quad (9b)$$

It can be reformulated to a compact form:

$$\pi^{retail,t} = \alpha^t - \mathbf{B}^t \mathbf{q}^{retail,t}, \forall t \in \mathcal{T} \tag{9c}$$

where  $\alpha^t \in \mathcal{R}^N$  is a vector that each element represents a parameter of each retailer.  $\mathbf{B}^t \in \mathcal{R}^{N \times N}$  is a symmetric strictly diagonally dominant matrix that each element in a row/column represents the parameter of each retailer.

Let  $\Omega^t$  be the inverse matrix of  $\mathbf{B}^t$ , and (9c) can be reformulated as below:

$$\mathbf{q}^{retail,t} = \Omega^t \alpha^t - \Omega^t \pi^t, \forall t \in \mathcal{T} \tag{9d}$$

where  $\Omega^t = \begin{pmatrix} \omega_{1,1}^t & \dots & \omega_{1,N}^t \\ \dots & \dots & \dots \\ \omega_{N,1}^t & \dots & \omega_{N,N}^t \end{pmatrix}, \forall t \in \mathcal{T}$  are all symmetric matrices.

Therefore, the market share function of each retailer can be derived as:

$$q_n^{retail,t} = \sum_{j \in \mathcal{N}} \omega_{n,j}^t \alpha_j^t - \omega_{n,n}^t \pi_n^{retail,t} - \sum_{j \in \mathcal{N} \setminus \{n\}} \omega_{n,j}^t \pi_j^{retail,t}, \quad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{9e}$$

which is equivalent to (2c).

### Appendix B. Linearization of the objective function of MPEC

#### B.1. Reformulation of bilinear terms

The Lagrange function of the minimization problem (3a)–(3e) is formulated as follows.

$$\begin{aligned} \mathcal{L}(\Xi_{lower2} | \Xi_{lower2}^{dual}) &= \sum_{t \in \mathcal{T}} \left\{ \sum_{m \in \mathcal{M}} q_m^t c_m - \left( q_k^{bid,t} \pi_k^{bid,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{bid,t} \pi_i^{bid,t} \right) \right\} \\ &+ \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \left( \underline{\mu}_m^t (q_m^{min} - q_m^t) + \overline{\mu}_m^t (q_m^t - q_m^{max}) \right) \\ &+ \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} \left( \underline{\zeta}_i^t (q_i^{bid,min,t} - q_i^{bid,t}) + \overline{\zeta}_i^t (q_i^{bid,t} - q_i^{bid,max,t}) \right) \\ &+ \sum_{t \in \mathcal{T}} \left( \lambda^t \left( \sum_{i \in \mathcal{N}} q_i^{bid,t} - \sum_{m \in \mathcal{M}} q_m^t \right) \right) \end{aligned} \tag{10a}$$

Then, the dual program can be derived below:

$$\begin{aligned} \text{Maximize } \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \left( \underline{\mu}_m^t q_m^{min} - \overline{\mu}_m^t q_m^{max} \right) \\ + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} \left( \underline{\zeta}_i^t q_i^{bid,min,t} - \overline{\zeta}_i^t q_i^{bid,max,t} \right) \end{aligned} \tag{10b}$$

Subject to:

$$c_m - \underline{\mu}_m^t + \overline{\mu}_m^t - \lambda^t = 0, \forall m \in \mathcal{M}, \forall t \in \mathcal{T} \tag{10c}$$

$$- \pi_i^{bid,t} - \underline{\zeta}_i^t + \overline{\zeta}_i^t + \lambda^t = 0, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{10d}$$

Since the primal program (3a)–(3e) is a linear program, the strong duality theorem holds. This indicates that the value of the primal objective function (3a) is the same as the value of the dual objective function (10b). Therefore, we can then obtain a system of equations:

$$\text{Objective function (3a)} = \text{Objective function (10b)} \tag{10e}$$

$$\text{Constraints (6d), (6e)} \tag{10f}$$

$$\underline{\zeta}_i^t (q_i^{bid,min,t} - q_i^{bid,t}) = 0, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{10g}$$

$$\overline{\zeta}_i^t (q_i^{bid,t} - q_i^{bid,max,t}) = 0, \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{10h}$$

After solving the system of Eqs. (10e)–(10h), we can derive the equality below.

$$\begin{aligned} \sum_{t \in \mathcal{T}} \lambda^t q_k^{bid,t} &= \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \left\{ q_m^t c_m - \underline{\mu}_m^t q_m^{min} + \overline{\mu}_m^t q_m^{max} \right\} \\ &- \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{N} \setminus \{k\}} \left\{ \pi_j^{bid,t} q_j^{bid,t} + \underline{\zeta}_j^t q_j^{bid,min,t} - \overline{\zeta}_j^t q_j^{bid,max,t} \right\} \end{aligned} \tag{10i}$$

Analogously, the Lagrange function of the problem (4a)–(4d) is formulated as follows.

$$\begin{aligned} \mathcal{L}(\Xi_{lower3} | \Xi_{lower3}^{dual}) &= \sum_{t \in \mathcal{T}} \left\{ \pi_k^{LPEM,t} q_k^{LPEM,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} \pi_i^{LPEM,t} q_i^{LPEM,t} \right\} \\ &+ \sum_{t \in \mathcal{T}} \left\{ \psi_{k,out}^t (q_k^{LPEM,t} + q_k^{LPEM,max,t}) + \psi_{k,in}^t (q_k^{LPEM,max,t} - q_k^{LPEM,t}) \right\} \\ &+ \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N} \setminus \{k\}} \left\{ \sigma_{i,out}^t (q_i^{LPEM,t} + q_i^{LPEM,max,t}) + \sigma_{i,in}^t (q_i^{LPEM,max,t} - q_i^{LPEM,t}) \right\} \\ &- \sum_{t \in \mathcal{T}} \left\{ \lambda^{LPEM,t} \left( \sum_{i \in \mathcal{N} \setminus \{k\}} q_i^{LPEM,t} + q_k^{LPEM,t} \right) \right\} \end{aligned} \tag{10j}$$

The dual program of (4a)–(4d) is derived below.

$$\begin{aligned} \text{Minimize } \sum_{t \in \mathcal{T}} \left\{ q_{k,out}^{LPEM,max,t} \psi_{k,out}^t + q_{k,in}^{LPEM,max,t} \psi_{k,in}^t \right\} \\ + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N} \setminus \{k\}} \left\{ \sigma_{i,out}^t q_{i,out}^{LPEM,max,t} + \sigma_{i,in}^t q_{i,in}^{LPEM,max,t} \right\} \end{aligned} \tag{10k}$$

Subject to:

$$\pi_k^{LPEM,t} + \psi_{k,out}^t - \psi_{k,in}^t - \lambda^{LPEM,t} = 0, \forall t \in \mathcal{T} \tag{10l}$$

$$\pi_i^{LPEM,t} + \sigma_{i,out}^t - \sigma_{i,in}^t - \lambda^{LPEM,t}, \forall i \in \mathcal{N} \setminus \{k\}, \forall t \in \mathcal{T} \tag{10m}$$

The primal program (4a)–(4d) is also a linear program. Therefore, the strong duality theorem holds. A system of equations can be derived as follows.

$$\text{Objective function (4a)} = \text{Objective function (10k)} \tag{10n}$$

Constraint (10l)

$$\psi_{k,out}^t (q_k^{LPEM,t} + q_k^{LPEM,max,t}) = 0, \forall t \in \mathcal{T} \tag{10o}$$

$$\psi_{k,in}^t (q_k^{LPEM,max,t} - q_k^{LPEM,t}) = 0, \forall t \in \mathcal{T} \tag{10p}$$

A solution of the system of Eqs. (10n)–(10p), and (10l) is shown below.

$$\begin{aligned} \sum_{t \in \mathcal{T}} \lambda^{LPEM,t} q_k^{LPEM,t} &= \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N} \setminus \{k\}} \left\{ \sigma_{i,out}^t q_{i,out}^{LPEM,max,t} \right. \\ &\left. + \sigma_{i,in}^t q_{i,in}^{LPEM,max,t} - \pi_i^{LPEM,t} q_i^{LPEM,t} \right\} \end{aligned} \tag{10q}$$

#### B.2. Reformulation of objective function of MPEC

There are three bilinear terms in the objective function of the MPEC program, which are  $\lambda^t q_k^{bid,t}$ ,  $\lambda^{LPEM,t} q_k^{LPEM,t}$  and  $\pi_k^{retail,t} q_k^{retail,t}$ . The first two bilinear terms are linearized in (10i) and (10q), respectively. The last bilinear term can be linearized by substituting  $\sum_{j \in \mathcal{N}} \omega_{k,j}^t \alpha_j^t - \omega_{k,k}^t \pi_k^{retail,t} - \sum_{j \in \mathcal{N} \setminus \{k\}} \omega_{k,j}^t \pi_j^{retail,t}$  for  $q_k^{retail,t}$  based on (2c).

After linearizing the bilinear terms, the final objective function of MPEC program is derived as follows.

$$\begin{aligned} \Phi = & \sum_{t \in \mathcal{T}} \left\{ \sum_{m \in \mathcal{M}} \left( q_m^t c_m - \underline{\mu}_m^t q_m^{\min} + \overline{\mu}_m^t q_m^{\max} \right) \right. \\ & - \sum_{j \in \mathcal{N} \setminus \{k\}} \left( \pi_j^{bid,t} q_j^{bid,t} + \zeta_j^t q_j^{bid,min} \right. \\ & \left. - \overline{\zeta}_j^t q_j^{bid,max} \right) + c_k \left( p_k^{c,t} + p_k^{d,t} \right) \Delta t - \pi_k^{retail,t} \sum_{j \in \mathcal{N}} \omega_{k,j}^t \alpha_j^t + \omega_k^t \pi_k^{retail,t^2} \\ & + \pi_k^{retail,t} \sum_{j \in \mathcal{N} \setminus \{k\}} \omega_{k,j}^t \pi_j^{retail,t} + \sum_{i \in \mathcal{N} \setminus \{k\}} \left( \sigma_{i,out}^t q_{i,out}^{LPEM,max,t} \right. \\ & \left. + \sigma_{i,in}^t q_{i,in}^{LPEM,max,t} \right. \\ & \left. - \pi_i^{LPEM,t} q_i^{LPEM,t} \right) \left. \right\} \end{aligned} \quad (10r)$$

## Appendix C. Input data

### C.1. Data in case 1

See Tables C.3–C.9.

### C.2. Information of generators in DAW market

See Table C.10.

### C.3. Data in case 2

See Tables C.11–C.17.

### C.4. Data in case 3

See Tables C.18–C.24.

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