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Bilaterally Open Electricity Markets with High Penetration of Renewables

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Abstract—**This paper investigates a multi-generator-multi-consumer scenario in a day-ahead electricity market with high penetration of renewable energy and price-sensitive consumers. The electricity generated by renewables will also be traded in the market. To take care of both the supply and demand sides as well as achieve a balance in between, we propose a two-folded clearing mechanism. Specifically, at the demand side, we adopt an evolutionary game to model the selection behavior of the population of consumers, while at the supply side, a distributed optimization approach is employed to maximize the profit of generators. Finally, simulation results show that the proposed mechanism converges fast to clear the market. In addition, sensitivity analyses are carried out to assess the impact from the risk tolerance of consumers.**

Index Terms—**Day-ahead market, renewable generation, evolutionary game, pricing mechanism, distributed algorithm.**

I. Introduction

The deregulation of electric power industries has been widely witnessed in recent years to improve the efficiency of power generation and utilization [1]. A bilaterally open electricity market provides a platform in which power generations and consumers can have free access to wholesale electricity trading, thus attracts a lot of recent research interests. However, it is also notable that high penetration of renewable generations not only provides cheaper and cleaner electricity commodity, but also brings significant uncertainties and risks into market operation. Therefore, the market mechanism should be carefully designed, namely, both the advantages and disadvantages of renewable generations should be taken into account.

The day-ahead market is based on hourly market clearing prices, which are calculated for each hour of the next operating day [2]. A large existing literature uses stochastic programming to facilitate the market participation of renewable generators. [3] presents a stochastic optimization to minimize the grid-wide social costs, with a risk cost of wind generations taken into account. In [4], [5], the optimal bidding strategy of renewable generators is derived from a bilevel optimization model, which can be converted into a single-level MILP. In most cases, renewables are treated as negative loads and price takers in a market, where both renewable generators and conventional generators participant. [6] proposes a pricing scheme for a pool with wind generators under a finite set of scenarios. The market prices are determined by the marginal cost of the marginal traditional generator. A very small literature investigates the price-setting mechanism of renewable productions. [7] analyzes a price mechanism for renewable-only market in which producers submit bids consisting of a single price. In [8], the wind power can enter a green energy market to serve delay-tolerant demand. Due to the different power quality, the market prices of renewables are also different, compared with conventional markets. As renewables are distinguishable in terms of reliability and marginal cost, it shall be interesting to formulate a viable model for markets with high penetration of renewables to determine the market prices of different power sources.

On the other hand, as the consumers are equipped with responsive appliances, the demand side can provide flexibility to deal with fluctuating renewable energy [9]. Most previous studies, e.g., [10]–[12] focus on the interactions among utility companies and residential consumers in a retail market where consumers must buy electricity via utility companies without taking the power generators into consideration. Moreover, the majority of existing studies focus on aggregated objectives of interest, e.g., maximizing social welfare, minimizing cost of supply or maximizing consumer surplus [13], [14]. To the best of our knowledge, few studies have investigated the optimization of the self interest of market participants in the bilaterally open market.

Since the strategic behavior of both the variable renewable generators and consumers contributes to the market variation, it is of great significance to introduce a risk measure of cost incurred by renewables and motivate profit-oriented market participants to maintain the supply-demand balance. Therefore, distinguished from previous studies that concentrate on unilaterally trade to reach a social optimal, this paper formulates a bilaterally open day-ahead market model and proposes a distributed market clearing mechanism that uses pricing as a lever to balance individual interests of market participants.

Our contributions are summarized as follows:

- We model the strategic behavior of a large number of price-sensitive consumers and multiple traditional

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generators as well as unreliable renewable generators in a bilaterally open day-ahead electricity market.

- A twofold market clearing mechanism is proposed that includes a generator-level pricing procedure to match supply with demand, and a demand evolutionary game to capture the behavior of consumers. The market clearing mechanism can be realized in a distributed fashion with convergence guarantee.
- Simulation results validate the fast convergence and high efficiency of the proposed algorithms.

This paper is organized as below. Sec. II describes the system model of a multi-generator-multi-consumer electricity market. Sec. III establishes the demand-side evolutionary game while the generator-level pricing procedure is characterized in Sec. IV. Then, Sec. V validates the analysis through numerical results.

II. System Model

We consider that a day-ahead market operated by an independent system operator (ISO) where both traditional and renewable generators as well as consumers participate. Renewables are quite unreliable, but enjoy much cheaper marginal generation cost compared with traditional generation, which makes renewable generators inherently distinct in market behavior. To characterize the differences of the power delivered to consumers in terms of reliability, we group renewables together to form a renewable market, as opposed to the pervasive traditional market. Note that the consumer mentioned in this paper could either be a large industrial/commercial load or an aggregator of residential loads, and it could freely choose to procure electricity from either market. Suppose all the consumers are equipped with two-way communication infrastructure. Each consumer will send his demand of traditional energy and renewable energy to the ISO, which gathers all demand information from both markets, then receives price information. Furthermore, the power demand for each consumer is assumed to be precisely predictable by exploring the consumption history. The ISO, as a non-profit organization, is responsible for maintaining market operation, updating electricity prices and clearing both the traditional and renewable markets.

Let $\mathcal{K} = \{1, 2, ...K\}$ denote the set of traditional generators, $\mathcal{J} = \{1, 2, ...J\}$ denote the set of renewable generators and $\mathcal{I} = \{1, 2, ...I\}$ denote the set of consumers. In the day-ahead market, each generator will submit a quantity-only bid to its corresponding market. For a traditional generator $k \in \mathcal{K}$, its cost function $C_k^G(q_k^G)$ is defined as the cost to supply q_k^G amount of power in the traditional market G. In general, the generation cost can be described as a quadratic function [15], which is increasing and strictly convex. Here, we adopt the typical form:

$$C_k^G(q_k^G) = \frac{1}{2}\phi_k^G {q_k^G}^2 + \gamma_k^G q_k^G + \eta_k^G \tag{1}$$

where coefficients $\phi_k^G > 0, \gamma_k^G, \eta_k^G \geq 0$ are constants. Then the utility function U_k^G of traditional generator k under the traditional market price p^G is

$$U_k^G(p^G, q_k^G) = p^G q_k^G - (\frac{1}{2}\phi_k^G {q_k^G}^2 + \gamma_k^G q_k^G + \eta_k^G), \underline{q_k^G} \leq q_k^G \leq \overline{q_k^G} \tag{2}$$

where $\underline{q_k^G}$ and $\overline{q_k^G}$ denote the lower bound and upper bound of traditional generation output, respectively.

Typically wind and solar generators have much lower marginal cost compared with traditional generators [7], [16]. Although the characteristics of renewable energy resources are quiet different from each type, it's beyond the scope of this paper. We assume the cost $C_j^R(q_j^R)$ for renewable generator $j \in \mathcal{J}$ to supply q_j^R amount of power in the renewable market R as

$$C_j^R(q_j^R) = \frac{1}{2}\phi_j^R {q_j^R}^2 + \eta_j^R \tag{3}$$

where $0 < \phi_j^R < \phi_k^G, \forall k \in \mathcal{K}, \forall j \in \mathcal{J}$, since the coefficient ϕ_j^R is nearly zero. Then, the utility function of renewable generator j can be expressed as

$$U_j^R(p^R, q_j^R) = p^R q_j^R - (\frac{1}{2}\phi_j^R {q_j^R}^2 + \eta_j^R), \underline{q_j^R} \leq q_j^R \leq \overline{q_j^R} \tag{4}$$

where $\underline{q_j^R}$ and $\overline{q_j^R}$ denote the lower bound and upper bound for renewable generation output, respectively.

If a consumer $i \in \mathcal{I}$ purchases the demand x_i^M from market $M \in \{G, R\}$, the electricity bill will be

$$b_i(x_i^M) = p^M x_i^M \tag{5}$$

where p^M denotes the corresponding market price.

Consider a case when all of these price-sensitive consumers choose to purchase power from the renewable market for a lower electricity bill. It is anticipated that with the increase of power demand from renewable generators, the probability of fulfilling the demand also decreases, because of the stochastic nature of renewables. If the real renewable generation cannot satisfy the demand, the curtailment would occur. That is, there is a tradeoff for consumers between electricity cost and risk of demand reduction. Often, traditional generators exhibit more expensive but also more reliable electricity supply, opposite to renewable generators.

Let d^M denote power demand of the market M. To distinguish supply risks between renewable generations and traditional generations, a generalized risk cost function is introduced as $f(d^M)$, which is monotone non-decreasing with the power demand d^M. The slope of f in renewable market R would be large for its unreliability, i.e., $\frac{\partial f(d^R)}{\partial d^R} \gg \frac{\partial f(d^G)}{\partial d^G} \simeq 0$. Moreover, the risk cost is shared proportionally among all market participants. Then, the overall cost of consumer i depends on not only its self-decision but also group-effect, which can be described as

$$c_i^M = b_i(x_i^M) + \omega \frac{x_i^M f(d^M)}{d^M}, \quad \forall M \in \{G, R\} \tag{6}$$

where the risk factor ω represents the weight between purchasing cost and risk cost. With the increase of the risk factor, the risk tolerance of the consumer becomes smaller. All the consumers favor the market with lower overall cost.

Since all of the market participants are benefit-oriented, a two-level mechanism should be designed to capture strategic behavior of both the supply and the demand sides as well as clear both markets. At the consumer level, an evolutionary game is applied to help the ISO monitor the demand evolution. On the other hand, at the generator level, the ISO utilizes the resulting demand to iteratively update market prices such that both markets are cleared by allowing generators to freely adjust their own quantities of power output.

III. Evolutionary Game of Demand Side

Evolutionary games have been widely used in multi-buyer-multi-seller scenarios due to its precise characterization of population evolutions [17], which matches our problem settings. Under the hypothesis of bounded rationality, we analyze the evolutionary stable strategy of the consumer population by implementing replicator dynamics.

A. Evolutionary Game Formulation

With the assistance of bi-directional communication structure, consumers can connect with each other in the smart grid. Then, multiple consumers can be regarded as a monomorphic population, because they have the same motivation for reducing energy cost. The evolutionary game at the demand side can be described as follows,

- Population: the set of consumers $\mathcal{I} = \{1, 2, ...I\}$ in electricity market, where I is big enough.
- Players: each consumer $i \in \mathcal{I}$ who behaves rationally and independently.
- Strategy: the strategy set $\mathcal{S} = \{s^G, s^R\}$, where s^G denotes selection of the traditional market, and s^R denotes selection of the renewable market.
- Utility: the negative cost function of consumer i: $-c_i^M$.

After the ISO announces market prices, each consumer decides to buy power from either traditional market or renewable market. In the same communication network, the consumer can also observe and copy the strategies of others. It means a lower cost strategy can be spread through the population quickly. Denote y^M as the proportion of the population that chooses strategy s^M, where $0 \le y^M \le 1$, $\sum_{M\in\{G,R\}} y^M = 1$. Finally, the population state can be represented as $Y = [y^G, y^R]$.

B. Dynamics of Population Behavior

The aggregated demand for market M is

$$d^M = y^M \sum_{i\in\mathcal{I}} x_i^M, \quad \forall M \in \{G, R\} \tag{7}$$

Let $D = \sum_{i\in\mathcal{I}} x_i^M$ denote the total demand, which is a constant in the evolutionary process. Taking (7) into the cost function (6), we can derive the expected cost of the consumers who choose the strategy s^G as

$$\pi^G = p^G y^G D + \omega f(y^G D) \tag{8}$$

Similarly, the expected cost of the consumers who choose the strategy s^R is

$$\pi^R = p^R y^R D + \omega f(y^R D) \tag{9}$$

Then, the replicator dynamics of the population can be designed as

$$\frac{\partial y^M}{\partial t} = y^M(\bar{\pi} - \pi^M), \quad \forall M \in \{G, R\} \tag{10}$$

where $\bar{\pi}$ denotes the average expected cost of this monomorphic population, and is given by

$$\bar{\pi} = y^G \pi^G + y^R \pi^R \tag{11}$$

We can infer from (10) that if the consumers who choose traditional market G spend less than the average expected cost, then the strategy s^G will be replicated among the population, so that the probability y^G will grow.

C. Evolutionary Equilibrium

The evolutionary equilibrium is achieved when there is no difference between the cost of one strategy and the average cost of the population. In this case, no one will change its strategy. Therefore, we can derive the stable condition as

$$\frac{\partial y^M}{\partial t} = 0 \tag{12}$$

It can be rewritten into a clearer form

$$\pi^G = \pi^R = \bar{\pi} \tag{13}$$

Taking the derivative of $\sum_{M\in\{G,R\}} y^M$ with respect to time leads to

$$\begin{aligned} \frac{\partial \sum\limits_{M\in\{G,R\}} y^M}{\partial t} &= \sum_{M\in\{G,R\}} y^M(\bar{\pi} - \pi^M) \\ &= \sum_{M\in\{G,R\}} \pi^M y^M - \bar{\pi} \sum_{M\in\{G,R\}} y^M \\ &= \bar{\pi} - \bar{\pi} \\ &= 0 \end{aligned} \tag{14}$$

Therefore, $\sum_{M\in\{G,R\}} y^M = 1$ always holds in the dynamics. Since the energy purchased by consumers is nonnegative, $0 \le y^M \le 1$ is guaranteed in the evolutionary game.

We define the evolutionary equilibrium by $Y^* = [y^{G*}, y^{R*}]$. Then, the convergence to the evolutionary equilibrium with the replicator dynamics can be proved via the Lyapunov method [18]. Due to space limitation, only a sketch will be given.

***Theorem** 1:* The replicator dynamics will converge to the evolutionary equilibrium Y^*.

Proof: Let m denote one of the strategy. Define the error function $g^m = y^{m*} - y^m$ and the Lyapunov function $V^m(t) = (g^m)^2$. Obviously, $V^m(t)$ is positive definite. The time derivative of $V^m(t)$ can be discribed as

$$\begin{aligned}\frac{\partial V^m(t)}{\partial t} &= -2(y^{m*} - y^m)\frac{\partial y^m}{\partial t} \\ &= -2y^m(y^{m*} - y^m)(\bar{\pi} - \pi^m)\end{aligned} \quad (15)$$

First of all, the nondecreasing of expected cost function π^m with respect to y^m is guaranteed, because the function $f(y^m)$ is nondecreasing. Consider m to be the strategy with the lowest cost, we will have $m = \arg\min\{\pi^1, \pi^2, ...\pi^m, ...\}$. Then, the probability for m will increase, that is $y^{m*} > y^m$. Furthermore, we can derive $\bar{\pi} - \pi^m > 0$ from (10) . Thus, the time derivation of $V^m(t)$ is negative definite, i.e., $\dot{V}^m \leq 0$. According to Lyapunov stability criterion [18], we can conclude that the dynamic of strategy m will converge to the equilibrium, so do the other strategies. Therefore, the dynamics will converge to the evolutionary equilibrium. ■

D. Iterative Algorithm

The replicator dynamics given in (10) can be expressed in terms of iterations

$$y^M(n+1) = y^M(n) + \alpha y^M(n)(\overline{\pi}(n) - \pi^M(n)) \quad (16)$$

where n denotes the iteration number and α denotes the step size. The termination condition is

$$|\bar{\pi}(n) - \pi^M(n)| < \varepsilon, \quad \forall M \in \{G, R\} \quad (17)$$

where ε is small enough. The explicit iterative procedure is summarized in Algorithm 1.

Algorithm 1: Replicator dynamics algorithm

1 **Initialization:** Every consumer in population $\mathcal{I}$ randomly chooses one market to buy electricity from, and y^M, $M \in \{G, R\}$ is initialized;
2 Set index $n = 1$;
3 **repeat**
4 Calculate the cost $\pi^G(n)$ and $\pi^R(n)$ according to (8) and (9), respectively;
5 Compute the average cost $\bar{\pi}(n)$ according to (11);
6 Change its strategy and update the probability $y^M(n)$ according to (16);
7 $n = n + 1$;
8 **until** (17) *is satisfied*;

IV. Demand-tracking Procedure of Supply Side

The market clearing mechanism at the supply side can be depicted by a closed-loop feedback system. As shown in Fig. 1, the ISO is the central controller, which reacts to the market changes and sets prices to induce market decisions of participants. Its inputs include power generation and demand, and its outputs are market prices. At the supply side, every generator submits a quantity-only bid in response to dynamic prices. In this section, we propose an effective algorithm that makes use of strategies of generators for profit maximization and sets the market prices based on responses of participants. By means of the proposed control law, the sum of supply from both the traditional and renewable markets can efficaciously tracks the demand.

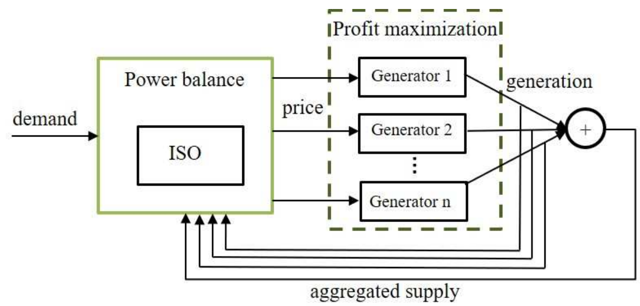


Fig. 1. Block diagram of demand-tracking procedure

A. Dynamic Interactions between ISO and Generators

As shown in (2) and (4), the utility functions of both traditional generator $k \in \mathcal{K}$ and renewable generator $j \in \mathcal{J}$ take the quadratic form. Therefore, the profit maximization problem of a generator is convex and can be efficiently solved with a closed-form output solution

$$\begin{aligned} q_k^G &= \arg\max U_k^G(p^G, q_k^G) \\ &= \begin{cases} \underline{q_k^G} & \underline{q_k^G} > (p^G - \gamma_k^G)/\phi_k^G \\ (p^G - \gamma_k^G)/\phi_k^G & \underline{q_k^G} \leq (p^G - \gamma_k^G)/\phi_k^G \leq \overline{q_k^G} \\ \overline{q_k^G} & (p^G - \gamma_k^G)/\phi_k^G > \overline{q_k^G} \end{cases} \end{aligned} \quad (18)$$

In the same way, we can obtain the optimal power generation for renewable generator j as

$$\begin{aligned} q_j^R &= \arg\max U_j^R(p^R, q_j^R) \\ &= \begin{cases} \underline{q_j^R} & \underline{q_j^R} > p^R/\phi_j^R \\ p^R/\phi_j^R & \underline{q_j^R} \leq p^R/\phi_j^R \leq \overline{q_j^R} \\ \overline{q_j^R} & p^R/\phi_j^R > \overline{q_j^R} \end{cases} \end{aligned} \quad (19)$$

Thus, given the price, all the generators could always find the optimal bidding strategy for maximum profit.

B. Iteration Algorithm

When the ISO updates prices in an iteration, reselection of the consumer population motivates generators to change their bidding generations. The updating strategy for market prices $p^M \in \{p^G, p^R\}$ is designed as

$$p^M(h+1) = p^M(h) + \beta[d^M(h) - \sum_{l \in \mathcal{K} or \mathcal{J}} q_l^M(h)] \quad (20)$$

where $M \in \{G, R\}$, h is the iteration index, β denotes the step size, and δ is a small positive threshold. The termination criterion of the iterative algorithm is

$$|d^M(h) - \sum_{l \in \mathcal{K} or \mathcal{J}} q_l^M(h)| < \delta, \quad \forall M \in \{G, R\} \tag{21}$$

This iterative process can be characterized by Algorithm 2.

Algorithm 2: Demand-tracking algorithm

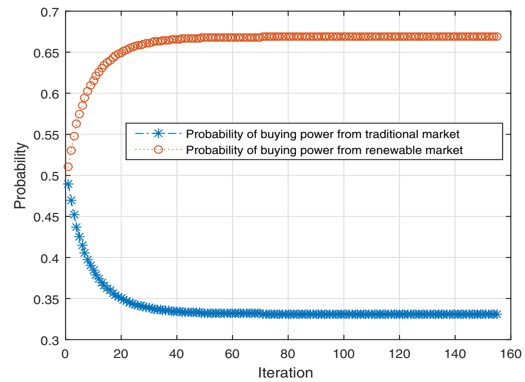
Initialization: the ISO broadcasts initial prices p^M;
Set iteration index $h = 1$;
while *the stopping condition* (21) *is not satisfied* **do**
  for *a generator* $k \in \mathcal{K}$ *and* $j \in \mathcal{J}$ **do**
    Each generator makes its best response $q_k^G(h)$ or $q_j^R(h)$ according to (18), (19) respectively;
  end for
  Calculate the total supply of traditional market and renewable market;
  Operate **Algorithm 1** to get the demand $d^M(h)$, $M \in \{G, R\}$ of the corresponding market;
  ISO updates $p^M(h)$ according to (20);
  $h = h + 1$;
end while

C. Convergence Analysis to Market Equilibrium

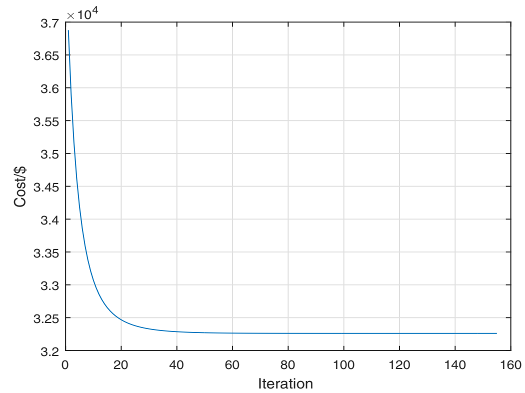
The demand-tracking procedure can be explicitly expressed as follows. The ISO publishes prices, then the consumers select one market for power as modeled by the evolutionary game. In the meanwhile, each generator makes its best response to determine its own optimal operating point. The generator whose response deviates from the optimal operating point will suffer from extra loss. Next, the ISO updates the prices in both the markets after observing supply and demand trajectories. Finally, it will converge to the market equilibrium where neither a generator nor a consumer has the incentive to change its decision unilaterally. It is guaranteed that supply matches demand, i.e., the market clearing status.

V. Numerical Results

We examine the efficiency of the proposed algorithm with a simple case of three traditional generators and four renewable generators. For traditional generators, the quadratic and linear coefficients (ϕ_k^G, γ_k^G) of their cost functions are set to be $(0.0157, 10)$, $(0.021052, 9)$, $(0.03956, 13)$, respectively. We also set the quadratic coefficients ϕ_j^R of renewable generators as 0.00815, 0.0091052, 0.0129, 0.013, respectively. The constant coefficients η_k^G and η_j^R are set to be 0. Although the risk cost function f can take any non-decreasing form, without loss of generality, the risk cost function of renewable market is set to be $f(d^R) = 1 - e^{-5d^R}$, while the risk function can be omitted in traditional market.



(a) Population dynamics



(b) Convergence of the average cost

Fig. 2. Convergence process of the demand side

The performance of Algorithm 1 is shown in Fig. 2. Within a few iterations, the behavior of the consumer population quickly converges to the evolutionary equilibrium in Fig. 2(a). The convergence of average cost is presented in Fig. 2(b). During the dynamic process, the consumers with higher-cost strategies will replicate the lower-cost ones. Therefore, the average cost decreases at each step. Clearly, no consumer can further reduce its cost.

As shown in Fig. 3, the supply matches the demand and the clearing prices become stable after a few iterations. Thus the efficiency of Algorithm 2 is validated.

Meanwhile, we extract hourly load data on September 1, 2017 from the PJM market [19], and the risk factor ω is set to be time-varying. Fig. 4(a) shows the demand allocation in different markets. In peak hours, the traditional energy is preferred, while in valley hours, the renewable energy will contribute more. With the increasing of risk factor, the results of the population behavior are presented in Fig. 4(b). It shows that consumers will turn to much more reliable energy resource with smaller risk tolerance.

VI. Conclusion

In this paper, we formulate an innovative clearing mechanism for bilaterally open electricity markets with high

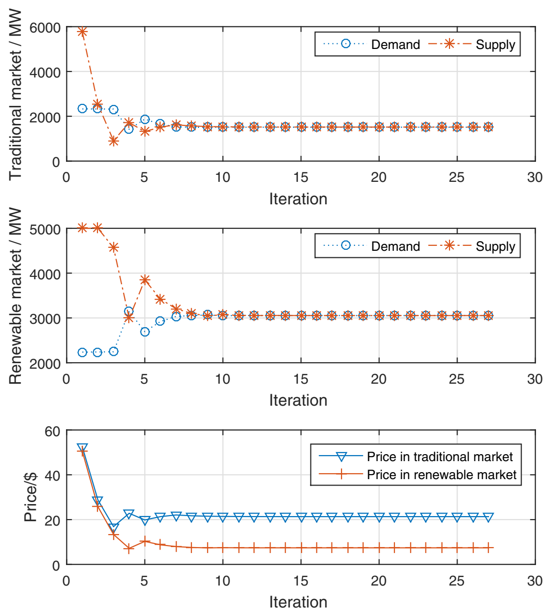
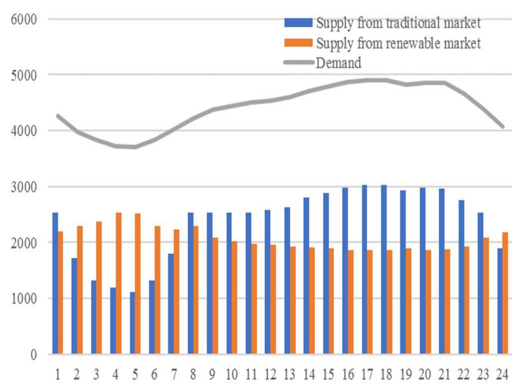
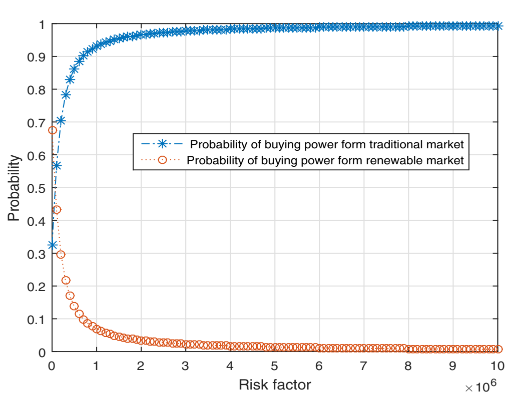


Fig. 3. Convergence process of the supply side



(a) Demand allocation in different markets



(b) Probability of market selection

Fig. 4. Sensitive analysis of the risk factor

penetration of renewables. At the demand side, we propose an evolutionary game, while at the supply side, a distributed optimization based mechanism is verified to converge to the market equilibrium. The market clearing prices are determined by an market equilibrium that is achieved via iterative algorithms. Simulation results also validate our theoretical analysis.

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