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Distributed energy trading with transmission cost: a Stackelberg game approach

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Dear editor,

Distributed generation combines different renewable energy sources at the edge of the grid, such as wind and solar power. It helps manage energy demand more efficiently and further relax the stress on the grid if these energy sources are properly utilized. This can be mainly realized by engaging the end-users to actively participate in energy trading.

Recently, there has been significant interest in devising market-based energy trading mechanisms in an efficient and economical way. For instance, Tushar et al. [1] investigated a discriminate pricing scheme for energy trading using cake cutting game. In [2], the authors proposed to use a distributor to gather surplus energy and distribute it to consumers based on historical contribution levels. A distributed energy trading mechanism was presented in [3], which achieved proportional sharing on trading participants. Readers can refer to a recent survey [4] for a comprehensive overview of energy trading. Nevertheless, most of the above schemes oversimplify models, omitting practical issues, e.g., transmission losses [5] and wheeling cost [6]. The way how these practical factors influence trading behaviors of both sides of supply and demand, and especially the impact of transmission losses and their influence levels, are largely unexplored. This observation motivates the current study.

A novel energy trading mechanism based on Stackelberg game is proposed for analyzing optimal pricings and distributed energy schedulings in microgrids, by explicitly considering transmission cost. The performance is evaluated theoretically and numerically, which shows such an energy trading mechanism has economical significance for all participants and preserves fairness among consumers. The most important implication is that transmission cost has a great impact on energy trading and cannot be ignored.

Multi-leader multi-follower (MLMF) Stackelberg game model. Consider a realistic scenario where a number of microgrids equipped with renewable energy generators and battery energy storage systems (BESSs) trade energy with each other in a distributed trading mechanism across a distribution network. Divide a day into T time periods. In each period t, microgrids are grouped into retailers N_r^t and consumers N_c^t. Retailer $j \in N_r^t$ has a surplus power generation Q_j^t and stored energy S_j^{t-1}, while consumer $i \in N_c^t$ has to procure an amount of energy R_i^t to satisfy its local demand.

For each transaction volume $D_{i,j}^t$ between retailer j and consumer i, the amount of transmission losses can be represented as $f(D_{i,j}^t) = \alpha_{i,j} {D_{i,j}^t}^2 + \beta_{i,j} D_{i,j}^t$, where $\alpha_{i,j}$ is associated with the power losses over the distribution lines and $\beta_{i,j}$ is related to the losses due to other factors such as voltage conversion, dust, and so forth [5]. Moreover, according to [6], the wheeling cost $\Delta C_{i,j}$ for unit energy flowing is charged by the power grid enterprise to recover the investment and operation maintenance cost of the grid infrastructure.

The multiple times energy trading problem can be decoupled as multiple sub-problems. Thus, we only consider one period problem and for simplicity, we omit t if no confusion occurs.

The MLMF Stackelberg game model proposed in this study can be formally defined as $\Omega = \{N_r \cup N_c, \{S_n\}_{n\in N_r}, \{s_m\}_{m\in N_c}, \{Z_n\}_{n\in N_r}, \{Z_m\}_{m\in N_c}\}$, where $\{S_n\}_{n\in N_r}$ and $\{s_m\}_{m\in N_c}$ denote the strategy space of retailers (retail prices P_j and each sales volume $E_{i,j}$) and consumers (each purchase $D_{i,j}$), respectively. The payoff functions of retailers and consumers are denoted by $\{Z_n\}_{n\in N_r}$ and $\{Z_m\}_{m\in N_c}$, respectively.

Supply side analysis. Each retailer $j \in N_r$ aims to maximize its individual welfare Z_j, i.e., the sales profit and the satisfaction $U(S_j^t)$ attained from the stored energy S_j^t. Hence the welfare of retailer j can be formulated as

$$\max \quad Z_j = \sum_{i\in N_c} P_j E_{i,j} + U(S_j^t) \tag{1}$$

$$\text{s.t.} \quad \sum_{i\in N_c} E_{i,j} \leqslant Q_j + S_j^{t-1}, \tag{2}$$

$$S_j^t = S_j^{t-1} + r_t^c - r_t^d, \tag{3}$$

$$Q_j + r_t^d - r_t^c = \sum_{i\in N_c} E_{i,j}, \tag{4}$$

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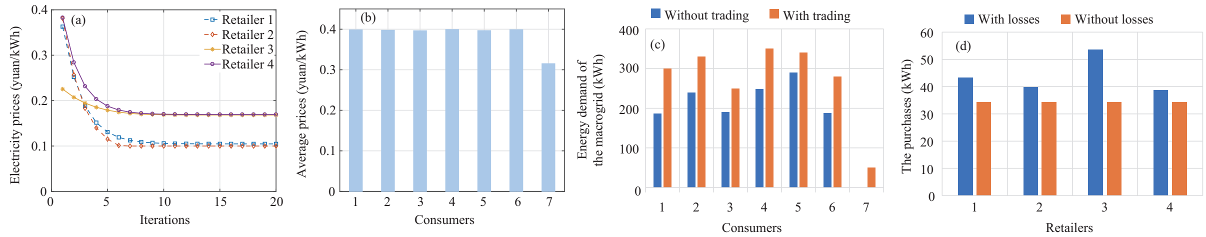

Figure 1 (Color online) (a) Convergence of the Best response algorithm; (b)–(d) simulation results.

where $E_{i,j} \geqslant 0$ is the sales volume from retailer j to consumer i. Constraint (2) means that the amount of energy sold cannot be greater than the available power. $Pr^{\min} \leqslant P_j \leqslant Pr^{\max}$, where $Pr^{\min}$ and $Pr^{\max}$ represent the acquisition price and the retail price of the macrogrid, respectively. This enables each consumer and retailer to participate in energy trading markets actively. Constraints (3) and (4) are the energy storage dynamics and the balancing condition for BESSs of retailer j. Besides, $S_j^t \in [0, ST_{ca}]$, $r_t^c \in [0, ST_c^m]$, and $r_t^d \in [0, ST_d^m]$ denote the stored energy, the charging rates, and the discharging rates, respectively.

The satisfaction degree $U(S_j^t)$ is usually assumed to be a concave and continuously differentiable function. Thus, we use a quadratic function to represent it: $U(S_j^t) = -\lambda_j {S_j^t}^2 + \gamma_j S_j^t$, where λ_j^t and γ_j^t denote the satisfaction parameters varying with periods according to conditions of power supply and demand.

Thus, with the Karush-Kuhn-Tucker conditions, the sales volume can be expressed as follows:

$$\sum_{i \in N_c} E_{i,j}^* = Q_j + S_j^{t-1} + \frac{P_j^* - \gamma_j}{2\lambda_j}, \ \forall j \in N_r. \tag{5}$$

Demand side analysis. Based on the unit prices P_j ($\forall j \in N_r$) of retailers and P_0 (containing the wheeling cost) of the macrogrid, each consumer $i \in N_c$ chooses the best sellers to buy energy in order to minimize their purchasing cost Z_i:

$$\min \ Z_i = P_0 D_{i,0} + \sum_{j \in N_r} (P_j + \Delta C_{i,j}) D_{i,j} \tag{6}$$

$$\text{s.t.} \ \sum_{j \in N_r} (D_{i,j} - f(D_{i,j})) + D_{i,0} = R_i, \tag{7}$$

where $D_{i,0}$ denotes the purchase from the macrogrid. Constraint (7) indicates that each consumer i should always ensure that the total purchases which minus losses meet its needed energy R_i.

It is worth mentioning that the above problem is nonconvex due to constraint (7). To make it solvable, we relax (7) as $\sum_{j \in N_r} (D_{i,j} - f(D_{i,j})) + D_{i,0} \geqslant R_i$. With the Karush-Kuhn-Tucker conditions, we obtain the solutions in two cases.

(1) $D_{i,0} = 0$, which means that consumer i does not need to purchase any power from the macrogrid. Then

$$D_{i,j}^* = \begin{cases} \dfrac{1-\beta_{i,j}}{2\alpha_{i,j}} - \dfrac{P_j^* + \Delta C_{i,j}}{2\alpha_{i,j}} h, & 0 < h < H_{i,j}, \\ 0, & h \geqslant H_{i,j}, \end{cases} \tag{8}$$

which satisfies $\sum_{j \in N_r} [-\alpha_{i,j} {D_{i,j}^*}^2 + (1-\beta_{i,j}) D_{i,j}^*] = R_i$ and $H_{i,j} = \frac{1-\beta_{i,j}}{P_j + \Delta C_{i,j}}$. In fact, Eq. (8) is a slightly different version of the water-filling solution and can be calculated by an improved exact algorithm (see Appendix B).

(2) $D_{i,0} \neq 0$, which means that consumer i has to trade with retailers and the macrogrid. Then

$$D_{i,j}^* = \frac{P_0(1-\beta_{i,j}) - (P_j^* + \Delta C_{i,j})}{2\alpha_{i,j} P_0}, \tag{9}$$

$$D_{i,0}^* = R_i - \sum_{j \in N_r} (D_{i,j}^* - f(D_{i,j}^*)). \tag{10}$$

From the above analysis, $\{S_n\}_{n \in N_r}$ and $\{s_m\}_{m \in N_c}$ are non-empty, convex and compact subset of Euclidean space. Besides, $\{Z_n\}_{n \in N_r}$ is continuous and concave while $\{Z_m\}_{m \in N_c}$ is continuous and convex. Moreover, there exists only one non-negative solution for retailers as given in (5), and only one optimal response for consumers as given in (8)–(10). Therefore, pure strategy Stackelberg equilibrium (SE) uniquely exists in the MLMF game model [7]. A best response algorithm shown in Appendix A is proposed to obtain the SE by using an iterative method.

Results and discussion. We apply the proposed energy trading scheme to a distribution network consisting of 11 microgrids as shown in Figure C1. The simulation settings can be found in Appendix C. Firstly, Figure 1(a) depicts the convergence of the best response algorithm in MLMF Stackelberg model. Within about 15 iterations, all the prices converge to the equilibrium points starting with any initial points, which testifies the efficiency and convergence of the proposed model.

Figure 1(b) depicts average prices of consumers, which is given by $P_{\mathrm{av},i} = \frac{\sum_{j \in N_r} (P_j^* + \Delta C_{i,j}) D_{i,j}^*}{\sum_{j \in N_r} (D_{i,j}^* - f(D_{i,j}^*))}$. Average prices of all consumers are always below the price P_0 of the macrogrid and keep little difference, except for the one of consumer 7, which is because the demand of consumer 7 can be met by tradings among microgrids and consumer 7 does not need to trade with the macrogrid. Meanwhile, for the first six consumers, the biggest gap of average prices is only 0.003 yuan/kWh. This indicates the proposed MLMF Stackelberg model not only maximizes the respective benefit of all market participants, but also enables consumers to share resources equally, and thus ensures fairness and practicality. In this manner, consumers will be motivated to join markets while retailers will profit and participate in tradings, which promotes the formation and development of trading markets.

Figure 1(c) shows energy demand from the macrogrid. By comparison, it is clear that the market trading volumes can fully meet the energy demand of consumer 7 and the others significantly reduce purchases from the macrogrid, about 15%–38%. Thus, it can efficiently relieve the power generation pressure and realize the optimal utilization and coordination of new energy sources.

As illustrated in Figure 1(d), Tables C3 and D1, when ignoring the losses, owing to the slightly different prices of retailers, there is only a little difference in trading volumes among all consumers. On the other hand, in the presence of transmission losses, trading volumes with four retailers have a clear opposite relationship with the value of $\alpha_{i,j}$ and P_j, i.e., consumers will prefer a nearby retailer with a low price for tradings to lower the purchasing cost. By contrast, the largest change in trading volumes is 59%, which shows that transmission losses have a huge impact on trading behaviors of both parties and the same is true for wheeling cost. In addition, from Table C4, clearly, electricity prices of retailer 4 are the highest and the ones of retailer 2 are the lowest. It is observed that P_7 is 69% higher than P_2. The reason is that badly located retailers will lower prices to attract consumers and those close to consumers will instead raise prices to increase their sales profits. Additional discussions can be found in Appendixes D and E.

Conclusion. A distributed energy trading mechanism based on the MLMF Stackelberg model is proposed, considering transmission cost. The unique SE guarantees the respective benefit of all market participants. The numerical studies have identified that transmission cost has a great impact on energy tradings and cannot be ignored.

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Supporting information Appendixes A–E. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Tushar W, Yuen C, Smith D B, et al. Price discrimination for energy trading in smart grid: a game theoretic approach. IEEE Trans Smart Grid, 2017, 8: 1790–1801

2 Park S, Lee J, Bae S, et al. Contribution-based energy-trading mechanism in microgrids for future smart grid: a game theoretic approach. IEEE Trans Ind Electron, 2016, 63: 4255–4265

3 Hekmatshoar B. Thin-film silicon heterojunction FETs for large area and flexible electronics: design parameters and reliability. IEEE Trans Electron Device, 2015, 62: 3524–3529

4 Tushar W, Yuen C, Mohsenian-Rad H, et al. Transforming energy networks via peer-to-peer energy trading: the potential of game-theoretic approaches. IEEE Signal Process Mag, 2018, 35: 90–111

5 Wei C, Fadlullah Z M, Kato N, et al. GT-CFS: a game theoretic coalition formulation strategy for reducing power loss in micro grids. IEEE Trans Parallel Distrib Syst, 2014, 25: 2307–2317

6 Supplementary notice on launching the pilot program of distributed power generation marketization. 2018. http://www.gov.cn/xinwen/2018-01/03/content_5252800.htm

7 Wei F, Jing Z X, Wu P Z, et al. A Stackelberg game approach for multiple energies trading in integrated energy systems. Appl Energy, 2017, 200: 315–329