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Event-Driven Energy Trading System in Microgrids: Aperiodic Market Model Analysis With a Game Theoretic Approach

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ABSTRACT This paper presents the design of an event-driven energy trading system among microgrids. Each microgrid can be either a provider or a consumer depending on the status of its energy generation and local demands. Under this approach, an aperiodic market model is newly proposed such that trading occurs when one of the consumers requests energy from the trading market. To promote the trading system, a consumer-side reward concept is introduced. The consumer makes a decision on the size of the posted reward to procure energy depending on its required energy level. Providers then react to this posted reward by submitting their energy bid. Accordingly, the posted reward is allocated to the providers in proportion to their energy bids. Moreover, for practical concerns, a transmission and distribution loss factor is considered as a heterogeneous energy trading system. The problem is then formulated as a non-cooperative Stackelberg game model. The existence and uniqueness of Stackelberg equilibrium (SE) are shown and the closed form of the SE is derived. Using the SE, an optimal trading algorithm for microgrids is provided. The stability of the energy trading system is verified due to the unique SE. In this approach, no expected waiting time for trading is required for sustaining an energy trading market.

INDEX TERMS Microgrids, smart grids, power system economics, demand-side management, transactive energy.

I. INTRODUCTION

Due to a growing demand for higher energy efficiency, reduced greenhouse gas emissions, and improved reliability, there is a strong need to transform the traditional power system into a smartgrid that is a more responsive, efficient, and reliable system [1]–[4]. The smartgrid is enabled by advanced communication technologies [5]–[7], continuing developments in distributed generation (DG) [8]–[10] and renewable energy sources with energy storage systems (ESS) [11]–[13]. For efficiently and reliably managing and operating such a critical and complex future power system, the microgrid, which is an important building block of the smartgrid, is also widely believed to be a promising platform to integrate and coordinate a potentially huge number of distributed energy sources such as solar panels, wind turbines and other renewable energy sources in a decentralized manner [14]–[16].

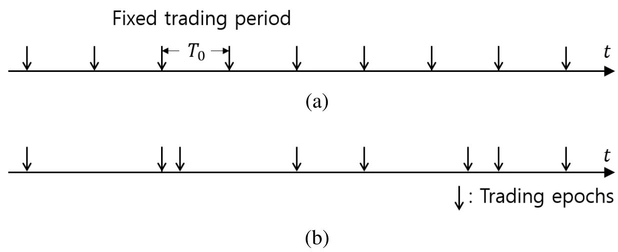

FIGURE 1. Trading epoch difference between a periodic model and a aperiodic model. (a) Trading epoch in most existing energy Trading Systems. (b) Trading epoch in the proposed energy Trading System.

In microgrids, the retailers, who generate energy from distributed energy sources, play a role of serving their local demands in a small geographical area with minimum reliance on the macrogrid. Comparing to a centralized energy supply from the macrogrid, this is more energy efficient by reducing transmission and distribution loss. It can also reduce the threat of blackouts by alleviating overload on the macrogrid [17]–[19]. Nevertheless, due to the highly variable, unpredictable, and intermittent generation of renewable energy sources, it is challenging to control the system for achieving optimal operation of microgrids to balance the energy demand and supply [20]–[22].

Energy trading is a promising solution for use with microgrids to encourage the trade of energy among retailers to better balance the energy demand and supply [23]. In this sense, retailers who have a surplus energy for sale to a local energy markets can be providers. On the other hands, other retailers who wish to buy additional energy to meet local demands due to insufficient energy generation can be consumers. Accordingly, depending on the status of their energy generation, retailers can be either providers or consumers otherwise known as prosumers (i.e., a synthesized word of producer and consumer) [24]–[27]. This phenomenon opens a competitive market for energy trading among retailers in microgrids since individual retailers participating in energy trading have their own interest to maximize regardless of the interests of other retailers. Thus, by considering this competitive situation, energy trading can be modeled and analyzed as a non-cooperative game to obtain a Nash equilibrium (NE) where no players have incentive to deviate from their strategies [28].

Several studies on energy trading in microgrids have adopted game theoretical analyses [29]–[37]. Specifically, various facilities such as Electric Vehicles (EVs) and ESSs have been considered for designing an energy trading market. Moreover, various competitive behaviors of microgrids in energy trading markets have been analyzed. Kim *et al.* [29] presented a power system with an aggregator and multiple retailers with EVs in their model. They proposed algorithms which take appliance loads into account for scheduling and the energy trading using EVs. Lee *et al.* [30] the cooperation among retailers is analyzed based on the coalitional game theory. Also, a fair pricing scheme is derived by using the asymptotic Shapley value. Tushar *et al.* [31] considered an energy trading system among retailers and a macrogrid, formulated the system model as a non-cooperative Stackelberg game to show that the maximum benefit of the consumer retailer is obtained at the unique Stackelberg equilibrium (SE). Mediwaththe *et al.* [32] developed an energy trading system with ESS for a demand-side load management within a neighborhood area network. They formulated their system model as a dynamic non-cooperative repeated game, and proposed Pareto-efficient pure strategies to determine the optimal trading amount for the next day. Zhang *et al.* [33] proposed a contract based direct trading model among retailers and derived the optimal contract for short-term and long-term markets. Latterly, a bidding concept for a fully distributed trading mechanism was researched in the energy market for microgrids. Lee *et al.* [34] proposed a bidding-based energy trading mechanism, in which the distribution of the energy is proportional to the unit price of consumers' bids. The mechanism is formulated as a Stackelberg game, in which a closed-form expression of the unique NE is provided for the corresponding strategies of the consumers and the providers. Wang *et al.* [35], [36] also proposed a bidding-based energy trading mechanism, and formulated the model as a Stackelberg game as in [34], but with incomplete information. They used a reinforcement learning algorithm to seek the NE of the constrained Stackelberg game with incomplete information. Most recently, there was the first study on non-pricing based energy trading model for microgrids. Park *et al.* [37] proposed a contribution-based energy-trading model as a preliminary work. In this model, there is a distributor that gathers the surplus energy from providers and distributes it to the consumers based on the consumers' historical contribution level.

Even though many studies related to energy trading in microgrid have been carried out, all of the previous works have adopted a periodical energy trading mechanism in microgrids. This means that a trading between retailers happens at a pre-defined trading epoch. The consumers, who need additional energy to meet local demand in the middle of trading interval, might suffer from energy shortages until the next trading epoch. Otherwise, they directly trade the energy with the macrogrid at a high price even though there might be candidate retailers with surplus energy for sale to local energy markets. This situation is inefficient and increases the reliance on the macrogrid.

In this light, this paper proposes an event-driven energy trading system. The proposed model consists of the following:

- A consumer determines an aperiodic energy trading epoch and triggers energy trading to the distributor when the energy level of the consumer falls below a certain level.
- Rewards are posted by the consumer who opens up the energy trading market
- Providers bid their energy to the consumer for sale depending on the posted rewards in the market.

Therefore, under the proposed event-driven approach, no expected waiting time for trading exists. This is due to the feature that the consumers can open up an energy trading market whenever their energy is insufficient. This has an additional benefit to reduce the reliance on the macrogrid. The contributions of this paper are summarized as follows.

- This paper designs an event-driven energy trading system where trading occurs when one of the consumers requests energy. Thus, it can react immediately when a consumer does not have sufficient energy.
- To promote energy trading, a reward concept on the consumer side has been newly proposed such that the consumer makes a decision on the amount of the reward (e.g., money or credit, etc.) to be posted to acquire energy with consideration of its required energy level. Providers then react to this posted rewards by submitting an energy bids. The posted rewards are allocated to the providers in proportion to their energy bids.

- This aperiodic market model represents a consumer-oriented system, which has not been considered in the existing works. For practical concerns, a transmission and distribution loss factor is considered as in [38]. Accordingly, a heterogeneous energy trading system is designed.
- The proposed energy trading system is formulated as a Stackelberg game model. This paper shows that there is the unique Stackelberg equilibrium (SE) in the proposed game model, and a closed-form of the SE is obtained. Using the suggested SE, an optimal bidding algorithm for retailers is provided. The stability of an energy trading system is also verified on the basis of the unique SE.
- The complexity analysis and rigorous simulation studies are provided to address practical concerns of the proposed algorithm. Specifically, the proposed algorithm has linearithmic complexity which can be applicable to a practical systems with acceptable expendability. Moreover, from the simulation under actual energy consumption and generation profiles, the proposed market model shown to be is validated in the time varying case.

The remainder of this paper is organized as follows. First, the proposed model is explained in detail in Section II. The problem is formulated as a Stackelberg game model and the unique Stackelberg equilibrium (SE) is discussed in Section III. Some numerical results are discussed in Section IV, and some practical concerns are discussed in Section V. Finally, the conclusion of this paper is provided in Section VI.

II. SYSTEM MODEL

In this section, an event-driven, aperiodic, and heterogeneous energy trading mechanism among retailers in microgrids is proposed. Consider microgrids with the set of M retailers, $\mathcal{I}_A$, and a *distributor*. The distributor is a game organizer, who holds a game when one of the retailers requests energy, say E_{req}, based on its expected amount of energy demand and energy generation. Here, this retailer is called *a consumer* and denoted by $\omega_0 \in \mathcal{I}_A$. In this paper, E_{req} is limited to be larger than or equal to $E_{\min}$ and smaller than or equal to $E_{\max}$. $E_{\min}$ is considered to prevent markets from opening too often in order to relieve the overhead, and $E_{\max}$ is required in order to equally distribute energy transmission opportunities. In this paper, $E_{\max}$ is suggested to be less than $2E_{\min}$.

After the consumer requests energy, the distributor announces to all the other retailers that a game will be held. Note that there are $M-1$ retailers except the consumer. Then, the retailers decide whether they are going to be providers or not. To this end, for the kth retailer $\omega_k \in \mathcal{I}_A$, $E_{k,\text{gen}}$ denotes the expectation of generated energy for some time interval T_0 and $E_{k,\text{dem}}$ denotes that of energy demand for the time interval T_0. Let E_k be the difference between them, that is, $E_k = E_{k,\text{gen}} - E_{k,\text{dem}}$. Here, a transmission and distribution loss factor η'_k of the kth retailer ω_k is defined as the energy loss rate by transferring energy from ω_k to ω_0. Now, an *energy transmission rate* (ETR) η_k of the kth retailer is defined as an additive inverse of the transmission and distribution of the kth retailer; that is, $\eta_k = 1 - \eta'_k$. In order to make the trading market efficient, the ETR is recommended to be bigger than some threshold η_0, and η_0 is given as 0.7. The threshold, 0.7, was chosen based on the actual ETR values from different countries, of which majority is higher than 0.7 [39]. Rearranging $\mathcal{I}_A$ in the descending order by the value of E_k among the retailers whose ETR is greater than η_0, a set of providers can then be defined as follows:

$$\mathcal{I} = \{\omega_k \in \mathcal{I}_A \mid \eta_k > \eta_0, E_k > E_{\min}\} = \{\omega_1, \omega_2, \cdots, \omega_N\}$$

with its index set $I = \{1, 2, \cdots, N\}$. Here, it is required that $N \geq 3$ to prevent sudden collusion among the providers.

After the retailers' decisions are made based on the previous criterion, those who decide to become providers inform the distributor that they will participate in the game as providers. The distributor then announces to the consumer the number of providers and ETR values of corresponding providers. The consumer offers a reward r that is sufficient to cover the required energy E_{req} using the information provided by the distributor. By predicting that the providers will perform optimally, the consumer will determine this reward via the *Determining Optimal Reward (DOR)* Algorithm, which will be outlined in the next section. The consumer now informs the determined amount of the reward r determined by the DOR algorithm to the distributor. The distributor then posts the amount of the posted reward r to all the providers. Each provider should next determine the amount of the bidding energy e_k, based on the amount of the total reward r. The algorithm for this is referred to as the *Determining Optimal Bidding (the DOB)* Algorithm, and is also outlined in the next section.

After each provider has executed the DOB Algorithm, the kth provider ω_k bids the energy as much as e_k, determined by the DOB Algorithm. The distributor then gathers the bid energy from all the providers and transmits the total energy to the consumer. Since the energy transmission rate of ω_k is η_k, the actual energy transferred from ω_k to the consumer is as much as $\eta_k e_k$. Thus, the total amount of energy transferred to the consumer is $\sum_{k\in I} \eta_k e_k$.

Now, the consumer provides the predetermined reward r. To this end, it is necessary to declare the reward allocation policy of the distributor. Assume that $\omega_k \in \mathcal{I}$ decides to bid the energy as much as e_k. The distributor distributes the reward r to the providers in proportion to their energy bids. That is, the amount of reward r_k that ω_k will receive by bidding energy e_k is given by

$$r_k = r\frac{\eta_k e_k}{\sum_{i\in I_p} \eta_i e_i}. \tag{1}$$

Note that Figure 2 shows the system model of the proposed energy trading system. A solid line denotes the provision of energy and a dotted line indicates the provision of a reward. Figure 3 illustrates the sequence of the energy trading system described above. Here, a dotted line indicates the

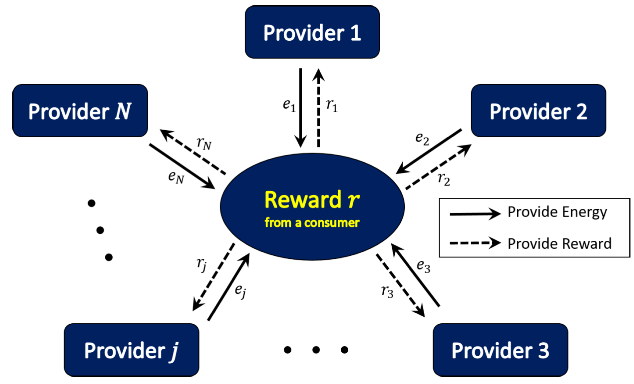

FIGURE 2. System model of the proposed energy trading system.

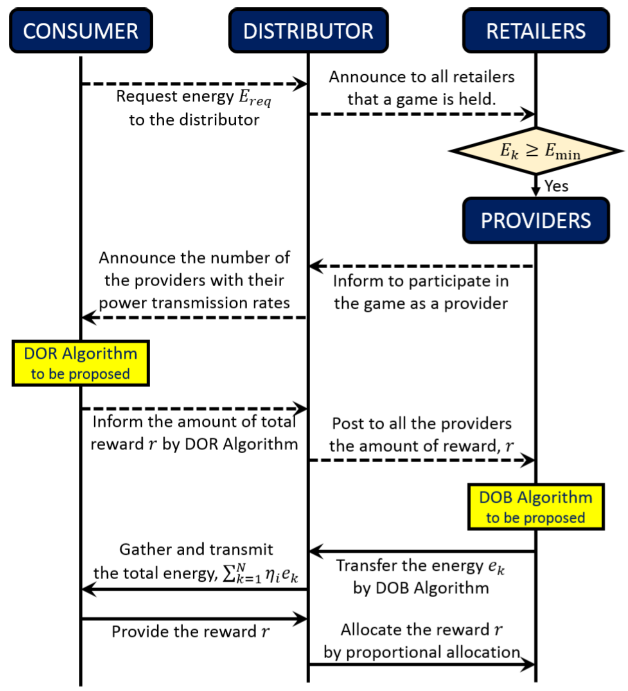

FIGURE 3. Sequence diagram of the proposed energy trading system.

communication necessary for energy trading, and a solid line indicates the transmission of actual energy or reward.

III. STACKELBERG GAME

In this section, the proposed event-driven energy trading mechanism is formulated as a Stackelberg game model, and the unique Stackelberg equilibrium (SE) is derived. Note that a Stackelberg game is a two-level non-cooperative game in which there are two types of players, leaders and followers. In the proposed system, the consumer acts as a leader, and the providers act as followers; thus the game is formulated as a singleleader-multiplefollower Stackelberg game. In what follows competition among providers is formulated as a non-cooperative strategic form game first, and then the unique Nash equilibrium (NE) is derived.

A. REWARD COMPETITION GAME AMONG PROVIDERS

The payoff of the kth provider ω_k, by bidding energy e_k, depends on two factors, the obtained reward r_k and the relieved energy $-e_k$. To define a payoff function for the kth provider ω_k, the following two terms are considered. One is reward r_k and the other term is energy e_k. To consider them together in the payoff function, the exchange rate between energy and reward must be included using a weight factor. Here, the weight factor is called $\mu > 0$, which is determined by considering the average exchange rate of reward and energy in this system, or the price of selling energy to the macrogrid, etc. Thus, the payoff function of ω_k can be obtained by considering these two terms with the weight factor, given by

$$u_k(e_k, \boldsymbol{e}_{-k}; r) = \begin{cases} r\dfrac{\eta_k e_k}{\sum_{i \in I} \eta_i e_i} - \mu e_k, & \text{if } e_k > 0; \\ 0, & \text{if } e_k = 0; \end{cases}$$

where $e_k \in [0, E_k]$, $\forall k \in I$ and $\boldsymbol{e}_{-k} = (e_i)_{i \in I \setminus \{k\}}$. The second condition $u_k(e_k, \boldsymbol{e}_{-k}; r) = 0 if e_k = 0$ is necessary in order that the energy allocation to ω_k be zero when $e_k = 0$, even though all other providers select the strategy $\boldsymbol{e}_{-k} = \mathbf{0}$. Note that this payoff function can take negative value if e_k becomes too large, that i the reward is too small in comparison with the energy bidding.

Now, the reward competition among the providers is formulated as a non-cooperative continuous strategic form game $G_r = \left(\mathbf{E}, u_k\right)_{k \in I}$ and is denoted as the *Reward Competition Game (RCG)* among the providers. Here, I is the index set of the providers, u_k is the payoff function given as above, and $\mathbf{E}$ is the strategy domain for all the providers, given by $\mathbf{E} = \prod_{k=1}^{N} [0, E_k]$. Here, the kth provider determines the optimal amount of energy using the DOB Algorithm to bid maximizing its payoff function u_k.

B. EVENT-DRIVEN STACKELBERG GAME AMONG RETAILERS

Now, in order for the consumer to obtain the amount of energy that is required, E_{req}, the consumer should post the exact optimal amount of reward. For a given reward r, from the DOB Algorithm for the providers, the consumer is able to know the total amount of energy to receive. Thus, the consumer can determine the proper amount of reward to post to obtain the required energy E_{req}; recall that this is done via the DOR Algorithm.

Note that the consumer chooses a strategy before the providers select their strategies. Thus, the competition between the consumer and the group of providers is formulated as a singleleader-multiplefollowers Stackelberg game; the consumer acts as a leader and the providers act as followers. Hereafter, this Stackelberg game among retailers is called the *Event-Driven Stackelberg Game (EDSG) derived from* G_r.

C. NASH EQUILIBRIUM AND STACKELBERG EQUILIBRIUM

In this subsection, the unique Nash Equilibrium (NE) of the RCG among providers and the unique Stackelberg Equilibrium (SE) of the EDSG among retailers are derived. To this end, a NE of the RCG and a SE of the EDSG are defined as follows.

Definition 1: A NE of the RCG G_r among the providers is a profile of strategies $\boldsymbol{e}^* = (e_k)_{k\in I}$ satisfying $u_k(e_k^*, \boldsymbol{e}_{-k}^*; r) \geq u_k(e_k, \boldsymbol{e}_{-k}^*; r)$, $\forall e_k \in [0, E_k]$, $\forall k \in I$.

However, it is difficult to get the unique NE solution of the RCG among the providers, thus a modified RCG $G_r' = \left(\mathbf{E}', u_k\right)_{k\in I}$, called the MRCG among providers, is defined with the modified strategy domain $\mathbf{E}' = \prod_{k=1}^{N}[0, \infty)$. The unique NE solution of the MRCG G_r' is derived, and then the unique SE solution $(r^*, \boldsymbol{e}^{**})$ of the EDSG is derived using G_r'. Showing $\boldsymbol{e}^{**}$ of the EDSG derived from G_r' lies on the domain $\mathbf{E}$ also prove that $(r^*, \boldsymbol{e}^{**})$ is the unique SE solution of the EDSG derived from G_r.

To define a Stackelberg equilibrium (SE) of the EDSG derived from G_r', a NE function is defined as follows.

Definition 2: Define a vector-valued function $\mathbf{F} : \mathbb{R} \to [0, \infty)^N$, called *a Nash equilibrium (NE) function*, given by $\mathbf{F}(r) = \boldsymbol{e}^*$ where $\boldsymbol{e}^*$ is the NE of the MRCG G_r'. Define also a real-valued function $f : \mathbb{R} \to [0, \infty)$, called *a sum of transferred energy function*, given by $f(r) = \sum_{i\in I} \left\{\eta_i \mathbf{F}(r)\right\}_i$. Since the required energy of the consumer is E_{req}, the SE of the EDSG should satisfy that the total transferred energy to the consumer is E_{req}, thus it can be defined as follows.

Definition 3: A Stackelberg equilibrium (SE) of the EDSG derived from G_r' is defined by the strategy set of the consumer and the providers $(r^*, \boldsymbol{e}^{**})$ such that $f(r^*) = E_{\text{req}}$ and $\boldsymbol{e}^{**} = \mathbf{F}(r^*)$.

Then, equation (1), Lemma 1, Lemma 2 and Theorem 1 suggest a closed-form of the unique NE solution of the MRCG.

Lemma 1: Consider an optimization problem, given by

Problem 1:

$$\max_{\mathbf{r}} \sum_{k\in I} v_k(r_k)$$
$$\text{s.t.} \sum_{k\in I} r_k \leq r \quad \& \quad r_k \geq 0, \quad \forall k \in \mathcal{I}$$

where

$$v_k(r_k) = \eta_k\left(r_k - \frac{1}{2r} r_k^2\right).$$

Then Problem 1 has the unique solution, given by

$$r_k^* = \begin{cases} r\left(1 - \dfrac{\nu}{\eta_k}\right), & \text{if this is} > 0; \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where ν is a real number satisfying $\sum_I r_k^* = r$. In particular, let $J \subset I$ be the index set satisfying $J = \{k \in I \mid r_k > 0\}$ with $|J| = M$. Then ν is given by $\nu = (M-1)/\mathcal{H}$ where $\mathcal{H} = \sum_{i\in J} 1/\eta_i$.

Proof: Since the objective function is a strictly concave differentiable function, and all the inequality constraint functions are differentiable convex functions, the KKT conditions gives the optimal solution to Problem 1, given as follows:

$$\eta_k\left(\frac{r_k^*}{r} - 1\right) - \lambda_k + \nu = 0, \quad \forall k \in I; \tag{3}$$
$$-r_k^* \leq 0, \quad \forall k \in \mathcal{I}; \tag{4}$$
$$\sum_{k\in I} r_k^* - r = 0; \tag{5}$$
$$\lambda_k \geq 0, \quad \forall k \in I; \tag{6}$$
$$\lambda_k r_k^* = 0, \quad \forall k \in I. \tag{7}$$

From (7), it is concluded that $r_k^* > 0$ or $r_k^* = 0$. First, considering the case of $r_k^* > 0$, it is clear that $\lambda_k = 0$. Thus, the stationary condition (3) becomes $r_k^* = r\left(1 - \dfrac{\nu}{\eta_k}\right)$. Now, consider the case of $r_k^* = 0$. Then, from the stationary condition (3), it is easily obtained that

$$r\left(1 - \frac{\nu}{\eta_k}\right) = r\left(1 - \frac{\lambda_k + \eta_k}{\eta_k}\right) = -r\left(\frac{\lambda_k}{\eta_k}\right) \leq 0.$$

To obtain an expression of ν, let $J \subset I$ be the index set satisfying $J = \{k \in I \mid r_k > 0\}$ with $|J| = M$. Then from the second primal feasibility condition (5), it is easily concluded that $\nu = (M-1)/\mathcal{H}$ where $\mathcal{H} = \sum_{i\in J} 1/\eta_i$. □

Here, a set of non-zero bidding providers, J is quite difficult to obtain manually. Thus the algorithm to obtain it is proposed in Algorithm 1, shown as above.

Algorithm 1 Algorithm for Determining J

Initialization :

(a) Arrange the index set of providers I and its ETR vectors $\{\eta_k\}_{k\in I}$ by the value of η_k in the ascending order

(b) Initialize the number of providers $N = |I|$ & $M = N$

(c) Initialize the index set $J = I$ and the index counter $i = 1$

(d) Initialize the harmonic sum $\mathcal{H} = 0$

(e) Initialize the negative counter $c = 1$

Repeat the iteration while $\{c = 1\}$

$$J = \{i, \cdots, N\};\ \mathcal{H} = \sum_{k\in J} \frac{1}{\eta_k};\ r_i^* = r\left(1 - \frac{M-1}{\eta_i \mathcal{H}}\right);$$

if $r_i^* > 0$, then $c = 0$; end if

else if $r_i^* \leq 0$, then $i = i + 1$; $M = M - 1$; end if

End iteration

Output : Index set J, after rearranged by the original order

Lemma 2: The MRCG $G_r' = \left(\mathbf{E}', u_k\right)_{k\in I}$ has the unique Nash Equilibrium $\boldsymbol{e}^*$, and the corresponding reward allocation is the unique solution to Problem 1.

Proof: The proof follows the similar argument of Johari [40], originated from Hajek and Gopalakrishnan [41], however, the proposed allocation policy has ETR parameters, η_k for the kth provider, as shown in (1).

Claim 1: If $\boldsymbol{e}^*$ is a NE of the MRCG G', then at least two components of $\boldsymbol{e}^*$ are positive.

Let $\boldsymbol{e}^* = \{e_1^*, \cdots, e_N^*\}$ be a NE of the MRCG G'. For the fixed kth provider ω_k, suppose $e_i^* = 0, \forall i \neq k$. Then $e_k^* > 0$ is obtained from $0 = u_k(0, \mathbf{0}\,; r) < u_k(e_k, \mathbf{0}\,; r), \forall e_k \in [0, r/\mu]$, because of the definition of u_k. However, if $e_k^* > 0$, then $u_k(e_k^*, \mathbf{0}; r) \leq u_k(e_k, \mathbf{0}; r), \forall e_k \in (0, e_k^*]$, because of zero-bidding of all the other providers. Thus, $e_i^* > 0$ for some $i \neq k$. Since it holds for every provider, Claim 1 is shown.

Claim 2: If the vector $\boldsymbol{e}^*$ has at least two positive components, then the function $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ is strictly concave and continuously differentiable in $e_k \geq 0$.

If $\boldsymbol{e}^*$ has at least two positive components, it is clear that $\sum_{i\neq k} \eta_i e_i^* > 0$. Thus, $(\eta_k e_k)/(\sum_{i\neq k} \eta_i e_i^* + \eta_k e_k)$ is strictly concave in e_k, which implies $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ is strictly concave in e_k. It is also easily checked that $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ is continuously differentiable in $e_k \geq 0$.

Claim 3: The vector $\boldsymbol{e}^*$ is a NE iff at least two components of $\boldsymbol{e}$ are positive, and for each k, the following condition holds:

$$\begin{cases} \dfrac{\eta_k}{\mu}\left[\dfrac{\sum_{i\in I\setminus\{k\}} \eta_i e_i^*}{(\sum_{i\in I} \eta_i e_i^*)^2}\right] = \dfrac{1}{r}, & \text{if } e_k^* > 0; \\ \dfrac{\eta_k/\mu}{\sum_{i\in I\setminus\{k\}} \eta_i e_i^*} \leq \dfrac{1}{r}, & \text{if } e_k^* = 0. \end{cases} \tag{8}$$

Let $\boldsymbol{e}^*$ be a NE. Then at least two components of $\boldsymbol{e}^*$ are positive and $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ is strictly concave and continuously differentiable in $e_k \geq 0$ by Claim 1 and 2. Thus, $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ has the unique maximizer e_k^* over $e_k \geq 0$, and the following optimality conditions hold:

$$\frac{\partial u_k}{\partial e_k}(e_k^*, \boldsymbol{e}_{-k}^*; r) \begin{cases} = 0, & \text{if } e_k^* > 0; \\ \leq 0, & \text{if } e_k^* = 0, \end{cases}$$

which implies the conditions (8).

Conversely, suppose that at least two components of $\boldsymbol{e}^*$ are positive, and the conditions (8) hold. Then $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ is strictly concave and continuously differentiable in $e_k \geq 0$ by Claim 2, and the conditions (8) imply that e_k^* is a maximizer of $u_k(e_k, \boldsymbol{e}_{-k}^*; r)$ over $e_k \geq 0$. Thus, $\boldsymbol{e}^*$ is a NE.

Claim 4: There exists the unique $\boldsymbol{r}^*$ and scalar ν such that

$$v_k'(r_k) = \eta_k\left(1 - \frac{r_k^*}{r}\right) = \nu, \quad \textit{if } r_k^* > 0; \tag{9}$$

$$v_k'(0) = \eta_k \leq \nu, \quad \textit{if } r_k^* = 0; \tag{10}$$

$$\sum_{k\in I} r_k^* = r. \tag{11}$$

Also, $\boldsymbol{r}^*$ is the unique solution to Problem 1.

It is easily shown that the conditions (9)-(11) and Problem 1 has the same unique solution. Note that the unique scalar ν in this claim is the same as the value of ν in the proof of Lemma 1.

Claim 5: If $(\boldsymbol{r}^*, \nu)$ satisfies (9)-(11), then the vector $\boldsymbol{e}^* = (\nu r_k^*/\mu\eta_k)_{k\in I}$ is a NE.

From the proof of Lemma 1, it is obtained that $\nu > 0$. From the condition (11), at least one component of $\boldsymbol{r}^*$ is positive. Now, suppose that $r_i^* = 0, \forall i \neq k$, then $r_k^* = r$. It follows that $\nu = 0$ from the condition (9), contradictory to $\nu > 0$, which concludes that at least two components of $\boldsymbol{r}^*$ are positive.

Now, in order to show that $\boldsymbol{e}^* = (\nu r_k^*/\mu\eta_k)_{k\in I}$ is a NE, it suffices to check two conditions (8) by Claim 3. Substituting $\boldsymbol{e}^* = (\nu r_k^*/\mu\eta_k)_{k\in I}$ and the unique solution (2) into (9)-(11), the conditions (8) are easily obtained. Thus, $\boldsymbol{e}^*$ is a NE solution.

Claim 6: If $\boldsymbol{e}^*$ is a NE, then the vector $\boldsymbol{r}^*$ defined by (1) and scalar ν defined by $1/\nu = r/(\mu \sum_{i\in I} \eta_i e_i^*)$ are the unique solution to (9)-(11).

It can be shown by the reverse argument of the proof of Claim 5. Also by Claim 4, such a pair $(\boldsymbol{r}^*, \nu)$ is unique.

Claim 7: There exists the unique NE $\boldsymbol{e}^*$, and the vector $\boldsymbol{r}^*$ defined by (1) is the unique optimal solution Problem 1.

Existence follows by Claim 4 and 5, and uniqueness follows by Step 6. Finally, $\boldsymbol{r}^*$ is an optimal solution to Problem 1 by Claim 4 and 6. □

Theorem 1 (Unique NE of the MRCG): The MRCG has the unique NE $\boldsymbol{e}^*$, given by

$$e_k^* = \begin{cases} \dfrac{r(M-1)(\eta_k\mathcal{H} - M + 1)}{\mu\eta_k^2\mathcal{H}^2}, & \text{for } k \in J; \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where $\mathcal{H} = \sum_{i\in J} 1/\eta_i$ and J is determined by Algorithm 1.

Proof: From Lemma 1 and the proof of Lemma 2, ν is given by $\nu = (M-1)/\mathcal{H}$ and $\boldsymbol{e}^* = (\nu r_k^*/\mu\eta_k)_{k\in I}$ is a NE solution of the MRCG. By substituting the solution to Problem 1 (2) into $\boldsymbol{e}^* = (\nu r_k^*/\mu\eta_k)_{k\in I}$, it is easily shown that the unique NE solution of the MRCG is given by (12). □

D. STACKELBERG EQUILIBRIUM (SE) OF THE EDSG

Lemma 3: The EDSG derived from G_r' has the unique SE r^* and $\boldsymbol{e}^{**}$, given by

$$r^* = \left(\frac{\mu\mathcal{H}}{M-1}\right)E_{\text{req}}; \tag{13}$$

$$e_k^{**} = \begin{cases} \left(\dfrac{\eta_k\mathcal{H} - M + 1}{\eta_k^2\mathcal{H}}\right)E_{\text{req}}, & \text{for } k \in J; \\ 0, & \text{otherwise,} \end{cases} \tag{14}$$

where $\mathcal{H} = \sum_{i\in J} 1/\eta_i$ and J is determined by Algorithm 1.

Proof: By Theorem 1, it is obtained that

$$\begin{aligned} f(r) &= \sum_{k\in I} \eta_k e_k^* \\ &= \sum_{k\in J}\left[\frac{r(M-1)(\eta_k\mathcal{H} - M + 1)}{\mu\eta_k\mathcal{H}^2}\right] \\ &= \frac{r(M-1)}{\mu\mathcal{H}^2}\sum_{k\in J}\left[\mathcal{H} - \frac{M-1}{\eta_k}\right] \\ &= \frac{r(M-1)}{\mu\mathcal{H}^2}\left[M\mathcal{H} - (M-1)\mathcal{H}\right] \\ &= \frac{r(M-1)}{\mu\mathcal{H}}. \end{aligned}$$

By the definition of the SE, r^* should satisfy $f(r^*) = E_{\text{req}}$, thus the SE is uniquely determined, given by (13)-(14) where $\mathcal{H} = \sum_{i\in J} 1/\eta_i$ and J is determined by Algorithm 1. □

Now, by the same argument in Definition 2 and 3, a NE function of the RCG and a SE of the EDSG derived from G_r can be defined, and the unique SE of the EDSG derived from G_r is obtained in the following theorem, which concludes this section.

Theorem 2: the EDSG derived from G_r has the unique SE r^* and $\boldsymbol{e}^{**}$, and they are exactly same as the unique SE solution of the EDSG derived from G'_r, given by (13)-(14).

Proof: It suffices to show that the unique SE r^* and $\boldsymbol{e}^{**}$ of the EDSG derived from G'_r lie on the same domain for the EDSG derived from G_r, $[0, E_{\max}]$. Thus, it is enough to show e_k^{**} is always less than $E_{\min}$ in all the cases.

Since each ETR is in [0.7, 1], it is easily checked that

$$\mathcal{H} = \sum_{i\in J}\frac{1}{\eta_i} \le \frac{1}{\eta_k} + \sum_{i\in J\setminus\{k\}}\frac{1}{\eta_i} \le \frac{1}{\eta_k} + (M-1)\Big(\frac{1}{0.7}\Big)$$

By this inequality and partial derivative of e_k^{**} with respect to η_k, it can be checked that

$$\begin{aligned}
\frac{\partial e_k^{**}}{\partial \eta_k} &= \Big(\frac{2(M-1)-\eta_k\mathcal{H}}{\eta_k^3\mathcal{H}}\Big)E_{\text{req}}\\
&\ge \frac{E_{\text{req}}}{\eta_k^3\mathcal{H}}\Big[2(M-1)-\eta_k\Big\{\frac{1}{\eta_k}+(M-1)\Big(\frac{1}{0.7}\Big)\Big\}\Big]\\
&\ge \frac{E_{\text{req}}}{\eta_k^3\mathcal{H}}\Big[(M-1)\Big(2-\frac{\eta_k}{0.7}\Big)-1\Big]\\
&\ge \frac{E_{\text{req}}}{\eta_k^3\mathcal{H}}\Big[(3-1)\Big(2-\frac{1}{0.7}\Big)-1\Big]\\
&\ge 0.14\Big(\frac{E_{\text{req}}}{\eta_k^3\mathcal{H}}\Big) > 0.
\end{aligned}$$

It means that e_k^{**} is increasing as η_k increases, thus it is maximized when $\eta_k = 1$.

It is clear that e_k^{**} takes its maximum when the number of providers are minimum and the other's ETR are their minimums, that is, $M = 3$ and $\eta_i = 0.7, \forall i \in I\setminus\{k\}$ with

$$3.85 < \mathcal{H} = 1 + \frac{1}{0.7} + \frac{1}{0.7} < 3.86.$$

Thus, the maximum value of e_k^{**} is given by

$$\Big(\frac{\mathcal{H}-2}{\mathcal{H}}\Big)E_{\text{req}} < \Big(\frac{3.86-2}{3.85}\Big)E_{\text{req}} < 0.48(2E_{\min}) < E_{\min}$$

which completes the proof. □

Recall that the algorithm by which the consumer determines the optimal reward is called the DOR Algorithm, and the algorithm by which the providers determine their optimal bidding energy is called the DOB Algorithm. Theorem 2 can achieve these two algorithms for retailers; r^* is the result of the DOR Algorithm and e^{**} is the result of the DOB Algorithm.

IV. NUMERICAL RESULTS

In this section, six numerical examples are provided to verify the proposed theorems and to investigate some behaviors of the unique NE solution. To this end, the number of providers is given by $N = 7$ and the energy transmission rates are given by

$$\{\eta_1, \cdots, \eta_7\} = \{0.7, 0.75, 0.8, 0.85, 0.9, 0.95, 1\} \quad (15)$$

as a default. In addition, the weight factor μ is set to be 0.1 in all the examples; it is determined by considering the actual price of renewable energy in Vandebron, an energy trading platform among retailers [42]. By Algorithm 1, it is easy to determine J, the index set of the providers who bid energy more than zero, as follows:

$$J = \{2, 3, 4, 5, 6, 7\} \subset I = \{1, 2, 3, 4, 5, 6, 7\}.$$

This means that only the first provider will not bid any energy to the distributor in this game, which is also verified in the numerical results in this section.

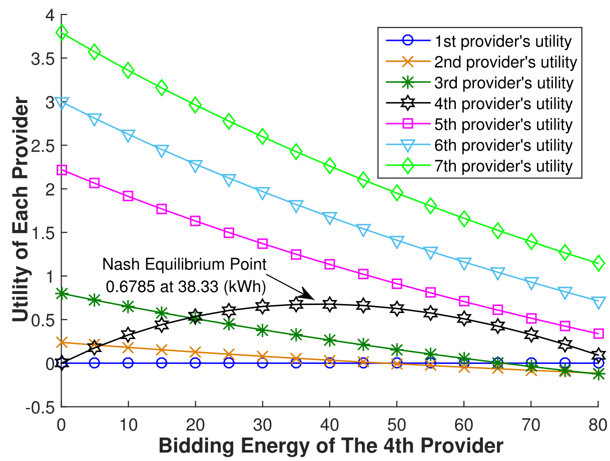

FIGURE 4. Utility of each provider when the bidding energy of the 4th provider varies from 0 to 80.

A. VALIDATION OF THEOREMS

First, Fig. 4 is a numerical example to verify Theorem 1 which provides the closed-form of the unique NE of the MRCG. In this example, the bidding energy of the 4th provider e_4 varies from 0 to 80 (kWh) when the total reward is fixed as \$30 and the bidding energy of the other providers is given by

$$\begin{aligned}
\{e_k\}_{k\in I\setminus\{4\}} &= \{e_1^*, e_2^*, e_3^*, e_5^*, e_6^*, e_7^*\}\\
&= \{0, 8.04, 21.08, 42.81, 51.96, 60.19\},
\end{aligned}$$

which can be obtained by Theorem 1. Now, to verify Theorem 1, it suffices to check that the utility of the 4th provider is maximized when $e_4 = e_4^*$. From Theorem 1, it can be obtained that $e_4^* = 38.33$ (kWh); and it is checked that the utility is maximized when $e_4 = 38.33$ (kWh) in the numerical result. It is thus verified by Theorem 1 that the DOB Algorithm for the providers operates well.

Next, Fig. 5 is a numerical example to verify Theorem 2, which provides the closed-form of the unique NE of the

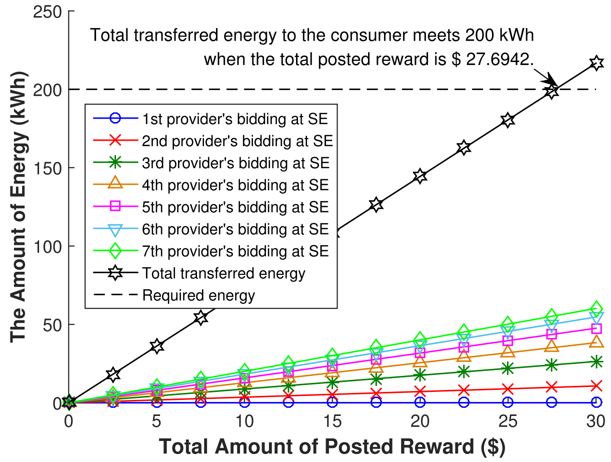

FIGURE 5. The amount of bidding energy and transferred energy when the total amount of the posted reward varies from 0 to 30.

EDSG derived from G_r. The required energy of the consumer in this example is 200 (kWh), and the bidding energy of all the providers is the NE solution of the MRCG, given by Theorem 1. In order to verify Theorem 2, the amount of the total reward posted by the consumer r increases from 0 until the total energy transferred to the consumer $\sum_k \eta_k e_k^{**}$ reaches 200 (kWh). From the example, the total amount of energy transferred to the consumer becomes 200 kWh when the total posted reward is \$27.6942. It is easily checked that it coincides with the SE r^*, given by Theorem 2.

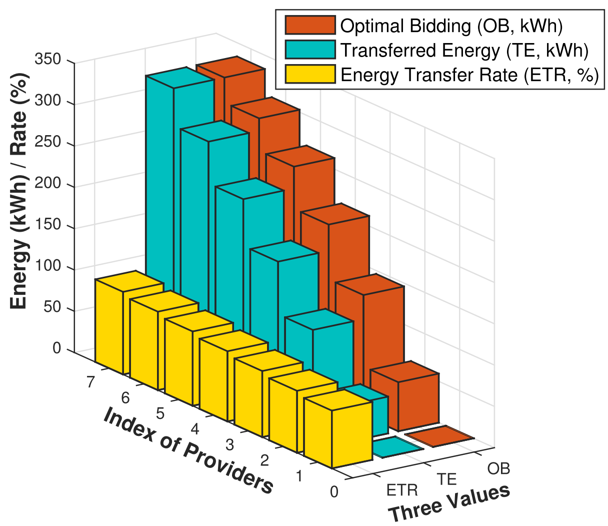

FIGURE 6. The behaviors of three values η_k, e_k^{**} and $\eta_k e_k^{**}$ at SE.

B. INVESTIGATION OF SE BEHAVIORS

To investigate Stackelberg equilibrium (SE) behaviors in this subsection, all the retailers in the following four numerical examples take their strategies as the unique SE of the EDSG derived from G_r, given by Theorem 2. Recall that the energy transmission rates are given by (15) and the weight factor is set to be 0.1.

In the numerical example for Fig. 6, the consumer's required energy is 1.2 (MWh). The following three values are presented to investigate the behavior of the proposed system; 1) η_k, the energy transmission rate for each provider given by (15), 2) e_k^{**}, the amount of bidding energy of SE from each provider, and 3) $\eta_k e_k^{**}$, the amount of energy of SE transferred from each provider. It is easily seen that only the first provider with $\eta_1 = 0.7$ does not bid any energy; the index set of the providers who bid non-zero energy is $J = \{2, 3, 4, 5, 6, 7\}$. It is found that the provider with larger ETR bids more energy than the provider with less ETR. This implies that the proposed system can increase the energy efficiency.

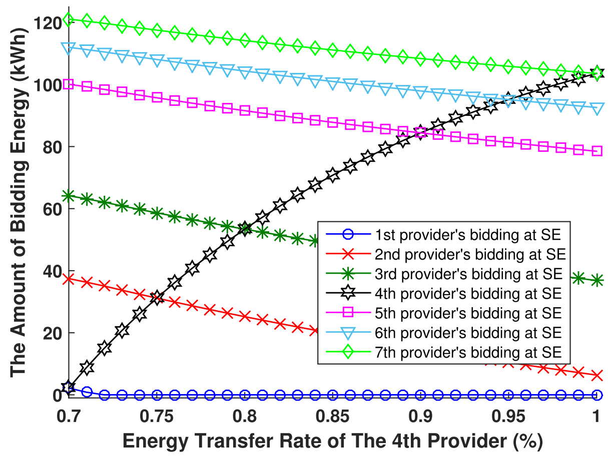

FIGURE 7. The amount of bidding energy when the energy transfer rate of the 4th provider varies from 0.7 to 1.

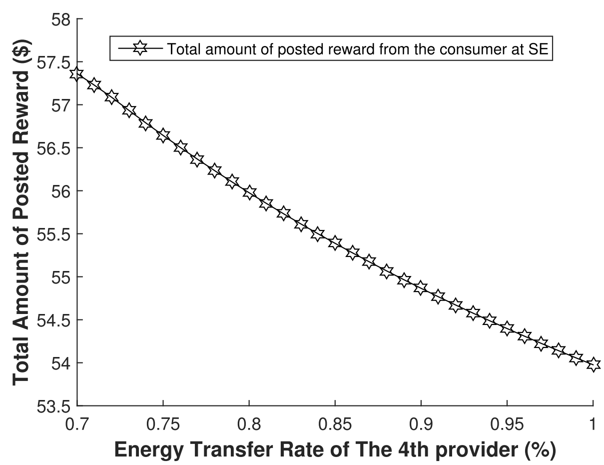

FIGURE 8. The amount of posted reward when the energy transfer rate of the 4th provider varies from 0.7 to 1.

Next, Fig. 7 and Fig. 8 illustrate the SE behaviors, e_k^{**} and r^*, respectively, as the 4th provider's ETR increases from 0.7 to 1. In these two examples, the consumer's required energy is 400 (kWh) and the other provider's ETR values are given by $\{\eta_1, \eta_2, \eta_3, \eta_5, \eta_6, \eta_7\} = \{0.7, 0.75, 0.8, 0.9, 0.95, 1\}$. As the 4th provider's ETR increases, there are three features in the figures that 1) its bidding energy is strictly increasing,

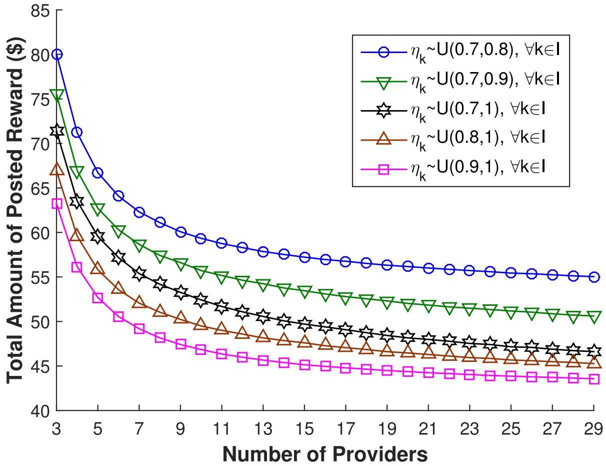

FIGURE 9. The amount of posted reward when the number of providers varies from 3 to 29.

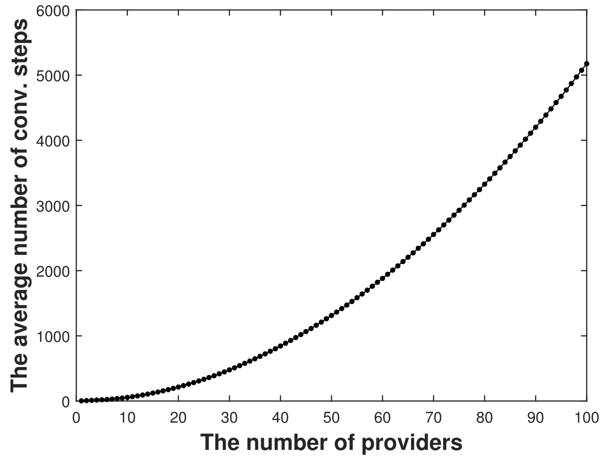

FIGURE 10. The average number convergence steps of the proposed algorithm.

2) the other provider's bidding energy is strictly decreasing except for the case of the 1st provider who becomes a zero-bidding provider, and 3) the total amount of the reward from the consumer is strictly decreasing.

Finally, Fig. 9 investigates the SE behaviors as the number of providers increases from 3 to 29. In this example, the consumer's required energy is 400 (kWh). Each provider's ETR is randomly given according to a uniform distribution in the following five scenarios, 1) $\eta_k \sim U(0.7, 0.8)$, 2) $\eta_k \sim U(0.7, 0.9)$, 3) $\eta_k \sim U(0.7, 1)$, 4) $\eta_k \sim U(0.8, 1)$, and 5) $\eta_k \sim U(0.9, 1)$. The total amount of the reward of the SE r^* is obtained by taking the average of 10^5 simulation runs. It is found that r^* decreases as the number of providers increases. This implies that, if competition among providers grows, the unit price of energy goes down. In addition, there is an interesting phenomenon that as the average ETR becomes bigger, r^* becomes smaller; this implies that a more efficient system makes the unit price of energy lower.

V. DISCUSSIONS ON PRACTICAL CONCERNS

In this section, some practical concerns of the proposed algorithm are discussed. Firstly, the complexity analysis of the proposed algorithm will be provided. Next, from simulation under actual energy consumption and generation profiles, the proposed market model is shown to be validated in time varying cases.

A. COMPLEXITY ANALYSIS OF PROPOSED ALGORITHM

In this subsection, the complexity analysis of the proposed algorithm is conducted. The proposed algorithm represents a process of the distributor to handle energy trading whenever the consumers open up the market based on their needs. In this regard, the proposed algorithm should be fast enough for real-time implementation. The process of proposed algorithm is divided into two steps: 1) selecting the providers that can be candidates for market participants in the energy trading transaction, and 2) obtaining the SE afterwards.

Fig. 10 represents the average number of convergence steps of the proposed algorithm, depending on the number of providers; in reality, the number of providers is less than 100. The figure shows that it follows the linearithmic complexity which is less than the polynomial complexity. This is because the first process, Algorithm 1, involves a process of sorting providers in an ascending order and an iteration algorithm. It is clear that the algorithm for sorting in an ascending order has a time complexity of $O(N \log N)$ using the quicksort algorithm. Next, the algorithm inside the iterations of Algorithm 1 has the time complexity of $O(N)$ since it is an algorithm to find the end point by incrementing the index from 1 to the number of providers. That is, the proposed algorithm has a time complexity of $O(N \log N)$ for the number of providers N. Moreover, we also check that even in an extreme case, where the number of providers is 10000, the computation of the proposed algorithm only requires 1.62 seconds with 3.4-GHz quad-core Intel Core i5 CPU, which is fast enough for a practical implementation.

B. SIMULATION STUDIES

In this subsection, rigorous simulation studies are conducted to represent how the proposed algorithm works in time varying cases. In this simulation, a small geographical area with 50 microgrid retailers is constructed. For a practical simulation, actual energy generation and consumption profiles for each retailer are used as input values of the simulation. Specifically, for an energy consumption profile configuration of each retailer, the energy consumption profile from Energy Information and Data is imported [43]. This profile consists of the building energy consumption profiles such as supermarkets, schools, and other various building types. For an energy generation profile, two different types of power generation source are considered: wind and solar radiation. Here, the amount of wind and solar power generation is related to wind speed and the amount of solar radiation, respectively. Thus, to simulate the energy generation from

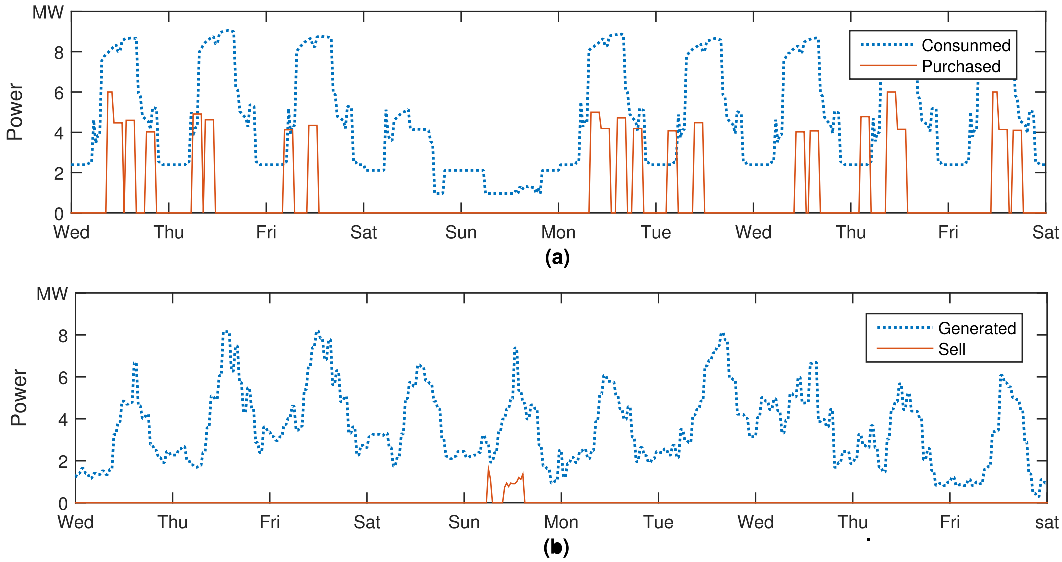

FIGURE 11. Time-varying energy trading simulation with the proposed energy trading algorithm. (a) Amount of consumed energy & Amount energy purchased from other retailers. (b) Amount of generated energy & Amount of energy sell to other retailers.

two different types of energy sources, actual wind speed and solar radiation data are brought from Korea Meteorological Administration [44].

For practical implementation, a distributor schedules multiple events of energy trading where there are market opening requests from consumers when the effect of the previous transaction is not over yet. That is the proposed market model that supports only one event at a time so that multiple events cannot be hold simultaneously, and it can be occurred in the system with a lot of consumers. This problem can be solved by the following two steps:

- Restrict only participants with higher ETR to join in the market (e.g., bigger than 0.7), then only retailers in a small geographical area can participate in the market considering energy transmission efficiency; then the collision between transactions occurs less frequent.
- If a transaction conflict occurs despite the proper adjustment of the ETR, run the transaction process against the remaining retailers who did not participate in the transaction.
- If the above two processes do not work, wait until the trading of the surrounding retailers is over and then open the trading market with the highest priority.

Now, the simulation results of the proposed algorithm are shown in Fig. 11. These figures show the energy status and behavior of a retailer over time in the simulated energy trading situation. Specifically, Fig. 11(a) depicts the energy consumption profile and the amount of energy purchased from other retailers. Fig. 11(b) depicts the energy generation profile and the amount of energy sold to other retailers. Here, each marking on the x-axis indicates 12:00 AM on each date, that is, the middle part between each marking is 12:00 PM.

As shown in the figure, the energy consumption of this retailer increases in the afternoon except Sunday. Similarly, the retailer produces a lot of energy in the afternoon due to the increased energy generation from solar power generation. Here, when the amount of energy consumed is greater than the amount of energy generated, the retailer buys the required amount energy from other retailers in the energy trading market as shown in Fig. 11(a). On the other hand, in the case of Sunday's daytime, it can be easily shown that the retailer sells the remaining energy to the energy trading market as shown in Fig. 11(b). Finally, it is seen that the proposed algorithm works well under time varying cases and dynamically triggers energy trading depending on the retailer's energy status regardless of periodical trading interval.

VI. CONCLUSION

In this paper the authors have proposed an event-driven energy trading system among microgrids. The system is based on a consumer-oriented and aperiodic market model. A rigorous game theoretic analysis for deriving the equilibrium solution of this novel system has been represented. Numerical results verify the theorems and investigate the utility of microgrids with respect to variations of some parameters. Finally, the stability of the proposed energy trading system has been demonstrated from the unique equilibrium solution.

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