DISTRIBUTED ITERATIVE LOCAL ENERGY BIDDING IN AGENT-BASED MICROGRIDS

Yajun ZHANG
University of Bath – UK

Chenghong GU
University of Bath – UK

Furong LI
University of Bath – UK

ABSTRACT

This paper designs a new distributed iterative bidding mechanism for energy trading among microgrids (MGs) at the local level. The market is based on one consumer and multiple providers. When one MG as a consumer and other MGs which have surplus power to supply becomes providers. The providers compete by iterative bidding cycles and the final winner will trade with the consumer MG. Due to the non-cooperative relationship among providers, players cannot access other's information except the feedback from the system operator. This asymmetric information competition among providers is formulated by a Bayesian game for analysis. The Bayesian Nash Equilibrium (BNE) will be arrived and the optimal price can be provided to the consumer. The simulation demonstrates that although different bidding strategies lead to different process, the final result remains, illustrating the effectiveness of this trading model.

I. INTRODUCTION

The increasing demand for power brings a huge challenge for the traditional power grid. In this context, the smart grid emerges as a trend with advanced information and communication technology (ICT) is more reliable and efficient[1]. In smart grid context, the microgrid (MG) is regarded as a promising solution for integration and coordination of distributed energy resources at the local level. As a significant block, the MG has many potential advantages. In MG, local demand can be served by local distributed energy sources directly without importing the main grid. It can reduces the transmission loss over long distance and also minimizes the reliance on the main grid, efficiently relieving the burden of macrogrid. If the distributed energy sources in a MG have surplus power, they can benefit by selling it to other MGs. The energy trading among MGs can help balance energy supply and demand at the local level.

In this sense, the concept of multi-agent system can be adopted in the trading mechanism. The multi-agents which executes trading among MGs[2]. An agent-based MG can be considered as a consumer or a provider to participate in energy trading.

In recent years, many studies focus on MG energy trading. In paper [3], the bidirectional trading mechanism is designed with the utilization of EVs (electric vehicles). Authors present collaborative and non-collaborative models. In paper [4], authors design a contract game, which provides small-scale electricity suppliers (SESs) and electricity consumers (ECs) a chance to participate in direct energy trading for revenue under asymmetric information. In paper [5], a distributed decision-making scheme is developed among MGs. The quantity depends on the consumer MG and the price depends on the provider MG. The interactions are formulated into Stackelberg game and the optimal trading quantity and price can be obtained in SE .

The game theory, as a useful method, formulates energy trading scheme as a game model and provides solutions. Paper [6] investigates optimal energy trading strategy for individual multiple energy MGs. A two-stage stochastic game model was developed for MG management and algorithm was presented to find Nash equilibrium (NE), considering the risk from uncertain energy supply and demand. In paper [7], authors propose an event-driven energy trading system for MGs in a consumer-oriented market model, where the Stackelberg game model was adopted and Stackelberg equilibrium (SE) was derived as the desired results. Paper [8] presents a distributed energy trading mechanism among interconnected MGs and the multi-sellers-multi-buyers trading process was formulated as Stackelberg game to maximize the revenues for both sides.

When one MG requests energy, it is a consumer and other MGs with surplus power become providers to bid for meeting the energy requirement. In terms of a single-consumer-multiple-providers model, previous work usually focuses on distributing the required energy to all sellers. The design of trading mechanism only gives sellers one chance to bid. In this situation, sellers are likely to provide high bidding price due to unknown information about competitors to fail in trading.

This paper presents a new iterative bidding scheme for local energy trading between agent-based MGs. The trading model consists of one buyer and multiple providers. The mechanism presents multiple rounds of bidding cycles to achieve optimum. When sellers send their bidding prices to the operator, they will receive the feedback from the operator so that they have opportunities to change their bidding strategies and update bidding price in next round. The chance of price adjustment aims to make the trading results closer to optimal. The non-cooperative sellers could obtain some information about competitors by receiving feedback to play game better and the distributed auction leads to vigorous competition in sellers which will benefit buyers with lower prices. The method is mathematically illustrated and the effectiveness has been validated by the case study.

II. LOCAL ENERGY TRADING MODEL

An energy trading mechanism which supports multiple rounds of bidding cycles is proposed in this section. The MGs are considered as consumer or provider, depending on their energy demand and generation. When a MG has energy deficiency, it becomes a consumer and other MGs which have surplus energy to supply this deficiency are providers. Once a consumer asks for energy, the biding game starts. The system operator is acted as the game organizer, who arranges qualified providers to bid for the auction and chooses the best trading for consumer MG.

A. Consumer model

For consumer MG, there is a deficiency in energy, denoted by E_{req} . In order to compensate this shortage, it has to buy quantity E_{req} from other MGs at price (P) or generates this part by itself. The objective is to minimize the total cost of compensation as follows:

$$\min_{P} C = \begin{cases} E_{req} \cdot P \ , & if\ P < P_{gen} \\ E_{req} \cdot P_{gen} \ , & if\ P \geq P_{gen} \end{cases} \qquad (1)$$

where , C represents the total cost of the compensation. P_{gen} denotes the cost of generation, which is a constant.

B. Provider model

For provider MGs, they have abundant energy, denoted by E_a. Besides the supply for their own demand E_{demand}, the surplus energy, denoted by E_{extra}, can be sold to the consumer, E_{req} at price P. Then the seller model is

$$E_a = E_{demand} + E_{extra} \qquad (2)$$

$$\max_{P} R = E_{req} \cdot P \qquad (3)$$

$$\text{s.t.} \quad E_{extra} > E_{req},\ P > P_{cost}$$

where, P_{cost} is the unit generation cost in the MG, which also decides the minimum bidding price limitation for provider. All selling prices of MGs have to be higher than P_{cost} to assure it is profitable.

III. ENERGY TRADING PROCESS

This trading is based on single consumer and multiple providers among agent-based MGs, where each MG has agent to access information and participate in the trading.

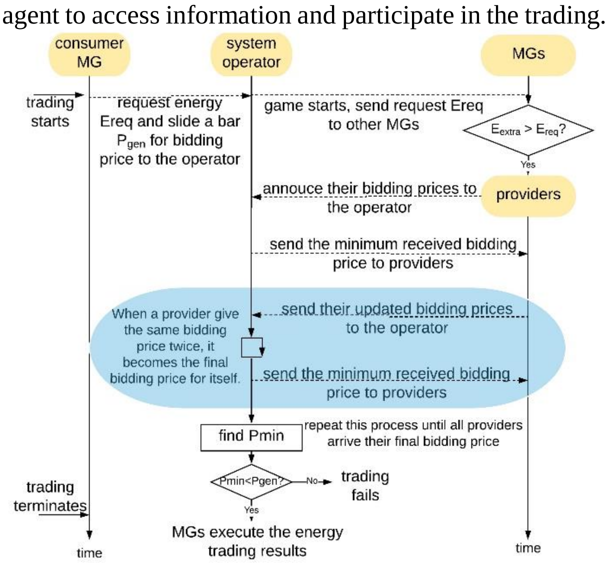

Figure 1 sequence diagram of the proposed trading system

The process of the local energy trading is illustrated in Figure 1. As shown, when one MG has a power deficiency, it can send a request for energy E_{req} and P_{gen} for price to the operator. The system operator informs all rest of MGs the quantity of demand. According to E_{req}, other MGs will check their energy surplus to identify whether they can sell. The qualified providers send their bidding price to the operator. Then, the operator finds the minimum bidding price and reveals it to all providers. Accordingly, providers can update their bidding prices. This process is repeated for a few cycles. If a provider bids the same price twice, this price becomes its final bidding price. When all providers have their final bidding prices, the process stops and the provider with minimum price is the winner. When this price is lower than P_{gen} generation cost in consumer, the energy trading will be executed, otherwise the trading fails.

This trading scheme focuses on the distributed iterative bidding among providers. After submitting their bidding prices, providers will receive a feedback on minimum price in this round from the operator. As a reference, they can reduce their prices to make them more competitive in next bidding cycle. In terms of providers with the minimum bidding price, they may slow down the reduction interval to see whether others have the lower prices or their price is low enough to win the bidding. In addition, they have to make sure that their bidding prices can generate profits for them, not lower than the minimum value. They will choose their strategy to try to win the bidding with a higher price as they can.

IV. BAYESIAN GAME THEORY ANALYSIS

A. Bayesian game formulation

For buyer MG, a lower bidding price is preferred but from the perspective of sellers, a high power price is better. However, higher price has less competitiveness in the bidding. According to the non-cooperation relationship among sellers, they do not know others' information except the minimum price feedback in each cycle from the system operator. There is a competition with incomplete information in sellers.

The Bayesian Game is an appropriate framework for modelling this distributed iterative bidding. The sellers are modelled as a set of players with different bidding strategies and payoff functions. The Bayesian Nash equilibrium (BNE) is the desired outcome corresponding to the optimal price.

$$P^* = \arg \min_{P \leq P_{gen}} C(E_{req}, P) \qquad (4)$$

The system operator performs as a central controller to organize the trading. A distributed algorithm is designed to execute the proposed scheme to find the BNE through iterative bidding cycles.

Algorithm 1

1: The consumer sets the energy E_{req} and limitation P_{gen} for final bidding price.

2: The k providers initializes bidding price $P = \{P_1, P_2, P_3, \ldots, P_k\}$, where the cost of compensation for consumer is $C(E_{req}, P)$

$$C = E_{req} \cdot P$$

Meanwhile, providers can also set their minimum bidding price $\min P = \{P_{min}^1, P_{min}^2, P_{min}^3, \ldots, P_{min}^k\}$ and their bidding price reduction interval $\Delta P = \{\Delta P_1, \Delta P_2, \Delta P_3, \ldots, \Delta P_k\}$, and keep it to themselves.

3: **For** iteration $i \rightarrow i+1$, **do**

4: In responding to bidding price P^i provided by sellers, the system operator informs them the lowest price P_{min} at this round, where

$$P_{min} = arg \quad \min C(E_{req}, P^i)$$

5: The sellers update P^{i+1} based on step size ΔP which they set at beginning according to their bidding strategy.

$$P^{i+1} = P_{min} - \Delta P$$

The sellers present their updated bidding price P^{i+1} to system in this new bidding cycle.

6: **If** $P_x^{i+1} = P_x^i$ for provider x, where $1 \leqslant x \leqslant k$, **then**

This bidding price P_x^i becomes its final bidding price which can't be changed anymore.

7: **End if**

8: In responding to P^{i+1}, the system operator informs them the new lowest price P_{min} at this round, where

$$P_{min} = \min P^{i+1}$$

9: **End for**

10: Repeat 3 to 9 until the termination condition is satisfied that all providers arrive at their final bidding price.

11: The final minimum bidding price P_{min} is obtained.

12: **If** $P_{min} < P_{gen}$, **then**

The transaction is concluded. The consumer will buy E_{req} power at price P_{min} from bidding winner.

Otherwise, the transaction fails. The consumer has to produce E_{req} with unit production cost P_{gen} by itself.

13: **End if**

B. A distributed algorithm for obtaining BNE

The core of the scheme is the bidding price variation in iterative cycles. Sellers have their own strategies to change ΔP and update price P^{i+1}. In Algorithm 1, the reduction intervals are fixed in two types: 1) when the feedback value P_{min} proposed by other sellers, it will reduce by ΔP based on P_{min} to improve competitiveness. 2) when its price is the minimum in last round, it can just slightly change in the next turn. The aim is to retain the right of price adjustment in case of lower price and keep a higher price as possible if there are no competitors.

The BNE can be obtained when all sellers arrive at their final bidding prices. In comparison, the optimal price is the lowest. As long as it is below the buyer price bar, the transaction between the consumer MG and provider MG will be executed with the quantity E_{req} at price P_{min}.

V. CASE STUDY

In this section, the simulation case study is implemented to illustrate the proposed trading approach in several MGs (i.e., one consumer and multiple providers). It is assumed that the buyer has a deficient energy of 10MWh, and its production cost is £41/MWh. There are 5 sellers in this energy bidding, named S1 to S5. Their minimum bidding prices and initialized bidding prices are in Table *1*.

Table 1 sellers' parameters

sellers		S1	S2	S3	S4	S5
(£/MWh)	Min bidding price	39	42	34	45	35
	Initialization	45	48	43	50	43

There are two cases in the simulation according to the different normal price reduction intervals, low level and high level. In addition, if the find that P_{min} is proposed by themselves in last round, their reduction in next round will change to £0.1/MWh.

A. Low level of bidding price reduction

With different bidding strategies, sellers' normal price reduction intervals are displayed in Table 2.

Table 2 low level reduction interval for sellers

sellers	S1	S2	S3	S4	S5
ΔP (£/MWh)	0.5	0.3	0.4	0.2	0.6

With the parameters shown, the algorithm is implemented in the transaction. The sellers' bidding price variations over all cycles are displayed in Figure 2. As shown, their bidding prices have the familiar tend, gradually falling to their price bars. The BNE is arrived at the 20th bidding cycle, where five sellers all arrive at their final bidding prices. At the end of this bidding, the final winner bidding price is £34.4 /MWh from S3, which is much lower than the buyer's production cost £42/MWh. The transaction is concluded and the buyer's cost cannot be further reduced.

It can be seen from Figure 2 that there are sharp decreases in the second round. At the beginning, according to their own cases, the initial bidding prices have some differences. After the first feedback, from the second cycle, all reductions are based on the same values, i.e. the last minimum price P_{min}. Figure 3 shows the minimum bidding price P_{min} gradually converges to BNE, around £34/MWh. It proves that this distributed iterative bidding scheme works and the BNE can be achieved.

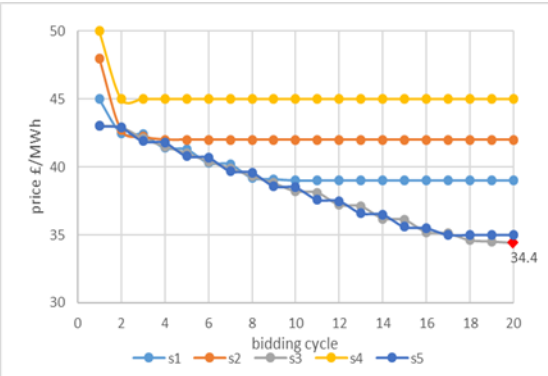

Figure 2 bidding price variation with low reduction interval

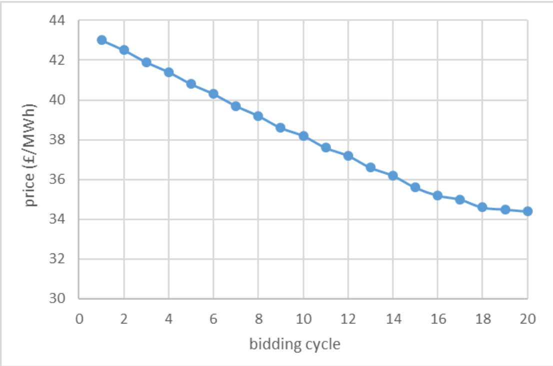

Figure 3 minimum bidding price variation in low reduction interval

B. High level of bidding price reduction

In this section it the sellers' normal price reduction intervals are displayed in Table 3.

Table 3high level reduction interval for sellers

sellers	S1	S2	S3	S4	S5
ΔP (£/MWh)	0.5	0.3	0.4	0.2	0.6

Figure 4 displays that the sellers bidding prices in iterations. As shown, the variation is similar to that with low-level reduction in Figure 2. However, it is fast to reach the BNE in the 9th iteration bidding. The final winner is still S3 with bidding price £34/MWh. In Figure 5, under the high-level reduction bidding, P_{min} gradually falls down to the £34/MWh, which is similar to that in the low-level case.

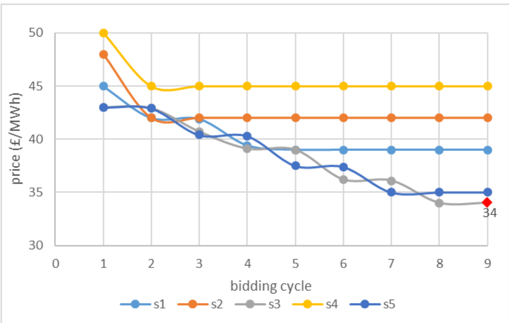

Figure 4 bidding price variation with high reduction interval

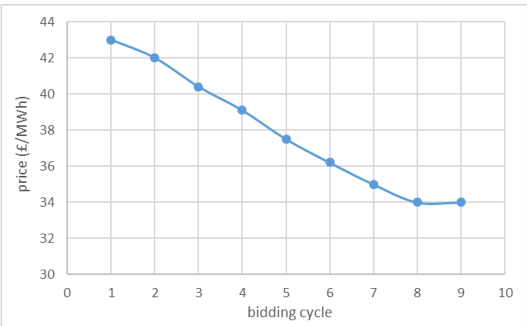

Figure 5 minimum bidding price variation in high reduction interval

According to Figures 2 and 4, although there are different number of bidding cycles to achieve final transaction, the bidding price variations of five sellers are similar. With the increasing bidding cycles and the growing fierce competition, S4, S2 and S1 reached their final price in succession. Then S3 and S5 continue to compete to their limitations. It illustrates that the final bidding winner mainly depends on the minimum price they can provide, rather than the reduction interval in bidding strategy.

In Figure 3 and Figure 5, they show that the bidding price gradually falls during the growth of bidding iteration. It demonstrates the advantage of this iterative bidding scheme that fierce competition leads to lower bidding price to benefit the buyer. No matter the higher or lower reduction level sellers choose, the minimum bidding price smoothly decreases to the final result.

VI. CONCLUSION

This paper proposes a novel distributed energy trading for a single-consumer-multiple-providers model to select the optimal trading target for consumer MG. The system is composed of agent-based microgrids, where each agent can represent MG to participate energy transaction. The competition process among providers is formulated as a Bayesian game. The unique Bayesian Nash Equilibrium can be obtained by the presented method. With this desired result, the consumer will trade with the winner provider at the optimal price.

VII. REFERENCE

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