Optimized Operation Framework of Distributed Thermal Storage Aggregators in the Electricity Spot Market

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***Abstract*—For distributed solid electricity thermal storage aggregators (DSETSA), the uncertainty of the marginal clearing price may lead to the problem of multi-bidding scenarios (including successful, part successful and failed biddings) in the electricity spot market. Moreover, the marginal operating cost affecting the bidding revenue in the spot market is not considered in the existing methods, which challenge the bidding of the aggregators. To address the challenge, this paper proposes an optimized operation framework for DSETSA. First, based on the incomplete information characteristics of the spot market, an optimal bidding model which incorporates marginal operating cost constraints for DSETSA under multi-bidding scenarios is proposed to increase the operation profit. Second, the DSETSA's multi-bidding scenario problem induced by the uncertainty of the marginal clearing price in the electricity spot market is cast into a probability distribution representation using the Bayesian incomplete information theory to increase the chances of winning bids. Finally, framework establishes the relationship between the bidding price, electricity demand and public traded electricity in the spot market. The effectiveness of the proposed framework is demonstrated through simulations.**

***Index Terms*—spot market, thermal storage aggregators, distributed solid electricity thermal storage, bidding strategy**

I. Introduction

WITH the participation of large companies and electricity retailers in the spot market, the role and share of spot trading in the electricity market are becoming increasingly significant. Since the individual customers are not able to participate in the market, aggregators can gather small-scale electricity customers to participate in the electricity market to make profits [1], [2]. However, in many studies, aggregators use contracted generation without participating in the spot market [3]-[5]. In this case, the bid of the aggregator affects its profit. Therefore, it is urgent to figure out solutions involving aggregators in the spot market and address their bidding issues.

The electricity spot market determines the trade center in each bidding period and discloses the total trading power information to all aggregators. DSETSA is required to provide electricity and price to the trade center in the electricity spot market. The aggregator determines the transaction priority from high to low according to the bidding price until the electricity in the spot market satisfies the aggregator's bidding demand for electricity, and then clears it uniformly with the marginal clearing price.

From the perspective of aggregators participating in power market modeling, the traditional energy storage aggregators mainly utilize batteries to store and release electricity [6], [7], which is a common way to participate in the electricity market [8]-[10]. These references do not consider the impact of customer heat demands on the marginal operating costs of aggregators [11]. Distributed solid electric thermal storage (DSETS) can convert electricity as thermal energy and provide it to customers to satisfy their heat demands [12]-[14]. Moreover, customers have limited capability of managing the storage devices, but aggregators can manage the storage devices as intermediaries [15]. [16] and [17] investigate energy storage transaction models between aggregators and customers. The challenge caused by the uncertainty of spot electricity price is not considered when the aggregator participates in the spot electricity market. Once the aggregator's bid falls below the marginal clearing price, it will lead to bidding failure, and the aggregator will bear the risk of higher operating costs. It motivates us to propose an operation optimized model for distributed solid electricity thermal storage aggregators (DSETSA).

Existing ways of participating in the electricity market include customers' demand response and optimal bidding strategy [18]. For demand response, [19] studies the model of aggregators' participation in the electricity market with the presence of demand elasticity and gives the bidding curves. [20] investigates the impact of bidding on other flexible aggregators on the demand side considering the demand

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response and proposes the optimal bidding strategy. [19] and [20] do not consider the impact of the uncertainty of electricity spot market price on the bidding of aggregators.

From the perspective of the bidding strategy of aggregators participating in the electricity spot market, [21] develops a two-tier optimization model based on demand response, which considers customers' actual load demand and aggregators' profits through a hierarchical optimized method. The upper layer is to maximize the revenue of the aggregator, and the lower layer is based on customers' electricity loads. [22] studies the bidding strategy based on data mining technology of customer historical consumption records bidding strategy. However, [22] does not consider the uncertainty of the marginal clearing price of the electricity spot market, which may cause bidding failure of aggregators.

Ref. [23] optimizes aggregators' participation in the electricity market and the bidding issue by utilizing a risk-constrained mean-variance approach. Further, [24] works on the aggregators' bidding issue by managing energy storage devices, and the model can be described as a mixed-integer linear programming problem with the optimized objective of minimum operational cost. The models in [23] and [24] do not consider the impact of the incomplete information game in the electricity spot market and the game among aggregators on the bidding results.

Ref. [25]-[27] study multiple aggregators' bidding strategies in the electricity market based on game theory. For instance, [25] and [26] analyze the relationship between aggregators and electricity consumers based on a game-theoretic two-tier optimization model, and the relationship between the aggregators and consumers is formulated as a Stackelberg game. However, [25] ignores the fact that the bidding information for multiple aggregators is not disclosed, which results in an incomplete information game. [26] develops a relationship between aggregators and electricity storage systems, which can demonstrate long-term cooperation between aggregators and energy storage systems using the Nash bargaining theory. [27] studies the electricity consumption behavior. The customer demand response is fitted by the least-squares method involving aggregators in the bidding in the electricity market according to its demand response curve. However, the uncertainty of the marginal clearing price caused by the bidding game among aggregators, the bidding based on the directly predicted customer load and the marginal clearing price are the challenges to increase the operating revenue of aggregators. In summary, the factors that currently hindering aggregators from participating in the promotion of the electricity spot market are the marginal operating costs of the aggregators, the uncertainty of the marginal clearing price, and the problem of multi-bidding scenarios (including successful, part successful and failed biddings). The proposed approach in this paper differs from [27] in 1) The proposed DSETSA model can supply the heat load of customers. 2) The DSETSA bidding in the spot market is analyzed based on its marginal operating cost.

To tackle the challenge of DSETSA bidding in spot market, an optimized operation model of DSETSA in the spot market is proposed. Compared with the existing methods, the contributions of this papers can be summarized as follows:

- The proposed DSETSA's optimized operation framework gathers the electric demand and heat demand of customers to participate in the spot market model with multi-bidding scenarios, which can effectively enhance the revenue of the aggregators.
- Combined with the revenue model and marginal operating costs of DSETSA in multi-bidding scenarios, an optimal bidding strategy for DSETSA in the electricity spot market is developed based on Bayesian incomplete information theory to increase the chances of winning the bidding.
- The relationship among the aggregator's bidding price, electricity demand and public traded electricity in the spot market is developed, which can be used by the aggregators to enhance the economic revenue.

II. PROBLEM DESCRIPTION

Aggregators, instead of customers, can participate in the electricity market by gathering their electric and heat demand and signing demand response contracts with them. However, the existing methods of using energy storage aggregators to participate in the electricity market are based on medium and long-term contracts [28], which is not able to maximize the revenue of the aggregators. The spot market is a part of the electricity market that facilitates resource allocation. This is the driving force to explore an optimal operation strategy for DSETSA and develop an optimal bidding method for DSETSA to participate in the spot market. DSETSA's participation in the electricity spot market may face the following problems: ***1)*** The impact of uncertainty of marginal clearing price in the electricity spot market on DSETSA's opportunities of winning the bidding. ***2)*** The impact of DSETSA' s game in the electricity spot market on DSETSA' s bidding to maximize revenue.

Fig. 1 shows the structure of the DSETSA gathering customers to participate in the spot market. The customers' heat load demand is supplied by the DSETS. The electric load demand is supplied by the electricity purchased by DSETSA from the spot market and the electric energy storage (EES). DSETSA can conduct demand response by signing contracts with customers to control the use time of shiftable loads, and customers will receive subsidies from the trade center. The DSETSA is the central hub of the model. Firstly, it aggregates the customer's electric and heat demand and uses the demand data as the basis to offer demand in the spot market and participate in the bidding. Secondly, the DSETSA manages DSETS and EES to charge or discharge energy at any time. Thirdly, it collects and classifies the customer loads into base loads and shiftable loads.

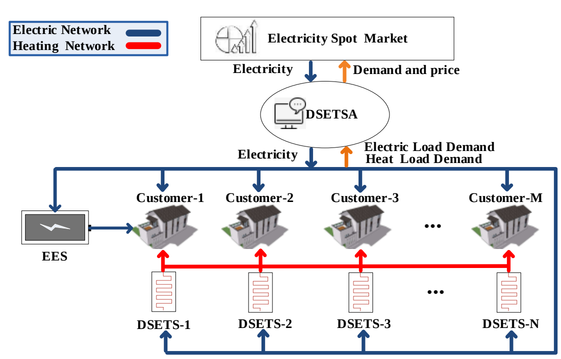

Fig. 1. The electric and heating networks in the spot market.

III. OPTIMIZED MODEL OF DISTRIBUTED THERMAL STORAGE AGGREGATOR

A. Power Balance Constraint.

The electricity purchased by the DSETSA is assumed to satisfy the electric and heat demand of the customers. In this model, the customer's electric demand is supplied by DSETSA, EES, and the grid. The heat demand is provided by DSETS. Therefore, the electric power to be purchased includes the stored power in the battery-based EES, the consumed power of DSETS and the power sold to customers. The electric power balance of DSETSA is expressed by (1).

$$P^{E}_{Pur,t} = P^{E}_{Load,t} + P^{E+}_{DSETS,t} + P^{E+}_{EES,t},\ t \in T \tag{1}$$

where $P^{E}_{Pur,t}$ is the total power purchased by the DSETSA from the electricity spot market, $P^{E}_{Load,t}$ is the customer's electric demand, $P^{E+}_{EES,t}$ is the electric demand of DSETSA for battery charging, $P^{E+}_{DSETS,t}$ is the electric demand for supplying DSETS, t is the index of the hours in a day (e.g. t = 1 is the 1st hour, t = 24 is the 24th hour), and T is the complete set of t.

The consumers' heat loads are provided by DSETS. The heat power balance is given by (2).

$$H_{Load,t} = \eta^{H-}_{DSETS} \cdot H^{-}_{DSETS,t},\ t \in T \tag{2}$$

where $H_{Load,t}$ is the heat demand of the customer, $H^{-}_{DSETS,t}$ is the discharge heat power of DSETS, and η^{H-}_{DSETS} is the heat power discharge coefficient.

The electricity sold by the DSETSA and provided by the power output of EES supply the customer's electric load. The electric power balance of DSETSA is shown in (3).

$$P^{E}_{Load,t} = P^{E}_{Sell,t} + \eta^{E-}_{EES} \cdot P^{E-}_{EES,t},\ t \in T \tag{3}$$

where $P^{E}_{Sell,t}$ is the electric power sold by the DSETSA to the customers, η^{E-}_{EES} is the EES discharge coefficient, and $P^{E-}_{EES,t}$ is the discharge power of EES.

The profit earned by DSETSA from the sale of electricity to customers can be expressed as (4).

$$F^{E}_{S} = \sum_{t=1}^{T} \tau^{E}_{t} P^{E}_{Sell,t},\ t \in T \tag{4}$$

where F^{E}_{S} is the revenue of DSETSA obtained by selling electricity to customers, and τ^{E}_{t} is the electricity price at time t.

B. Distributed Solid Electric Thermal Storage Model.

DSETS's thermal energy is stored in sets of magnesium bricks, and is released mainly through thermal convection, radiation and conduction. The conversion of electricity to heat power in DSETS will result in power losses, and the conversion constraint of electric power to heat power is given by (5). The energy balance of DSETS is expressed by (6).

$$H^{+}_{DSETS,t} = \eta^{E+}_{DSETS} \cdot P^{E+}_{DSETS,t},\ t \in T \tag{5}$$

$$E^{H}_{DSETS,t+1} = E^{H}_{DSETS,t} + (\eta^{E+}_{DSETS} \cdot P^{E+}_{DSETS,t} - H^{-}_{DSETS,t}) \cdot \Delta t,\ t \in T \tag{6}$$

where $H^{+}_{DSETS,t}$ is heat charging power of DSETS, η^{E+}_{DSETS} is the conversion efficiency, $P^{E+}_{DSETS,t}$ is the charging power of DSETS, $E^{H}_{DSETS,t}$ is the stored heat energy of DESTS, $H^{-}_{DSETS,t}$ is the discharging heat power, Δt is the charging or discharging time.

The charging and discharging power and capacity of the DSETS are limited by (7).

$$\begin{cases} P^{E+}_{DSETS,\min} \le P^{E}_{DSETS,t} \le P^{E+}_{DSETS,\max} \\ H^{-}_{DSETS\min} \le H^{-}_{DSETS,t} \le H^{-}_{DSETS,\max} \\ E^{H}_{DSETS,\min} \le E^{H}_{DSETS,t} \le E^{H}_{DSETS,\max} \end{cases} \tag{7}$$

where $P^{E+}_{DSETS,\max}$ and $P^{E+}_{DSETS,\min}$ are the maximum and minimum charging power of DSETS, $H^{-}_{DSETS,\max}$ and $H^{-}_{DSETS\min}$ are the maximum and minimum heat discharging power, $E^{H}_{DSETS,\max}$ and $E^{H}_{DSETS,\min}$ are the maximum and minimum stored heat energy.

The final thermal energy in DSETS needs to be consistent with the initial, as shown in (8).

$$\begin{cases} E^{H}_{DSETS,1} = E^{H}_{DSETS,24} + \eta^{E+}_{DSETS} \cdot P^{E+}_{DSETS,t} \cdot \Delta t \\ E^{H}_{DSETS,1} = E^{H}_{DSETS,24} - P^{E-}_{DSETS,24} \cdot \Delta t / \eta^{E-}_{DESTS} \end{cases} \tag{8}$$

DSETSA's profit from supplying customers' heat loads can be calculated by (9).

$$F^{H}_{H,t} = \tau^{H}_{t} P^{H}_{Load,t},\ t \in T \tag{9}$$

where F^{H}_{H} is the daily profit from heat sales of DSETSA, and τ^{H}_{t} is the heat price at t.

C. Electrical Energy Storage Model.

EES can be charged during periods of low spot electricity prices and discharged during periods of high electricity prices to supply the electric load demand to maximize DSETSA's revenue. The charging and discharging constraints of EES are constrained by (10).

$$\begin{cases} P^{E+}_{EES,\min} \le P^{E+}_{EES,t} \le \alpha^{+}(t) P^{E+}_{EES,\max},\ t \in T \\ P^{E-}_{EES,\min} \le P^{E-}_{EES,t} \le \alpha^{-}(t) P^{E-}_{EES,\max},\ t \in T \\ \alpha^{+}_{EES}(t) + \alpha^{-}_{EES}(t) \le 1 \quad ,\ t \in T \end{cases} \tag{10}$$

where $P^{E+}_{EES,\min}$ is the minimum charging power of EES, $P^{E+}_{EES,\max}$ is the maximum charging power, $P^{E+}_{EES,t}$ is the charging power at t, $P^{E-}_{EES,\min}$ is the minimum discharging power, $P^{E-}_{EES,\max}$ is the maximum discharging power, $P^{E-}_{EES,t}$ is the discharging power, $\alpha^{+}_{EES}(t)$ is the binary variable indicating charging status, and $\alpha^{-}_{EES}(t)$ is the binary variable indicating discharging status.

The energy constraints of EES are described in (11)-(13).

$$E^{E}_{EES,t+1} = \begin{cases} E^{E}_{EES,t} + \eta^{E+}_{EES} \cdot P^{E+}_{EES,t} \cdot \Delta t\ ,\alpha^{+}_{EES}(t) = 1 \\ E^{E}_{EES,t} - P^{E-}_{EES,t} \cdot \Delta t / \eta^{E-}_{EES}\ ,\alpha^{-}_{EES}(t) = 1 \end{cases} \tag{11}$$

$$E^{E}_{EES,\min} \le E^{E}_{EES,t} \le E^{E}_{EES,\max},\ t \in T \tag{12}$$

$$\begin{cases} E^{E}_{EES,1} = E^{E}_{EES,24} + \eta^{E+}_{EES} \cdot P^{E+}_{EES,t} \cdot \Delta t\ ,\quad \alpha^{+}_{EES}(t) = 1 \\ E^{E}_{EES,1} = E^{E}_{EES,24} - P^{E-}_{EES,t} \cdot \Delta t / \eta^{E-}_{EES},\quad \alpha^{-}_{EES}(t) = 1 \end{cases} \tag{13}$$

where $E^{E}_{EES,t}$ is the capacity of EES at t, η^{E+}_{EES} is the charging efficiency, η^{E-}_{EES} is the discharging efficiency, $E^{E}_{EES,\min}$ is the maximum stored energy, and $E^{E}_{EES,\max}$ is the minimum stored energy. $E^{E}_{EES,1}$ is the capacity of EES at the 1st hour, and $E^{E}_{EES,24}$ is the capacity of EES at the 24th hour.

D. DSETSA's Demand Response Model.

DSETSA will make a contract with customers to remove customers' shiftable loads from the peak load period to other periods. The electric load includes the base load and the shiftable load, where the shiftable load is the part that can be dispatched by the DSETSA. The shiftable load capacity is calculated by (14).

$$P_{SL,t}^{E}=P_{SLB,t}^{E}+v_{i}(t)\cdot P_{SLC,t}^{E}-v_{o}(t)\cdot P_{SLC,t}^{E},\ t\in T \tag{14}$$

where $P_{SL,t}^{E}$ is the shiftable load power at t, $P_{SLB,t}^{E}$ is the baseline value of the shiftable load power, $P_{SLC,t}^{E}$ is the customers' shiftable load power, $v_{i}(t)$ is the state variable indicating the cut-in shiftable load, and $v_{o}(t)$ is the state variable indicating the cut-out shiftable load.

To satisfy the customer's electricity demand, the constant load consumed by the customers during the day and the shiftable load to be within the acceptable range [27]. The shiftable load balance is expressed by (15), and the maximum cut-out time is limited by (16).

$$\sum_{t=1}^{T}P_{SL,t}^{E}=\sum_{t=1}^{T}P_{SLB,t}^{E},\ t\in T \tag{15}$$

$$\sum_{t=1}^{T}v_{o}(t)\le T_{\max},\ t\in T \tag{16}$$

where $T_{\max}$ is the maximum cut-out time.

The scheduling subsidy of the DSETSA is provided by the trade center and then distributed to the customers who completed demand response through the DSETSA. The subsidy for DSETSA and customers are calculated by (17) and (18).

$$F_{D}^{E}=\sum_{t=1}^{T}F_{D,t}^{E}=\sum_{t=1}^{T}\pi_{D,t}^{E}P_{SL,t}^{E},\ t\in T \tag{17}$$

$$F_{C}^{E}=\sum_{t=1}^{T}\pi_{C,t}^{E}\cdot F_{D,t}^{E},\ t\in T \tag{18}$$

where $F_{D,t}^{E}$ is the subsidy price at t, $\pi_{D,t}^{E}$ is the subsidy coefficient of the DSETSA at t, which is issued to the DSETSA by the trade center, $\pi_{C,t}^{E}$ is the subsidy coefficient of the customers at t, $F_{C,t}^{E}$ is the subsidy price received by the customers, F_{C}^{E} is the daily subsidy for customers.

E. DSETSA's Revenue Objective Function.

The DSETSA's expenses include the cost of purchasing electricity from the spot market, and the cost of subsidies from the DSETSA for customers. Adding (4), (9), (17), and (18), the objective function can be established by (19).

$$\begin{aligned}&MAX\ (F)=F_{S}^{E}-F_{B}^{E}+F_{H}^{H}+F_{D}^{E}-F_{C}^{E}\\&=\sum_{t=1}^{T}\tau_{t}^{E}P_{Sell,t}^{E}-\sum_{t=1}^{T}\tau_{t}^{S}P_{Pur,t}^{E}+\sum_{t=1}^{T}\tau_{t}^{H}H_{Load,t}+\sum_{t=1}^{T}(\pi_{D,t}^{E}-\pi_{C,t}^{E})F_{D,t}^{E}\end{aligned} \tag{19}$$

where F is the DSETSA's revenue function, F_{S}^{E} is the revenue of selling electricity to customers, F_{B}^{E} is the total cost of purchasing electricity from the spot market, F_{H}^{H} is the revenue received by the DSETSA for providing heat demand, F_{D}^{E} is the subsidy received by the DSETSA, F_{C}^{E} is the subsidy given by the DSETSA to customers participating in demand response, and τ^{s} is the price of electricity purchased by the DSETSA.

III. Bayesian Incomplete Information Game based Aggregator Offering Strategy

The incomplete information characteristics in the electricity spot market may lead to the uncertainty of the marginal clearing price, which causes the multi-bidding scenario problem and the bidding failure of DSETSA. The Bayesian incomplete information game theory can transform the uncertainty into probability to solve the challenges caused by incomplete information. To further enhance the revenue of DSETSA's participation in the electricity spot market, a Bayesian incomplete game model combining marginal operating costs and multi-bidding scenarios for DSETSA is proposed, which transforms the multi-bidding scenarios results into a new probability distribution based on the original model to enhance the opportunities of winning the bidding.

The characteristic of the spot market is that the amount of electricity traded is determined in each bidding period, and the total transaction electricity information is disclosed to all aggregators. The DSETSA is required to offer the amount and price of electricity to the trade center in the spot market, which is based on the customers' load demand. Fig. 2 shows the marginal electricity price clearing process in the spot market. Each aggregator will make a collective bidding at the trading time, and the trade center processes the bid to match the supply and demand in the market.

Its transaction process can be described as: *Seller a* and *Seller b* bid lower than *Seller c* and have priority to enter the pending transaction group. *Seller c* is at the margin of the transaction due to its higher price. At this time, the clearing price of all generators is settled according to the offer of *Seller c*. Similarly, the transaction method on the demand side, transactions are conducted from high to low, and the marginal electricity price is uniformly settled. *Aggregator D* is not successfully traded in the spot market because the bid is lower than the price of the marginal unit *Seller c*. The point E is the marginal clearing price and the total clearing power. The marginal clearing price is generally settled based on the bidding price of the marginal unit.

In Fig. 2, take load A as an example, S1 represents the cost of purchasing electricity when the bidding price of DSETSA in the electricity spot market is higher than the marginal clearing price. S2 represents the net profit of DSETSA providing the customer's load demands. L1 refers to the bidding range of electricity storage aggregators participating in the spot electricity market. L2 represents the bidding range based on Bayesian incomplete information game method proposed in this paper. The horizontal axis of load A represents the offered electric load demands in the electricity spot market, while the vertical axis represents the bidding price. The marginal clearing price fluctuates between the minimum and maximum bidding values. If the bidding price is lower than the marginal clearing

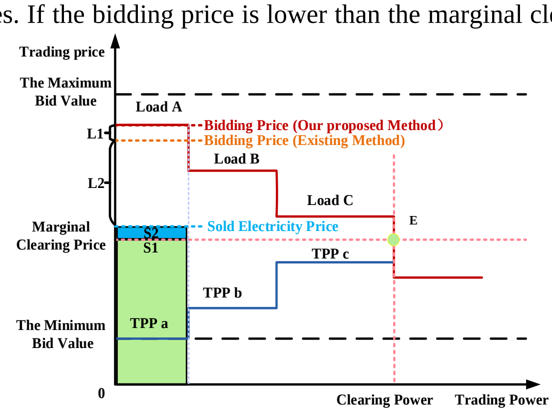

Fig. 2. The marginal electricity price clearing process in the spot market.

price, DSETSA will not profit in the electricity spot market. To increase the chances of winning bids for DSETSA, we consider its marginal operating costs and utilize DSETS to provide heating loads for customers, which increases the bidding price for DSETS to participate in the electricity spot market.

From the perspective of the DSETSA, the multi-bidding scenarios problem can be analyzed as: ***1)*** The DSETSA cannot succeed in the bidding, and thus it will not participate in the settlement of the transaction in the spot market. ***2)*** The DSETSA is fully or partially successful in the spot market, and it will be settled at the spot market marginal clearing price for the bidding period.

To maximize the DSETSA's revenue, we develop a bidding model based on the DSETSA's marginal operating cost and the Cournot model in the Bayesian incomplete information game. The marginal operating cost of DSETSA will be a bidding constraint. When the marginal clearing price in the spot market is higher than the marginal cost, the DSETSA will be profitable. The marginal operating cost of the DSETSA consists of the cost of the purchased power, the cost of energy storage losses, and energy storage device discharge losses. The marginal operating cost of DSETSA can be calculated by (20).

$$M_t^E = (\tau^n(1-\eta_{DSETS}^{H-}) \cdot P_{DSETS,t}^{E-} + (1-\eta_{EES}^{E-})P_{EES,t}^{E-}),\ t \in T \quad (20)$$

where M_t^E is the DSETSA's marginal operating cost, and τ^n is the net revenue coefficient of the heat load supplied by DSETS, which can be obtained by the difference between the heat load provided by DSETSA and the heat grid.

The bidding of DSETSA in the spot market is independent. DSETSA cannot obtain the exact bidding information of their competitors and they are transparent only in the trade center. To tackle the challenge of DSETSA's bidding in the spot market, this paper proposes a bidding model for DSETSA based on game theory combined with marginal operating costs. The following assumptions are made in this model: ***a)*** There are *n* aggregators participating in the spot market at the same time. ***b)*** Each aggregator is independent. ***c)*** The other *n*-1 aggregators are equivalent to one aggregator *j*, and the aggregator *j* is in the uniform distribution of the bidding space [29]. ***d)*** Each aggregator's bidding strategy is to maximize its own revenue. The bidding behavior is rational, and there is no malicious bidding behavior, [30].

According to the game theory of incomplete information and the trade rules of the spot market, the game model can be expressed as: the spot market considers the balance between supply and demand to prevent malicious bidding. The trade center sets the maximum and minimum bidding price in the spot market, and the action space A_i can be expressed by (21).

$$A_{i,t}^E = \left[R_{l,t}^E, R_{h,t}^E\right],\ t \in T \quad (21)$$

where $R_{l,t}^E$ is the minimum bidding price of the spot market, and $R_{h,t}^E$ is the maximum bidding price.

Based on the above assumption ***c)***, aggregators' bidding in a uniform distribution is limited by (22).

$$M_{i,t}^E = \left[M_{l,t}^E, M_{h,t}^E\right],\ t \in T \quad (22)$$

where $M_{l,t}^E$ and $M_{h,t}^E$ are the minimum and maximum marginal operating costs of DSETSA at *t*.

DSETSA bids at the marginal operating cost, and the bidding process can be described in (23).

TABLE I
POSSIBLE BIDDING SCENARIOS

	$B_{i,t}^E$	$B_{j,t}^E$	$B_{k,t}^E$	Prices ($)
$B_{i,t}^E$	×	$B_{i,t}^E > B_{j,t}^E > B_{k,t}^E$	$B_{i,t}^E > B_{k,t}^E > B_{j,t}^E$	$B_{k,t}^E$
$B_{j,t}^E$	$B_{j,t}^E > B_{i,t}^E > B_{k,t}^E$	×	$B_{j,t}^E > B_{k,t}^E > B_{i,t}^E$	$B_{k,t}^E$
$B_{k,t}^E$	$B_{k,t}^E > B_{i,t}^E > B_{j,t}^E$	$B_{k,t}^E > B_{j,t}^E > B_{i,t}^E$	×	0

$$\begin{cases} B_{i,t}^E = \omega_{i,t} M_{i,t}^E + \psi_{i,t},\ t \in T \\ \omega_{i,t} M_{i,t}^E + \psi_{i,t} \le M_i^t,\ t \in T \\ 0 < \omega_{i,t} \le 1,\ t \in T \end{cases} \quad (23)$$

where $B_{i,t}^E$ is the DSETSA's bidding price, $\omega_{i,t}$ and $\psi_{i,t}$ are the coefficients that make the bidding price lower than the DSETSA's operating cost and maximize the DSETSA's revenue. All possible scenarios of bidding are shown in Table I. where $B_{i,t}^E$ is the bidding result of the aggregator *i*, $B_{j,t}^E$ is the bidding result of the aggregator *j*, and $B_{k,t}^E$ is the marginal clearing price. It is impossible for all aggregators to bid in the same price. *PF*(*i*) is the bidding profit function of aggregator *i* in the multi-bidding scenarios which can be expressed by (24) and (25).

$$PF(i) = \begin{cases} (M_{i,t}^E - B_{k,t}^E) \cdot \upsilon Q_t^E & , B_{i,t}^E > B_{j,t}^E > B_{k,t}^E \\ 0 & , B_{i,t}^E > B_{k,t}^E > B_{j,t}^E \\ (M_{i,t}^E - B_{k,t}^E) \cdot \upsilon \zeta Q_t^E & , B_{j,t}^E > B_{i,t}^E > B_{k,t}^E \\ 0 & , B_{j,t}^E > B_{k,t}^E > B_{i,t}^E \\ 0 & , B_{k,t}^E > B_{i,t}^E > B_{j,t}^E \\ 0 & , B_{k,t}^E > B_{j,t}^E > B_{i,t}^E \end{cases} \quad (24)$$

$$\begin{gathered} 0 < \zeta < 1 \\ 0 < \upsilon \le 1 \end{gathered} \quad (25)$$

where Q_t^E is the total electricity traded in the spot market, In (1), $P_{Pur,t}^E$ is the amount of load purchased by aggregators *i* in the spot market, υ is the share of aggregator's electric power demand in total spot market electricity traded, ζ is the share of the spot market when part of the demand for the aggregators is satisfied. Bringing (24) into the Bayesian Nash equilibrium, the optimal bidding model can be calculated by (26).

$$\begin{aligned} \max(B_{i,t}^E) = {} & (M_{i,t}^E - B_{i,t}^E) \cdot \zeta P_{Pur,t}^E \cdot \mathrm{P}\left\{B_{i,t}^E < \omega_{j,t} M_{j,t}^E + \psi_{j,t}\right\} \\ & + (M_{i,t}^E - B_{i,t}^E) \cdot \upsilon Q_t^E \cdot \mathrm{P}\left\{B_{i,t}^E > \omega_{j,t} M_{j,t}^E + \psi_{j,t}\right\} \end{aligned} \quad (26)$$

Substituting (20) and (23) into (26), DSETSA's bidding price can be obtained by (27).

$$\begin{aligned} \max(B_{i,t}^E) = {} & (M_{i,t}^E - B_{i,t}^E) \cdot \zeta P_{Pur,t}^E \cdot \frac{\omega_{j,t} M_{h,t}^E + \psi_{j,t} - B_{i,t}^E}{\omega_{j,t}(M_{h,t}^E - M_{l,t}^E)} \\ & + (M_{i,t}^E - B_{i,t}^E) \cdot \upsilon Q_t^E \cdot \frac{B_{i,t}^E - \omega_{j,t} M_{l,t}^E - \psi_{j,t}}{\omega_{j,t}(M_{h,t}^E - M_{l,t}^E)} \end{aligned} \quad (27)$$

Eq. (27) is a quadratic function. Making its first-order derivative equal to 0 will give (28).

$$B_{i,t}^E = \frac{1}{2} M_{i,t}^E + \frac{\omega_{j,t} M_{l,t}^E - \zeta \omega_{j,t} M_{h,t}^E + (1-\zeta)\psi_{j,t}}{2\omega_{j,t}(1-\zeta)(M_{h,t}^E - M_{l,t}^E)} \quad (28)$$

The bidding of aggregator *i* can be obtained using (28). Substituting (21)-(24) into (28), the parameters $\omega_{i,t}$ and $\psi_{i,t}$ can be described in (29) and (30).

$$\omega_{i,t} = \frac{1}{2} \quad (29)$$

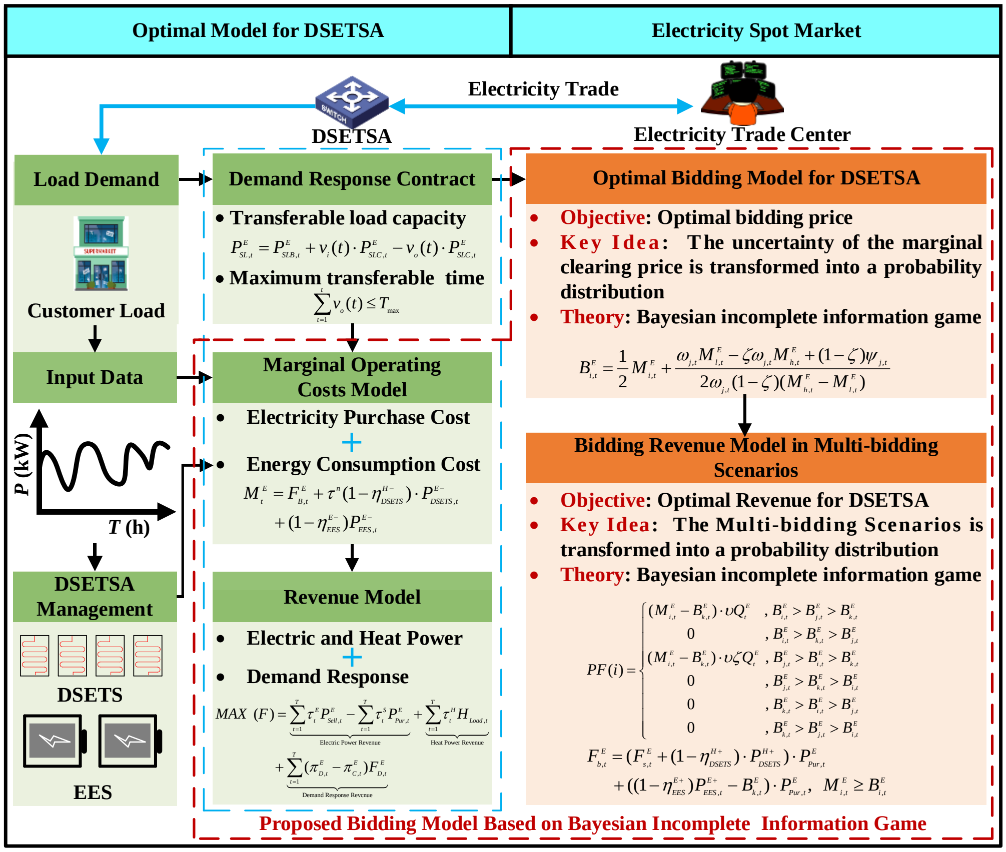

Fig. 3. The optimized operation framework of DSETSA in spot market.

$$\psi_{i,t} = \frac{(M_{l,t}^{E} - \zeta M_{h,t}^{E})}{2(1-\zeta)} \tag{30}$$

Substituting (27) and (28) into (21), the biding of DSETSA can be obtained by (31).

$$\begin{aligned} B_{i,t}^{E} &= \frac{1}{2} M_{i,t}^{E} + \frac{(M_{l,t}^{E} - \zeta M_{h,t}^{E})}{2(1-\zeta)}, \ t \in T \\ &= \frac{1}{2} \tau^{n} ((1-\eta_{DSETS}^{H+}) \cdot P_{DSETS,t}^{E+} + (1-\eta_{EES}^{E+}) P_{EES,t}^{E+} + \frac{(M_{l,t}^{E} - \zeta M_{h,t}^{E})}{(1-\zeta)}), \ t \in T \end{aligned} \tag{31}$$

In (31), a relationship between the bidding price, the marginal operating cost and the total traded electricity in the spot market is established. Since the spot market makes the total traded electricity Q_t^E public, and the aggregator's electric demand $P_{Pur,t}^{E}$ and ζ will be definite values, then the DSETSA can use (31) to bid in the spot market bidding. The transaction price is the marginal clearing price unified clearing. Therefore, the DSETSA is with the marginal clearing price when purchasing electricity, and its final purchase price can be expressed by (32) and (33).

$$B_{k,t}^{E} = B_{i,t}^{E}, \ t \in T \tag{32}$$

$$F_{B,t}^{E} = B_{k,t}^{E} \cdot P_{Pur,t}^{E}, \ t \in T \tag{33}$$

The constraint in (23) is added to the DSETSA bid to ensure that DSETSA has the maximum revenue from spot market. Finally, the revenue of DSETSA through the spot market bidding for electricity purchases can be given in (34).

$$F_{b,t}^{E} = \begin{cases} (F_{s,t}^{E} + \tau^{n}(1-\eta_{DSETS}^{H-}) \cdot P_{DSETS}^{H-} + (1-\eta_{EES}^{E-}) P_{EES,t}^{E-} - B_{k,t}^{E}) \cdot P_{Pur,t}^{E}, & M_{i,t}^{E} \geq B_{i,t}^{E} \\ 0, & M_{i,t}^{E} < B_{i,t}^{E} \end{cases} \tag{34}$$

The maximum revenue model of DSETSA is obtained by (19) and the bidding constraint of (34). Fig. 3 shows the optimized operation framework of DSETSA in electricity spot market.

IV. Case Study and Analysis

To verify the effectiveness of the proposed method, this paper analyzes the actual electricity spot market of a demonstration region in Guangdong province of China as an example. Simulations are carried out in MATLAB2018a using the solver GUROBI (9.5.0). The simulation parameters are set according to [14], [17], [27], [28], as shown in Table II.

It should be mentioned that the calculation is based on the electricity price in China: τ^{s}(\$/kWh) $= B_{k,t}^{E}$(\$/kWh) $=$ [0.033 0.032 0.031 0.030 0.028 0.022 0.021 0.021 0.032 0.035 0.038 0.041 0.033 0.036 0.038 0.039 0.039 0.037 0.037 0.036 0.036 0.034 0.034 0.032] [31]. The parameters η_{DSETS}^{E+}, η_{DSETS}^{H-}, $P_{DSETS,\min}^{E+}$, $P_{DSETS,\max}^{E+}$, $H_{DSETS\min}^{-}$, $H_{DSETS,\max}^{-}$, $E_{DSETS,\min}^{H}$ and $E_{DSETS,\max}^{H}$ are from [14]. The parameters $P_{EES,\min}^{E-}$, $P_{EES,\max}^{E-}$, $E_{EES,\min}^{E}$, $E_{EES,\max}^{E}$, η_{EES}^{E+}, η_{EES}^{E-}, $\pi_{C,t}^{E}$, $P_{EES,\min}^{E+}$, $P_{EES,\max}^{E+}$, $\pi_{D,t}^{E}$, τ_t^{H}, τ^{n} and τ_t^{E} are from [27].

TABLE II
Simulation Parameters

Items	Values	Items	Values	Items	Values
η_{DSETS}^{E+}	0.9	η_{DSETS}^{H-}	0.9	$P_{EES,\min}^{E-}$	0
$P_{DSETS,\min}^{E+}$	0	$P_{DSETS,\max}^{E+}$	300 kW	$P_{EES,\max}^{E-}$	40 kW
$H_{DSETS\min}^{-}$	0	$H_{DSETS,\max}^{-}$	300 kW	$E_{EES,\min}^{E}$	10 kW
$E_{DSETS,\min}^{H}$	100 kW	$E_{DSETS,\max}^{H}$	300 kW	$E_{EES,\max}^{E}$	120 kW
η_{EES}^{E+}	0.85	η_{EES}^{E-}	0.85	$\pi_{C,t}^{E}$	\$ 0.06
$P_{EES,\min}^{E+}$	0	$P_{EES,\max}^{E+}$	30 kW	$\pi_{D,t}^{E}$	\$ 0.09
τ_t^{H}	0.089	τ^{n}	\$ 0.003	τ_t^{E}	\$ 0.091

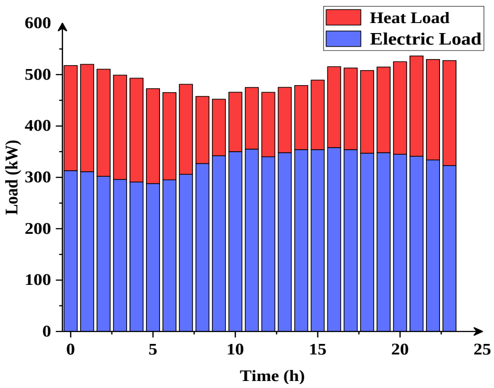

Fig. 4. The electric and heat load of the customers.

A. Effectiveness of the Bidding Strategy of DSETSA Participating in the Spot Market

Three strategies have been simulated for verifying the effectiveness of the bidding strategy proposed in this paper.

Strategy I: DSETSA participates in spot market bidding according to historical average transaction data.

Strategy II: DSETSA uses the demand response to participate in spot market bidding. The subsidized price received by DSETSA is based on the subsidy mechanism. The Response Rate (RR) is the customer's actual response divided by the signed contract. The subsidy coefficients are 0 (RR < 50%), 0.2 (50% < RR< 60%), 0.6 (60% < RR < 80%), 0.8 (80% < RR < 90%), 1 (90% < RR< 120%), the valley filling period is $ 0.051, and the peak shaving period is $0.296.

Strategy III: The bidding is based on the proposed Bayesian incomplete game theory and marginal operating cost constraints.

Fig. 5 shows the comparisons of the bidding performance of the three strategies.

In strategy I: The DSETSA bids successfully during 5-9 h and 18-23 h. DSETSA can arbitrage by selling electricity to customers during the successful bidding period. The bidding failures are caused by the calculation method based on the average of historical data cannot adapt to the rapid changes of the electricity prices in the spot market. In strategy II: The bidding is successful between 8-23 h. DSETSA can arbitrage by selling electricity to customers during the successful bidding period. The bidding fails during 0-7 h. The reason is that the demand response theory is used to obtain the customers' load based on the historical data baseline method, which will affect the aggregator's judgment on the bidding price to errors. The bidding prices of the aggregator with strategy II are calculated

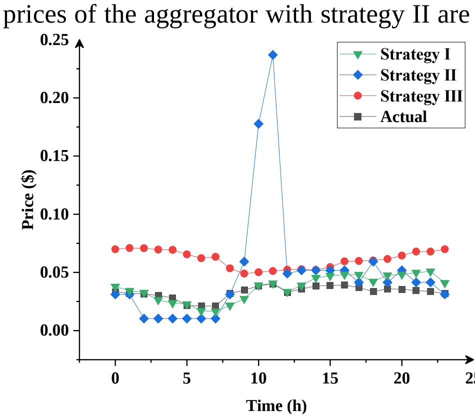

Fig. 5. The bidding results under three strategies.

TABLE III
COMPARISONS OF BIDDING STRATEGIES AND CALCULATION TIME OF DIFFERENT BIDDING STRATEGIES

Bid strategies	Aggregator revenue ($)	Computing time (s)
Strategy I	423.49	1.79
Strategy II	410.81	1.54
Strategy III	571.99	1.23

by a polynomial fitting method [27]. As the load of the power grid is higher during the period of 10-11 h, the power grid sets a greater demand response price subsidy to attract customers to transfer the consumption of loads. Therefore, aggregators will increase their bidding prices, and there is a price spike for strategy II. In strategy III: The bidding is successful during 0-24 h. The DSETSA can carry out arbitrage by supplying both electricity and heat to customers. The settlement price is the marginal clearing price in the spot market. The revenue of DSETSA in the three bidding strategies is shown in Table III.

DSETSA's bidding strategy for participating in spot market transactions can affect its revenue. According to the bidding strategies I and II, the DSETSA cannot obtain maximum profits. Compared with strategies I and II, the revenue of DSETSA with Strategy III is increased by $ 148.5 (34.91 %) and $ 161.18 (39.24 %). Compared with the two bidding models, the opportunities of DSETSA bidding success of the proposed model are increased by 29.17 % and 25 % respectively. For strategy I, the aggregator needs to predict the marginal clearing price of the electricity spot market, and then formulate the bidding strategy to achieve the maximum profit of the aggregator. Since this method needs to process a lot of data, the calculation amount is the largest in the three comparison methods. In strategy II, the aggregator's participation in the electricity spot market bidding is based on the amount of transferable and interruptible load which are signed by the customers in a demand response contract. In strategy III, using the marginal operating cost of the aggregator to bid can greatly reduce the complexity of the model.

B. Revenue of DSETSA Participating in the Spot Market

The traditional way for DSETSA to participate in the electricity market is by signing medium long-term contracts supply contracts. DSETSA decides the amount of electricity demand to be purchased according to the electricity prices in the contract and then re-sells the electric power to customers. Fig. 6 shows electricity prices in the spot market and medium long-term contracts.

These data are taken from an integrated demonstration region in Guangdong province, China. Traditional aggregators

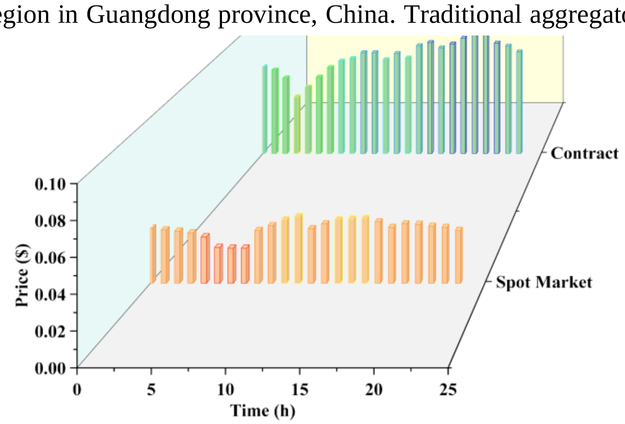

Fig. 6. The spot market and medium long-term contract electricity prices.

TABLE IV
COMPARISONS OF BIDDING STRATEGIES AND CALCULATION TIME OF DIFFERENT BIDDING STRATEGIES

Cases	Aggregator revenue ($)
Case I	130.23
Case II	571.99

sign medium long-term contracts to obtain the electricity demand. DSETSA bids in the spot market to obtain electricity demand through bidding strategy III.

Two cases are further considered:

Case I: Traditional aggregators purchase electricity by signing medium and long-term contracts. The electricity purchase price will be paid according to the contract.

Case II: DSETSA purchases electricity by bidding strategy III in the spot market, which will be paid according to the marginal clearing price. The purchased electricity is used to supply customers' electric and heat loads.

Comparisons of the revenue of the DSETSA in cases I and II are shown in Table IV.

In case II, the way DSETSA participates in the spot market through centralized bidding is better than the traditional way that DSETSA participates in contract power purchases.

C.The Revenue Analysis of DSETSA.

Fig. 7 shows the power balance of electric network. The sold electricity is equal to the electricity demand of customers. The DSETSA purchases electricity for electric and heat power storage during the period of 0-8 h when the spot electricity price is lower than another period. To cope with the spot market price peak at 11 h, the DSETSA only purchases electricity for the customer's electric power load. The customer's heat load can be supplied by the thermal energy stored in DSETS. In the same way, at 17 h, the electricity spot market price is in the peak area. DSETSA will use the energy stored in the DSETS to supply heat load to customers.

Fig. 8 shows the balancing of the heat power. The heat load of the customer is all supplied by DSETS. The conversion of electricity to heat power in DSETS will result in power losses, which are part of DSETSA's operating cost and it is the basis for bidding. Fig. 9 shows the revenues of DSETSA at different periods in a day. During 0-8 h, the electricity spot market price is lower than the period of 9-11 h, and the heat load demand is higher than in other periods. The heat storage capacity of DSETS copes with the electricity price peak at 11 h. During 16-19 h, the DSETSA is limited by the spot market electricity price and heat load demand. During 20-23 h, DSETSA has significant revenue.

The proposed approach in this paper is different from [27]. The proposed DSETSA model can supply the heat load to customers. Fig. 10 shows the total revenue of DSETSA. During 0-5 h and at 23 h, the electric power load is smaller than the heat power load. The revenue of DSETSA mainly depends on supplying the heat power load. The electricity price during 0-5 h in the spot market is much lower than the average electricity price. Therefore, the DSETSA can take advantage of heat power storage to purchase electricity and store it in DSETS during the valley period of electricity spot market price. During peak periods of electricity prices in the spot market, DESTS supplies the stored heat power to customers for higher profit. The total revenue of DSETSA is $ 586.04. DSETSA sells electric power to customers to obtain revenue of $ 362.65, and supplies heat loads to customers for $ 209.34. 35.72 % of its

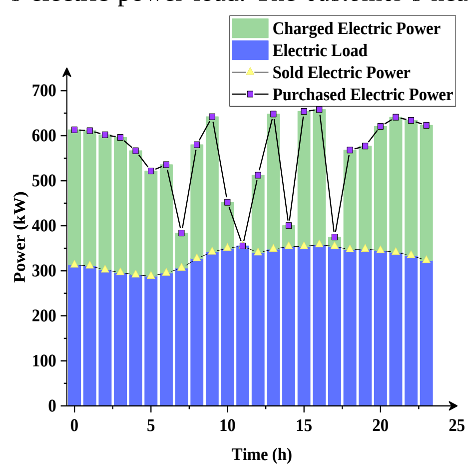

Fig. 7. The power balance of electric network.

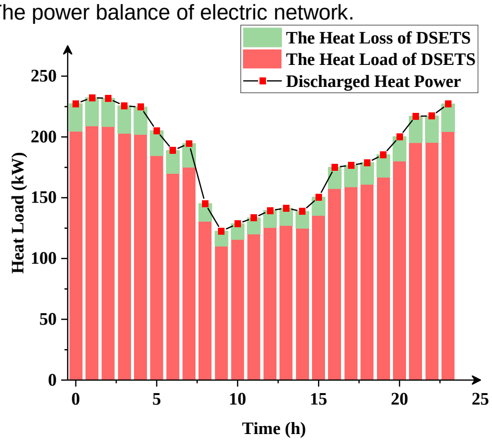

Fig. 8. The heat power balance of heating network.

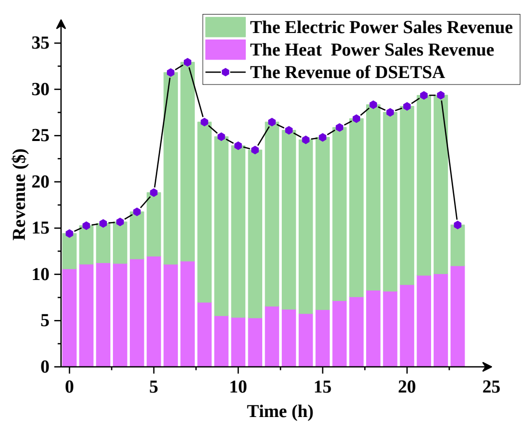

Fig. 9. The heat and electricity sales revenue of DSETSA.

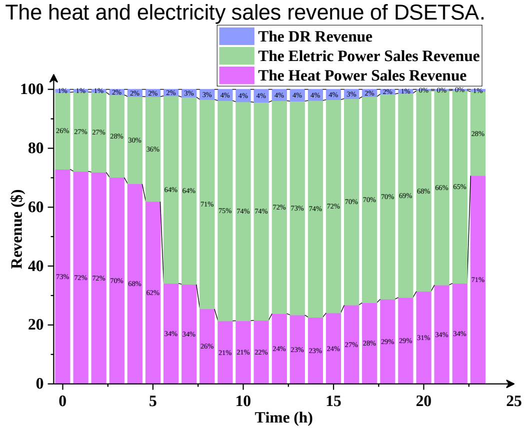

Fig. 10. The revenue state of DSETSA.

total revenue is from supplying heat load. 61.98 % of its total revenue is from supplying the electric load. DSETSA's total daily revenue from demand response (DR) is 2.3 % of the revenue supplied by the heat load. Compared to traditional aggregators that provide electric loads and participate in DR, DSETSA's revenue can be increased by 33.4 %.

V. CONCLUSION

To tackle the challenge that multiple aggregators participate in the spot market to obtain electricity demand through bidding, a bidding strategy of DSETSA based on a Bayesian incomplete information game is proposed. The multi-bidding scenarios problem of DSETSA caused by the uncertainty of the clearing price in the spot electricity market is transformed into probability distribution. The marginal operating cost of DSETSA is added to the optimal bidding revenue model as a constraint. The advantages of the proposed approaches have been verified and can be summarized as follows:

1) DSETSA's participation in the spot market through a bidding strategy is more profitable than only participating in medium and long-term contracts in the demonstration region in China studied in this paper. DSETSA's daily revenue has increased by $ 441.76.

2) Compared with the demand response bidding, the proposed bidding strategy increased the DSETSA's daily revenue by 39.24 %.

3) Aggregators who provide heat loads have more advantages in participating in the spot market, with heat revenue accounting for 35.72 % of its total revenue.

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