Optimal Bidding Strategy of an Aggregator Based on Customers' Responsiveness Behaviors Modeling

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***Abstract*—Residential customers account for an indispensable part in the demand response (DR) program for their capability to provide flexibility when the system required. However, their available DR capacity has not been fully comprehended by the aggregator, who needs the information to bid accurately on behalf of the residential customers in the market transaction. To this end, this paper devised an optimal bidding strategy for the aggregator considering the bottom-up responsiveness of residential customers. Firstly, we attempt to establish the customers' responsiveness function in relation to different incentives, during which a home energy management system (HEMS) is introduced to implement load adjustment for electrical appliances. Secondly, the function is applied to the aggregator's decision-making process to formulate the optimal bidding strategy in the day-ahead (DA) market and the optimal scheduling scheme for the energy storage system (ESS) with the aim to maximize its own revenue. Finally, the validity of the proposed method is verified using the dataset from the Pecan Street experiment in Austin. The obtained outcome demonstrates the practical rationality of the proposed method.**

Keywords— Aggregator, Bidding Strategy, Demand Response, Responsiveness modeling, Day-ahead market.

NOMENCLATURE

A. Sets and Indices

t,i,b,c	Index for time, shiftable appliances, ESS, and residential customers.
$\boldsymbol{T,I,B,C}$	Set of timeslots, shiftable appliances, ESS, and residential customers.

B. Parameters

π_t^{DA}	DA electrovalence at timeslot t
π_t^{DR}	DR price at timeslot t
π_t^{F}	Flexibility price at timeslot t
π_t^{Inc}	Incentive given to customers at timeslot t
P_t^{Base}	The customer baseline load
P_t^{bot}	The energy consumption baseline of TCL
P_t^{BL}	The energy consumption baseline of BL
P_t^{bob}	The baseline load of BL
T_t^{out}	The outdoor temperature at timeslot t
η	Energy efficiency ratio of AC
P^{air}	Rated power of AC
R	Equivalent thermal resistance
C	Equivalent heat capacity
ε	Heat transfer coefficient
$T_{set,i}^{in}$	Temperature setting for the i^{th} AC
τ_c	Control cycle of AC
N	Number of AC at the aggregated level
P_t^{bos}	The energy consumption baseline of SL
$q_{i,t}^{S}$	The energy consumption of the i^{th} shiftable appliance
$N_i^{\max}$	The maximum acceptable load transfer times
$p_{b,t,\min/\max}^{ES}$	Minimum/ Maximum power limitation for battery b at timeslot t
$E_{b,t,\min/\max}^{ES}$	Minimum/ Maximum energy limitation for battery b at timeslot t
η_c, η_d	Charging/ Discharging efficiency of ESS

C. Variables

P_t^{total}	Energy demand of customers after DR
P_t^{TCL}	The energy consumption of all the TCL
P_t^{SL}	The energy consumption of all the SL
$Flxc$	Flexibility of customers
$Flxb$	Flexibility of ESS
s	Binary variable denotes the on/off state of AC
T_t^{in}	The indoor temperature
τ_{on}	The time duration when the AC is on
τ_{off}	The time duration when the AC is off
$p_{c,t}^{S}$	Energy demand of SL at timeslot t
$u_{i,t}$	Binary variable that determines whether the i^{th} appliance shift out at timeslot t
$\alpha_{i,t}$	Binary variable that determines whether the i^{th} appliance shift in at timeslot t
$v_{b,t}$	Binary variable; 1 indicates that the battery b is discharging at timeslot t, 0 otherwise
p_t^{b}	Energy of battery b at timeslot t
P_t^{B}	Aggregated power of all the batteries
P_t^{F}	The flexibility offered by customers and ESS
P_t^{DA}	The electricity purchased from the DA market
R	Revenue of the aggregator
I_t^{DA}	Income of providing electricity to customers
I_t^{F}	Income of providing flexibility to ISO
C_t^{DA}	Cost of purchasing electricity

C_t^{Inc}	Cost of offering customers incentives

D. Abbreviation

IBDR	Incentive-based demand response
PBDR	Price-based demand response
HEMS	Home energy management system
BOS	Baseload of the shiftable loads
BOB	Baseload of the base loads
BL	Baseload
SL	Shiftable load
TCL	Thermostatically controlled load
EC	Customers who prefer high economic income
CC	Customers who prefer comfort

I. INTRODUCTION

Demand response (DR) is designed to induce lower electricity consumption in the way of either price signals or incentive schemes [1] at times of high market prices or when grid reliability is endangered, and thus serves as a promising mechanism for system operators to settle the problems in the restructured electricity market, price volatility and reliability concerns during peak demand [2]. It could achieve a similar regulation effect as the adjustment in generation side to cope with the imbalance between demand and supply, of which the latter becomes uncontrollable recently due to the integration of the intermittent renewable energy resources including wind farms [3, 4] and solar PV power plants [5, 6].

Residential customers approximately account for 30-40% of the whole energy consumption; therefore, the involvement of residential customers plays an indispensable role in the further promotion of DR. However, its potential has not been fully exploited yet due to the capacity of the widely distributed residential customers [7] is too small to meet the market access threshold. Active participation of residential customers in DR [8] and electricity market could be achieved through an emerging market entity, the aggregator, who functions as an intermediary between the market and customers [9]. Although the participation of aggregators will lead to a more complicated market structure, its positive impact on the economy, reliability [10], and sustainability of system operation is more important.

The aggregator could simply gather the flexibility of customers to participate in either price-based or incentive-based DR programs (PBDR or IBDR) [11, 12]; meanwhile, it could also function as a retailer that purchases electricity from the energy market to satisfy customers' daily usage. Except for residential customers, other flexible resources like ESS, distributed generations (DGs) are also an indispensable component of the aggregator, who can therefore trade in the energy, capacity, and balancing market taking advantage of these resources. Here we assume that the aggregator is in charge of both residential customers and ESS resources to participate in the IBDR and bids in the day-ahead (DA) market as a price-taker to optimize its own profit.

As a profit-seeking entity, how to bid accurately in the electricity market and thereby earn the maximal profit is an unavoidable issue for the aggregator and has been investigated by many literature [13-18], among which some seek to achieve the profit-maximize objectives of all the market participants [13]; some design a quantitative compensation mechanism for residential customers to promote their involvement in DR [14]; and some target at the uncertainties confronted by the aggregator during the trading process including the generation of DGs, electricity market prices and participation factor of customers [15-18]. While these researches obtain the corresponding optimal strategy under various scenarios, they fail to take the physical constraints of the residential customers in DR programs into consideration, e.g., the load reduction capacity of each household appliance, the corresponding preference settings, etc., which will directly affect the bidding strategy formulation of the aggregator. Since in an IBDR, the aggregator relies on the agile household appliances to offer flexibility in reaction to changes in the electricity tariff and develop the electricity purchasing scheme without compromising the preferences of the customers [19-21]. If the responsiveness and preference of customers could not be considered and modeled properly, the aggregator will encounter a situation where it could not purchase precisely in the electricity market and thus endure the risk of profit-loss.

The modeling of residential customers' flexibility has been the focus of many recent studies [22-26]. Mathematical flexibility characterization methods are presented in [22] for different types of loads [23, 24] in the residential sector. The second method involved is the empirical methodology, which quantifies the full probability distribution function of the flexibility in response to economic incentives considering the surrounding variables through the quantile regression method [25]. The third group is a support vector machine (SVM) based forecast model, it could either be combined with the identification and extraction of cardinal features that may pose significant influence on the aggregated DR capacity [26], e.g., the weather conditions and monetary reward; or be combined with the classification of feasible and non-feasible home energy management system (HEMS) operating trajectories [27], to forecast the flexibility for aggregated smart houses. Remarkable performance has achieved by these studies in handling the problem of quantifying customers' response, however, it would be better to further combine these studies with practical problems like the bidding problem of the aggregator. Few studies have proceeded from the household appliances' level and integrated the responsiveness of residential customers into the optimal bidding problem of the aggregator.

To this end, this paper aims to characterize the responsiveness of residential customers under different incentives, which would then serve as a foundation for the aggregator to trade precisely in the DA market. The HEMS is introduced here since it has been extensively deployed to better schedule the residential customers' electricity consumption during DR events considering external factors including the weather, daily activities, customers' preferences, population, etc. [28, 29]. The contributions of this paper can be summarized as follows:

(1) The acquisition of the responsiveness function of the aggregated residential customers in relation to different incentives through the polynomial regression method. The response is the accumulation of the flexibility from each electrical appliance, which is controlled through the HEMS.

(2) An optimal bidding model for the aggregator in the DA market considering both the residential customers and ESS is proposed at the premise of the obtained responsiveness function, which could improve the accuracy of the aggregators' transactions and therefore gain more revenue.

(3) The dataset from the Pecan Street experiments in Austin is utilized to verify the validity of the proposed

optimal bidding model and further prove its universality for various scenarios.

The remainder of this paper is organized as follows. In section II, the market structure is firstly introduced, followed by a brief introduction to the basic idea of this paper. Section III models the responsiveness of residential customers and then formulates the bidding strategy of the aggregator. A case study is carried out in section IV to verify the effectiveness of the model. Finally, the paper is summarized in section V, and the study prospect is advanced.

II. Problem Statement and Proposed Framework

A. Market structure

To better introduce the target problem of this paper, here the hierarchical market structure is firstly presented in Fig. 1. The direction of information flow in the figure is counter-clockwise inside the ellipse and clockwise outside. The aggregator offers DR service to the ISO and gains reward correspondingly. Besides, the aggregator bids in the DA market to purchase adequate electricity, which would be provided to the customers to satisfy their daily usage and to the ESS when they are charging. In accordance with the specific incentive given by the aggregator, the residential customers will change their inherent electricity consumption habits to earn compensation. The responsiveness of a customer could be traditionally calculated through the difference between power consumption in DR and without DR. To properly model the responsiveness of customers under specific incentive and then formulate the optimal bidding strategy of the aggregator correspondingly are the concentration of this paper.

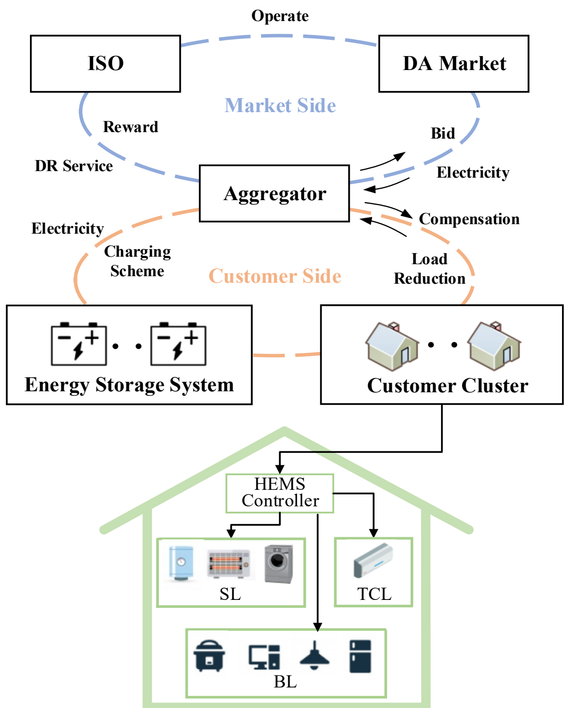

Fig. 1 The structure and mechanism of the electricity market

B. Residential customers

Each residential customer is assumed to be an independent individual who has control over all of its appliances through the HEMS. Since the bottom-up responsiveness of the residential customers will be investigated, that is, the response of household appliances, thus they can be further subdivided into: 1) Thermostatically controlled loads (TCL) that have the ability to store energy in the form of temperature, here only the air conditioner (AC) is considered; 2) Shiftable load (SL), including cloth-washer, furnace, and boiler, which can be transferred to other periods of time without significantly influence the regular usage of customers; 3) Baseload (BL), it mainly refers to appliances like electric cooker, refrigerator, lighting, computer, etc., which cannot be shifted or curtailed since they are the basic living guarantee.

For residential customers, various family backgrounds lead to different preferences. Here the customers are divided into two main categories: 1) customers who prefer high economic income (EC) and 2) customers who prefer comfort (CC). The former would respond positively to the incentives of aggregators so as to obtain more income while the latter pays more attention to their own comfortableness and are unwilling to change electricity consumption habits.

C. Basic idea and the proposed framework

The proposed bottom-up framework to handle the optimal bidding problem for the aggregator is presented in Fig. 2. It mainly includes two stages.

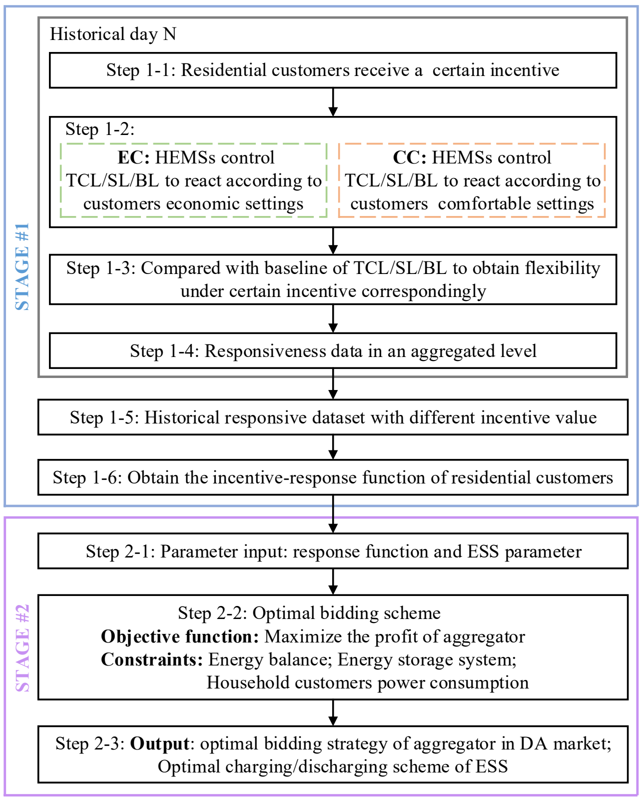

Fig. 2 Architecture of the proposed framework

The first stage is to solve the problem concerning the description of the aggregated responsiveness of residential customers under different incentives.

The first challenge that will be confronted here is data deficiency. Since once the DR program is implemented, the customers' profile would be altered. One possibility is that we have access to the DR data but no non-DR data, and the other case is the opposite. The electricity appliances consumption data of 200 residential customers is available here and is regarded as the baseline load. Therefore, on the basis of the mathematical modeling of air conditioners and the shiftable loads, we come up with the DR data, which will be further compared with the baseline to obtain the amount of responsiveness. Noted that the data of each load categories should be compared with the corresponding baseline first and then accumulated to obtain the overall responsiveness of a residential customer, rather than the difference between the baseline before and after DR. This is because both load reduction and shifting exists in this process, chances are that the electricity of one appliance is curtailed in a time period but another appliance is shifted in, which would result in the offset of their function. In this case, the customers could not be remunerated reasonably for the service they provide and would consequently lead to their inactive participation in DR programs. Therefore, the flexibility of each kind of load would be calculated first to ensure the accuracy of the obtained aggregated responsiveness.

The second challenge is how to model the change in the customers' preference with the variation of incentives. It is evident that with the alteration of incentive, the engagement of customers in DR would also change, specifically, the tolerable temperature range for the air conditioners and the acceptable load transfer times will change. However, it would be quite tedious to adjust these settings accordingly whenever the incentive changes. Thus, the change in preference settings is transformed into the change in the proportion of EC and CC customers at the aggregated level. The proportion of EC is supposed to follow the normal distribution, which is the most commonly exists distribution. The customers' preferences are sensitive to many factors, including the incentive, education experience, weather, etc.; therefore, it is reasonable to assume that it follows the normal distribution according to the central limit theorem. Noted that, if the DR dataset is available, there is no need to simulate the electricity consumption with DR but to estimate the baseline so as to calculate the responsiveness. After the acquisition of residential customers' responses under different incentives, the polynomial regression method is adopted to fit the customers' response function.

The second stage is the bidding optimization process for the aggregator taking into consideration both the residential customers and ESS. With the objective of maximizing the revenue of aggregators, the model would come up with the scheduling scheme of the ESS and the bidding strategy in the DA market.

III. PROBLEM FORMULATION

A. Residential customers

For residential customers, their daily electricity consumption with DR is the sum of the TCL, SL, and BL, presented in (1). Equation (2) calculates the flexibility offered by customers, or to say, the sum of the consumption changes of different load types. Noted that it is different from the net difference reflected in the customers' profile, which is also the basis for the ISO's reward. Different types of appliances would respond diversely under different given incentives, and the data-acquisition process could be shown as follows.

$$P_t^{total} = P_t^{BL} + P_t^{TCL} + P_t^{SL} \quad \forall t \in \boldsymbol{T} \tag{1}$$

$$Flxc_t = (P_t^{bot} - P_t^{TCL}) + (P_t^{bos} - P_t^{SL}) \quad \forall t \in \boldsymbol{T} \tag{2}$$

a) TCL

Air conditioner, as the most typical TCL, plays an indispensable part in the DR program, and thus its mathematical modeling method has been thoroughly investigated. Based on the previous study [30-32], the characteristic of air conditioner can be presented in (3)-(10). Equation (3) and (4) shows the relationship between the indoor/outdoor temperature and the power of the air conditioner. The preferred temperature setting for the EC is given in (5), which serves as the boundary constraints of the indoor temperature. For simplicity, the value for all the EC customers is set to be the same. Whether and how long should the air conditioner be on or off are determined by the outdoor temperature and indoor temperature settings, shown in (6)-(8). The transformation of the on or off state could be expressed clearly by equation (9). The electricity consumption of air conditioners at the aggregated level can be calculated through (10). It should be noted that the air conditioner could work at both the refrigeration and the heating state, and the corresponding modeling is quite similar, here the condition in a typical summer day is studied.

$$T_{t+1}^{in} = T_{t+1}^{out} - s\eta P^{air} R - (T_{t+1}^{out} - s\eta P^{air} R - T_t^{in})\varepsilon \tag{3}$$

$$\varepsilon = e^{-\Delta t/RC} = e^{-\Delta t/\tau_c} \tag{4}$$

$$T_{set,i}^{in} \subset \left[T_{\min,i}^{in}, T_{\max,i}^{in} \right] \tag{5}$$

$$T_{\max}^{in} = T^{out}(1-\varepsilon^{\tau_{off}}) + T_{\min}^{in}\varepsilon^{\tau_{off}} \tag{6}$$

$$T_{\min}^{in} = (T^{out} - \eta PR)(1-\varepsilon^{\tau_{on}}) + T_{\max}^{in}\varepsilon^{\tau_{on}} \tag{7}$$

$$\tau_c = \tau_{on} + \tau_{off} \tag{8}$$

$$s_{t+1} = \begin{cases} 0 & (T_t^{in} < T_t^{\min}) \cap (s_t = 1) \\ 1 & (T_t^{in} > T_t^{\max}) \cap (s_t = 0) \\ s_t & other\ situation \end{cases} \tag{9}$$

$$P_t^{TCL} = \frac{\tau_{on}}{\tau_c} N P_t^{air} \tag{10}$$

b) Shiftable load (SL)

Shiftable load contains the aforementioned cloth-washer, furnace, and boiler. The total amount of electricity consumption of these appliances ought to remain constant across the whole-time interval, as is presented in (12). Provided an electrical appliance is transferred to another time period, then the energy demand at this time will reduce by the energy that would have been consumed by it. Similarly, if another appliance moves in during this period, their load demand ought to be added, just as (11) denotes. It should be emphasized that the variation process of load demand is intermittent since the increase or decrease is based on appliance. Equation (13) indicates that for the ECs who are willing to offer load shifting, the maximum acceptable load transfer times would be given, while for the CCs the value is equal to zero. The amount of SL at the aggregated level could be calculated through (14).

$$p_{c,t}^{S} = p_{c.t}^{bos} - u_{i,t} \bullet q_{i,t}^{S} + \alpha_{i,t} \bullet q_{i,t}^{S}, \forall i \in \boldsymbol{I}, \forall c \in \boldsymbol{C}, \forall t \in \boldsymbol{T} \tag{11}$$

$$\sum_{t \in \boldsymbol{T}} p_{c,t}^{SL} = \sum_{t \in \boldsymbol{T}} p_{c,t}^{bos}, \forall c \in \boldsymbol{C} \tag{12}$$

$$\sum_{t \in \boldsymbol{T}} u_{i,t} = N_i^{\max}, \forall i \in I \tag{13}$$

$$P_t^{SL} = \sum p_{c,t}^{SL}, \forall c \in \boldsymbol{C} \tag{14}$$

c) BL

BLs are the critical loads whose operation would directly influence the normal life of customers and therefore could not be interrupted or transferred under any circumstances. The energy demand for BL would remain unchanged for any time period t, as is shown in (15).

$$P_t^{BL} = P_t^{bob} \tag{15}$$

B. ESS

The ESS is assumed to be a kind of flexible resource that directly controlled and dispatched by the aggregator. With the objective to maximize its own interests, it is profitable for an aggregator to arrange the ESS to discharge when the electricity price is high in order to avoid exorbitant cost and charge when the price is low so as to reserve energy at a lower cost. The physical constraints of the ESS could be mathematically expressed by (16)-(23). The power and energy boundary of ESS is given in (16) and (17) first, followed by the energy balance in the adjacent period in (19) for both charging and discharging states. As (20) presents, the energy of the ESS after one cycle (24h is regarded as a complete cycle here) ought to be consistent with that at the beginning. The most important constraint is, the aggregated power offered by the ESS along with the electricity purchased from the DA should satisfy the daily usage of customers, shown in (22). Equation (23) denotes that only the energy discharged by ESS is regarded as its flexibility.

$$p_{t,min}^{b} \le p_t^b \le p_{t,max}^{b} \quad \forall b \in B, \forall t \in T \tag{16}$$

$$EN_{t,min}^{b} \le EN_t^b \le EN_{t,max}^{b} \quad \forall b \in B, \forall t \in T \tag{17}$$

$$v = \begin{cases} 0, \ p_t^b \le 0, \ charging \\ 1, \ p_t^b > 0, \ discharging \end{cases} \tag{18}$$

$$EN_t^b = \begin{cases} EN_{t-1}^b - \eta_c \cdot p_{t-1}^b \cdot \Delta t, \ v = 0 \\ EN_{t-1}^b - p_{t-1}^b / \eta_d \cdot \Delta t, \ v = 1 \end{cases}, \forall b \in B, \forall t \in T \tag{19}$$

$$\begin{cases} EN_1^b = EN_{24}^b - \eta_c \cdot p_{24}^b \cdot \Delta t, \ v_{24} \le 0 \\ EN_1^b = EN_{24}^b - p_{24}^b / \eta_d \cdot \Delta t, \ v_{24} > 0 \end{cases}, \ \forall b \in B \tag{20}$$

$$P_t^B = \sum_{b \in B} p_t^b, \quad \forall t \in T \tag{21}$$

$$P_t^B + P_t^{DA} = P_t^{total}, \forall t \in T \tag{22}$$

$$Flxb_t = \sum_{v=1} p_t^b \quad \forall b \in B, \forall t \in T \tag{23}$$

C. Optimal bidding model

The aggregator is a profit-seeking entity with the target to maximize its profit. The revenue of the aggregator can be divided into two parts, one is the income of selling electricity to residential customers (25), and the other is the remuneration for the flexibility provided to ISO (26). Similarly, the expenditure during its transaction also contains two portions, the cost to purchase electricity from the DA market (27), and the incentive offered to customers so as to encourage their participation (28). What needs to be explained is that ISO awards the aggregator according to the difference between the load profile before and after DR, while the aggregator awards the customers based on the changes of various types of loads separately so as to compensate fairly. The constraints of ESS mentioned above, and the responsiveness function of residential customers serve as the constraints of this optimal bidding model.

$$\max \ R = I_t^{DA} + I_t^F - C_t^{DA} - C_t^{Inc} \tag{24}$$

$$I_t^{DA} = P_t^{total} \cdot \pi_t^{DA} \quad \forall t \in T \tag{25}$$

$$I_t^F = P_t^F \cdot \pi_t^F = [(P_t^{Base} - P_t^{total}) + Flxb_t] \cdot \pi_t^F \quad \forall t \in T \tag{26}$$

$$C_t^{DA} = P_t^{DA} \cdot \pi_t^{DA} \quad \forall t \in T \tag{27}$$

$$C_t^{Inc} = Flx_{c,t} \cdot \pi_t^{Inc} \quad \forall t \in T \tag{28}$$

III. Case Study

A. Dataset and Parameter Settings

The dataset utilized in this research is from the Pecan Street experiment in Austin, TX [33], where a total of 500 residential customers are investigated and the minute-resolution electricity consumption data at both the household level and appliance level are given. 200 of them are selected to verify the proposed optimal bidding strategy in summer; each is equipped with the electrical appliances involved in this research. Some relevant parameter settings are listed in Table I. It should be noted that the parameters of each AC should be different; here only one type is given.

TABLE I. PARAMETER SETTINGS

Parameter	Value	Parameter	Value
$E_{b,t,min}^{ES}, E_{b,t,max}^{ES}$	10, 120	$p_{b,t,min}^{ES}, p_{b,t,max}^{ES}$	-10, 30
η_c, η_d	0.95	E_0	40
R (°C / kW)	5.56	C (kW·h / °C)	0.18
$T_{\min}^{in}, T_{\max}^{in}$	24,30	η	2.7
$N_i^{\max}$	5	π_t^{Inc}	0.1877
μ	0	σ^2	5
π_t^{DA} ($)	{0.1213,0.1147,0.1086,⋯,0.1535,0.1389,0.1210}		
π_t^{F} ($)	{0.2296,0.2156,0.2106,⋯,0.3754,0.3303,0.2735}		
T^{out} (°C)	{29,28,29,28,27,26,27,28,30,31,32,34,35,36,37, 38,38,37,36,33,30,30,29,29}		

B. Responsiveness of residential customers under different incentives

The first step is to discover how would the residential customers' respond to the different incentive signals, which could be obtained through the accumulation of the responsiveness of different appliances. After the acquisition of the specific data, the polynomial fitting method is introduced to fit the response characteristic. The obtained mathematical expression is shown as follows:

$$y = 5.44 \cdot 10^6 \cdot x^5 - 4.891 \cdot 10^6 \cdot x^4 + 1.356 \cdot 10^6 \cdot x^3 - 1.042 \cdot 10^5 \cdot x^2 + 5364x + 32.65 \tag{29}$$

Both the response value and the fitted curve are presented in Fig. 3, which intuitively reflect the well following performance of the fitted curve. It could also be observed that the response curve exhibits a similar trend with the change in the proportion of residential customers.

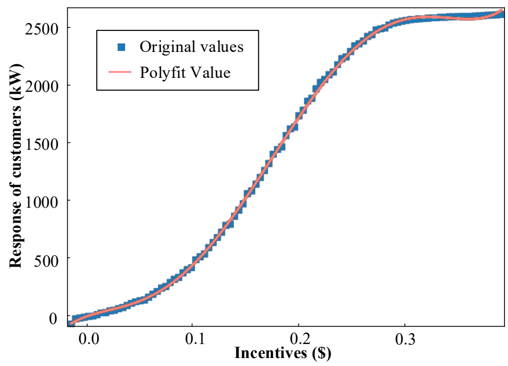

Fig. 3. Response of residential customers under different incentives

C. Selection of the optimal incentive value

To discover the optimal incentive value that the aggregator should offer to the customers, here various scenarios with different incentives are tested and the corresponding revenue of the aggregator could be obtained, as presented in Fig. 4, which indicates that the revenue increases with incentive and reaches the maximum at around 0.25, and then decreases subsequently. To seek out the peak point, we further listed the revenue and the proportion of EC around the peak in Table II, from which we could clearly observe that the optimal incentive value is 0.237 and the corresponding EC percent is 74%. This fact implies that if the incentive is less, the flexibility of aggregator is insufficient to achieve the maximum point, and if the incentive grows further, the increase of profit brought by the increase of flexibility could not offset the cost ought to be paid to customers.

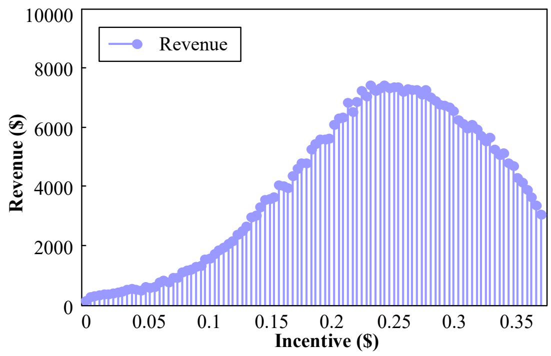

Fig. 4. Revenue of the aggregator under different incentives

TABLE II. REVENUE AND PROPORTION OF EC AROUND THE PEAK

Incentive	Revenue	EC (%)	Incentive	Revenue	EC (%)
0.229	7231.404	70.5	0.259	7365.672	82
0.233	7045.970	72.5	0.263	7206.750	83
0.237	**7418.050**	**74**	0.267	7301.044	84.5
0.240	7239.692	75.5	0.270	7257.877	85.5
0.244	7311.308	77	0.274	7274.607	86.5
0.248	7406.580	78	0.278	7102.186	87
0.252	7310.279	79.5	0.282	7265.140	88
0.255	7342.050	81	0.285	7009.526	89

D. Optimal bidding strategy under the optimal incentive

Then a further investigation of the aggregator's bidding strategy in the optimal cases is provided. The value of some important variables is presented in Table II and the corresponding outcome is shown in Fig. 5-7.

The detail composition of the flexibility of a residential customer is presented in Fig. 5, where columns in different colors represent different kinds of responsive appliances. The columns below the abscissa axis stand for that some appliances move in during this period. For example, the third negative column (the fourth column) consists of the electricity consumption of the cloth-washer and the water-heater, that is, the two appliances are shifted from their normal operation time period to this one. It could also be observed that the load primarily transfers from around 15-21h to 0-5h. This is in accordance with the profit-maximization target of the aggregator since the DA electricity price and original energy demand of customers are both high in the former period and low in the latter. Similarly, the optimal scheduling scheme of the ESS reflects the same regularity, displayed in Fig. 6. The ESS would be arranged to discharge when the DA price is high and charge when it is low.

The revenue of the aggregator in each time period is shown in the first subgraph in Fig. 7. It could be observed that the profit of the aggregator is negative in some periods (0-5h). Since the ESS will charge and some appliances will move in during this period as mentioned before, thus the aggregator has to spend more on the purchasing of electricity, which leads to the situation where the revenue of selling flexibility could not offset the cost; therefore, the revenue is negative consequently. Noted that the overall revenue is still positive, as can be found in Table III. The second subgraph compares the initial and adjusted baseline. The difference between them is composed of both load curtailment and transfer. The reason why the modified baseline exceeds the original baseline is the shift-in of some appliance. The flexibility composition is exhibited in the third subgraph. For the ESS, only the energy discharged is regarded as its flexibility, the energy-charged is not considered because it brings the aggregator additional electricity purchase assignment rather than flexibility.

TABLE III. RESULTS OF BIDDING WITH CERTAIN INCENTIVE

Parameter	Value	Parameter	Value
Flx_c	39467.36159	P_t^{total}	194368.9015
Flx_b	30579.67387	R	7418.05
I_t^F	13117.21542	I_t^{DA}	24619.62295
C_t^{DA}	22910.76607	C_t^{Inc}	7408.022286

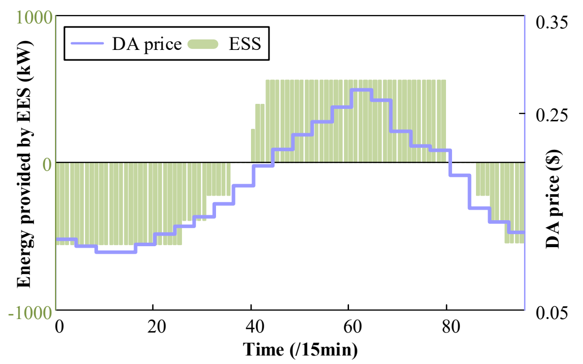

Fig. 6. The relationship of ESS charging/discharging scheme and DA price

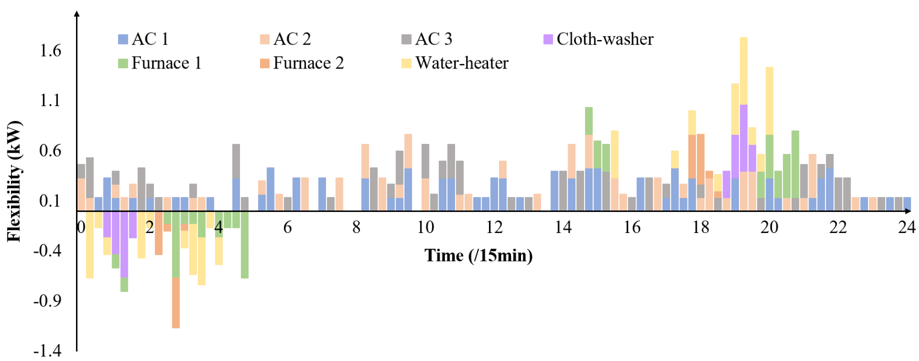

Fig. 5. Composition of a residential customer's flexibility

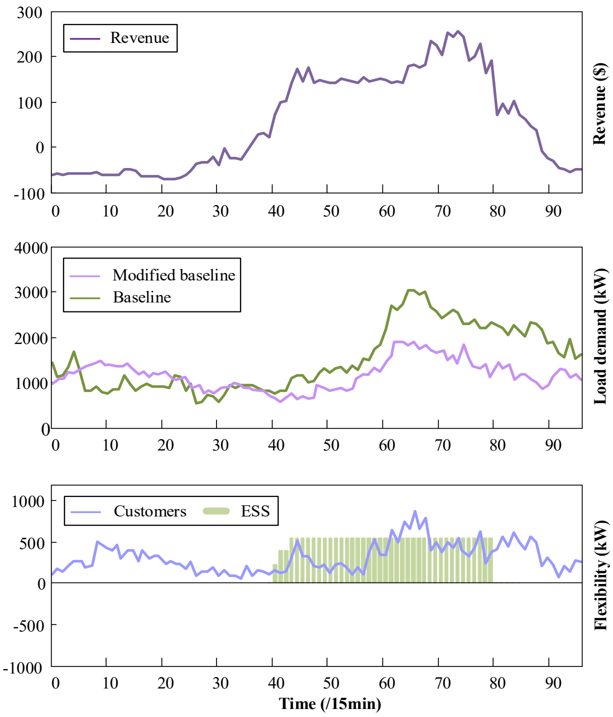

Fig. 7. Some outcome of the optimal bidding model

E. Sensitivity analysis under different distribution

The composition of residential customers cluster is a significant factor that influences the optimal bidding strategy of the aggregator. In the previous study, the proportion of EC is assumed to follow the normal distribution ($\mu = 0,\ \sigma^2 = 5$). To verify the rationality of the method proposed in this paper, a further comparison is carried out to investigate the bidding strategy under normal distribution with different expected values and variance. The parameter settings are presented in Table IV. The incentive value that could maximize the revenue of the aggregator could be obtained through the same procedure as before, the outcome is shown in Table V and Fig. 8-9.

As can be discovered, the optimal profit of the aggregator would decrease with the increase of the deviation value σ and the expected value μ. Since the deviation determines the distribution amplitude, the larger the deviation value is, the smoother the distribution curve will be, that is, the residential customers would become more insensitive to the incentive signal. When the aggregator provides customers with more incentive, the growth rate of EC would be slower, which lead to the situation where the same optimal incentive value corresponds to different EC proportion. Therefore, the flexibility offered by residential customers decreases and the aggregator earns less. As for the expected value μ, it determines the location of the distribution curve. A smaller value of μ stands for that many CC customers will transform to EC at a relatively low incentive, and the optimal incentive decrease consequently. Thus, the aggregator could achieve a higher profit. The results could serve as a recommendation for the aggregator to offer residential customers more DR-related information to help them better comprehend the potential benefits, which may inspire a higher engagement at a relatively low incentive value. For all the distribution of residential customers, the proposed bidding model could come up with the optimal bidding model of the aggregator, which would be suitable for other situations that may occur in practice.

TABLE IV. PARAMETERS OF DIFFERENT DISTRIBUTIONS

Distribution (D)	μ	σ^2	Distribution (D)	μ	σ^2
D1	0	1	D10	-2	5
D2	0	2	D11	-1.5	5
D3	0	3	D12	-1	5
…	…	…	…	…	…
D9	0	9	D17	2	5

TABLE V. RESULTS OF DIFFERENT DISTRIBUTIONS

	EC (%)	Optimal Incentive	Optimal profit		EC (%)	Optimal Incentive	Optimal profit
D1	92	0.237	9044.74	D10	73.5	0.165	9780.76
D2	84	0.237	8392.89	D11	73.5	0.184	9147.52
D3	79	0.237	7720.56	D12	73.5	0.203	8625.34
D4	76	0.237	7543.01	D13	73.5	0.221	7920.97
D5	73.5	0.237	7418.05	D5	73.5	0.237	7418.05
D6	71.5	0.237	7205.29	D14	73.5	0.259	7208.09
D7	70	0.237	7029.39	D15	73.5	0.278	6803.43
D8	69	0.237	6881.31	D16	73.5	0.296	6244.16
D9	68	0.237	6751.33	D17	73.5	0.315	6008.75

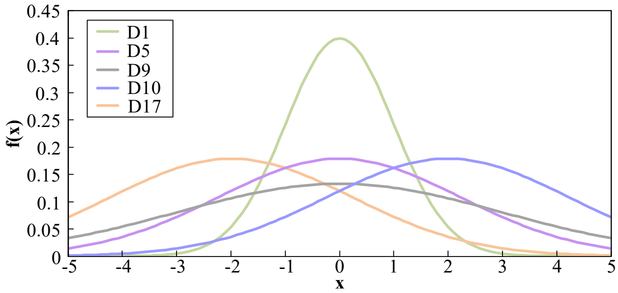

Fig. 8. Probability density function of different distributions

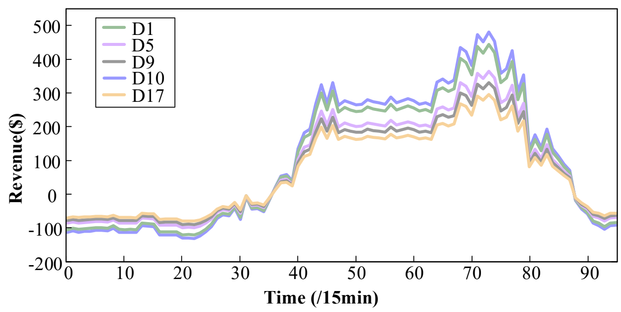

Fig. 9. Revenue of the aggregator under different distributions

F. Comparision

To verify the rationality of the method proposed in this paper, a further comparison is carried out. The general optimal bidding strategy without considering the specific usage of each appliance (method 2), as is proposed in [14], will be investigated together with the method introduced here (method 1).

The outcome is presented in Table VI and Fig. 10. As can be discovered, the revenue and the flexibility of method 1 are inferior to that of method 2. The interpretation for the low income of method 1 is that the change of load is not continuous as method 2, thus is incapable of reaching the optimal value. This could also serve as the explanation for Fig. 10. The total flexibility in method 2 is more and the curves are generally smoother than method 1 where the changes are on the basis of the whole appliances. Since the formulation of ESS charging scheme follows the same basic principle, that is, charge when the electricity price is low and discharge con the contrary; thus, the scheme is essentially the same while for method 1 the value is not the optimum mathematically. The inconformity in flexibility leads to the consequence that the actual load demand is also different. The aggregator in the first method needs to purchase more electricity from the DA market and meanwhile gain less from selling flexibility, therefore the net revenue decreases. The result further proves the rationality of this method because the optimal value obtained by the previous method could not realize physically.

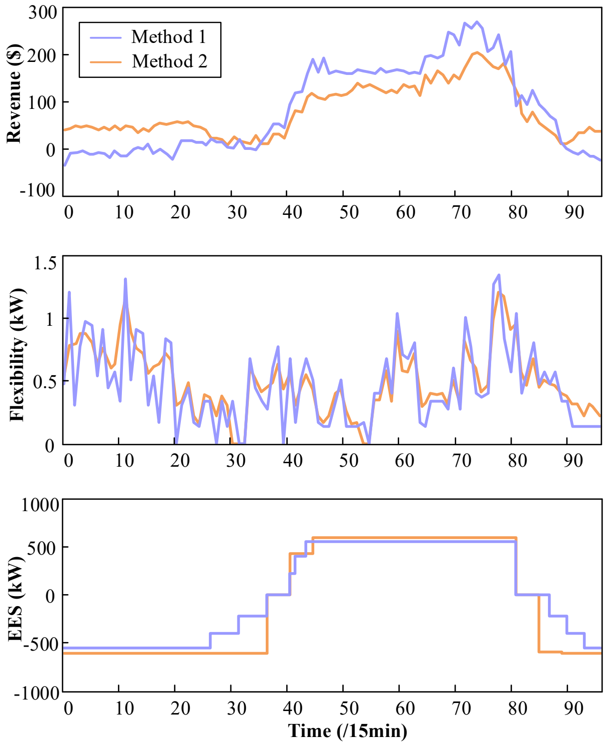

Fig. 10. Comparison between method 1 and method 2

TABLE VI. VALUES OF SOME IMPORTANT VARIABLES

	Method 1	Method 2
Revenue of aggregator ($)	5232.285	**6986.661**
Flexibility of one customer (kW)	44.27	**45.79**
ESS flexibility (kW)	21569.22	**23321.52**
DA electricity purchase (kW)	**96621.95**	94236.83
Actual demand of customers(kW)	**137097.15**	128643.62

IV. CONCLUSION

This paper proposes an optimal bidding strategy of the aggregator on the basis of the responsiveness modeling of residential customers. Three types of loads are taken into consideration and the residential customers are categorized into EC and CC according to their preference for comfort or economic profit. After the acquisition of the customers' response at the aggregated value, the polynomial fitting is suggested as a reasonable choice for processing the response function, which would be applied to the formulation process of the optimal bidding strategy of the aggregator. The numerical results verify the validity of the proposed bidding model, which is also be suitable for customers' clusters with different levels of sensitivity to incentives. And it could also be concluded that the obtained bidding strategy is optimal physically rather than mathematically. Furthermore, since the revenue of the aggregator peaks when the EC percent is around 73, it could be implied that increasing the proportion of EC could improve the revenue to some extent. It might be better for the aggregator to induce more customers to provide more flexibility.

It still needs be noted that the initial focus of this work is to integrate customers' behavior modeling into the bidding process of the aggregator. Future investigations to be undertaken will take into consideration the uncertainties in customers' behavior, weather condition forecast and price forecast [34]. Furthermore, the popularity of electric vehicles [35] as well as the increasing number of residential customers who own distributed generation units [36-39] (especially PV equipment, e.g. solar water heaters) that brings tremendous impact to the customers' normal electricity consumption. In addition, the optimal bidding strategy while the power system parameters have been modified by cyber-attack [40] will be discussed in the future research.

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