Day-ahead Market Optimal Bidding Strategy and Quantitative Compensation Mechanism Design for Load Aggregator Engaging Demand Response

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***Abstract*—In a typical electricity market, the load aggregator (LA) bids in the wholesale market to purchase electricity and meet the expected demand of its customers in the retail market. However, given that the uncertainty of the wholesale market prices (WMPs), the LA has to undertake all the risk caused by the price volatility in the wholesale market, which makes the LA may fall into loss in some cases such as price spike. To this end, firstly, this paper proposes an optimal bidding strategy model for the LA that implements the demand response program (DRP), which enables the LA to reduce the risk of profit loss caused by price volatility. The bidding model is a mixed integer linear programming (MILP) problem, which can be solved efficiently. Secondly, making a rational and quantitative compensation mechanism is significant for the LA to induce its customers to participate in DRP while there are few studies investigating it, hence, this paper designs a quantitative compensation mechanism for the LA. Case studies using a dataset from the Thames valley vision (TVV) verify the effectiveness of the proposed bidding model. Besides, the results show that all entities in the electricity market enable to obtain benefits through the implementation of DRP.**

Keywords—Load Aggregator, Bidding Strategy, Electricity Market, Demand Response, Wholesale Market Price

NOMENCLATURE

A. Abbreviations

WMP	Wholesale market price
CBL	Customer baseline load
MAXLEC	Maximum load envelope curve
MINLEC	Minimum load envelope curve
LS	Load shift contract
LC	Load curtailment contract
LA	Load aggregator
RL	Rescheduled load
EMA	Exponential moving average
MILP	Mixed integer linear programming

B. Sets and Indices

$\boldsymbol{C}$	Set of all customers; $\boldsymbol{C} = \boldsymbol{C}_{\mathrm{LS}} \cup \boldsymbol{C}_{\mathrm{LC}}$
$\boldsymbol{C}_{\mathrm{LS}}$	Set of LS customers
$\boldsymbol{C}_{\mathrm{LC}}$	Set of LC customers
$\boldsymbol{T}$	Set of timeslot, $\boldsymbol{T}= \{0,\ldots,23\}$
$\boldsymbol{T_w}$	Set of period of DR event, $\boldsymbol{T_w}= \{t_{\mathrm{start}},\ldots,t_{\mathrm{end}}\}$
c	Index of customers
t	Index of hour

C. Parameters

$d_{c,t}^{\mathrm{base}}$	Estimated CBL for customer c at timeslot t
$d_{c,t}^{\min}$	Minimum demand of customer c at timeslot t
$d_{c,t}^{\max}$	Maximum demand of customer c at timeslot t
$q_{c,t}^{\mathrm{LS}}$	Quantity of load shift customer c at timeslot t
$q_{c,t}^{\mathrm{LC}}$	Quantity of load curtailment customer c at timeslot t
$\eta_{c,t}^{\mathrm{LC}}$	Proportion of the CBL that the LC customer c would like to curtail at timeslot t
bid_t^{NDR}	Bidding without DR at timeslot t
M^{NDR}	Cost of bidding without DR
R^{NDR}	Revenue of LA without DR
R^{LS}	Revenue of LA obtained from LS customers
$F_{\mathrm{RA}}^{\min}$	Minimum amount of load reduction required by ISO/RTO during the DR event
IC_c^{LS}	Initial cost paid to LS customer c
IC_c^{LC}	Initial cost paid to LC customer c
OC_c^{LS}	Operation cost paid to LS customer c
OC_c^{LC}	Operation cost paid to LC customer c
λ^{LS}	Proportion of the additional profit that the LA would like to share with LS customers
λ^{LC}	Proportion of the additional profit that the LA would like to share with LC customers
π_t^{DA}	Day-ahead price at timeslot t
γ	Fixed price charged to customers
ρ_t	DR price at timeslot t
$N_{c,\max}^{\mathrm{LS}}$	Maximum-shifting time of LS customer c
α_c^{LS}	Potential LS capability rate
α_c^{LC}	Potential LC capability rate
β_c^{LS}	Operation cost rate of LS customer c
β_c^{LC}	Operation cost rate of LC customer c
DRR	Demand response reward
TP	Total profit of LA
ΔTP	Additional profit of LA
NAP	Net additional profit of LA
$CPSC$	Compensation to customer
$DRCR$	Demand response contribution rate
DVA	Deviation from CBL
RDA	Reduction amount

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D. Variables

$d_{c,t}^{\mathrm{LS}}$	Demand of LS customer *c* at timeslot *t*
$d_{c,t}^{\mathrm{LC}}$	Demand of LC customer *c* at timeslot *t*
$F_{c,t}^{\mathrm{LS}}$	Flexibility of LS customer *c* at timeslot *t*
$F_{c,t}^{\mathrm{LC}}$	Flexibility of LC customer *c* at timeslot *t*
$u_{c,t}^{\mathrm{LS}}$	Binary variable; 1 indicates that the load is shifted, 0 otherwise
$u_{c,t}^{\mathrm{LC}}$	Binary variable; 1 indicates that the load is curtailed, 0 otherwise
bid_t^{LS}	Bidding for LS customers at timeslot *t*
bid_t^{LC}	Bidding for LC customers at timeslot *t*
M^{LS}	Cost of bidding for LS customers
M^{LC}	Cost of bidding for LC customers
R^{LC}	Revenue of LA obtained from LC customers
$F_{\mathrm{RA},t}^{\mathrm{A}}$	Actual amount of the load reduction at timeslot *t*

I. INTRODUCTION

An individual electricity customer amounts to a small portion of the total demand and hence has limited negotiation power in the wholesale market, which indicates that each customer is still not eligible to directly purchase electricity from the wholesale market [1], [2]. Instead, customers usually purchase the electricity via an agent in the retail market. Such an agent is referred to as load aggregator (LA), who acts as an intermediator between the wholesale market and the retail market. Conventionally, the LA bids and procures electricity in the wholesale market to meet the expected demand of its customers and charges a fixed tariff from the customers in the retail market. Owning to the fact that the wholesale market prices (WMPs) are uncertain [3]-[5], the LA has to undertake all the risk of WMP volatility when it bids in the wholesale market. Namely, no matter how high the WMPs are, the LA is obligated to purchase the electricity to meet the aggregated demand of its customers, which makes the LA may fall into loss in some cases such as price spike. Actually, the LA prefers to purchase more electricity when the WMPs are low, and purchase less electricity when the WMPs are high. Recently, advances in smart metering technology, smart appliances and control devices enable the LA to reschedule the load of its customers, which indicates that the load turns to be more flexible [6]-[8]. Therefore, the LA is able to optimize its bidding strategy by utilizing the load flexibility.

The authors of [9]-[12] optimize the self-scheduling problem of an LA who bids in the day-ahead (DA) market to purchase energy on behalf of a plug-in electric vehicle fleet. Through their studies, the optimal bidding plans of the LAs can be achieved. In [13], [14] stochastic optimization methods are deployed to tackle the uncertainty of WMPs when the LAs bid in the wholesale market. Through their studies, demand-price bidding curves can be obtained. Nevertheless, it should be noticed that as one of the promising resources to the electricity markets [15]-[18], demand response (DR) is not taken into consideration in [9]-[14] when the LAs bid in the wholesale market. Experiences with energy markets have shown that lack of DR has been a major contributing factor to occurrences of energy markets meltdown [19]. For example, California's energy crisis should have been mitigated to a large extent if sufficient DR resources were in place. Moreover, DR enables to efficiently integrate large shares of renewable energy resources (RES) [20]-[27]. Accordingly, several demand response programs (DRPs) have been implemented by the independent system operators (ISOs) / regional transmission organizations (RTOs) to ensure the reliability of the electricity market and the safety of the power system [28]-[30]. For example, day-ahead demand response program is implemented by New York ISO (NYISO) and day-ahead load response program is implemented by Pennsylvania–New Jersey–Maryland (PJM) for load reduction during a period of DR event. That means, not only can an LA purchase the electricity from the wholesale market for its customers, but also it is able to aggregate the DR resources from its customers and provide DR service to ISOs/RTOs in the electricity market nowadays. By compensating to its customers, the LA is capable of gaining direct control of their appliances (i.e., load curtailment or shifting) during the DR events to optimize its bidding plan. However, heretofore there are merely few studies quantifying the compensation to the customers, which is significant to the LA for inducing the customer to participate in DRP.

To this end, firstly, this paper proposes an optimal bidding strategy of the LA in DA market with the implementation of DRP (i.e., load curtailment or load shifting), which enables the LA to reduce the risk of profit loss caused by price volatility. Secondly, this paper proposed a quantitative compensation mechanism design for the LA, which is of great importance to induce its customer to participate in the DRP. Specifically, the customer baseline load (CBL) that is a counterfactual consumption level (i.e., the amount of electricity that customers would have consumed in the absence of DR event) is leveraged in this paper [31]. Utilizing the CBL enables the LA to quantify the load reduction and measure the deviation between the rescheduled load (RL) and the baseline load [32]. In this paper, different CBL estimation methods are also applied to discuss their impacts on the bidding strategy. Moreover, some indexes are defined in this paper such as demand response contribution rate (DRCR), which reflects the contribution degree of each customer in the DRP [33]. Therefore, with quantitative analysis of compensation mechanism, the LA is able to compensate to customers in a rational way. It should be noticed that the discussion about how to control the appliances in each customer's premise is out of the scope of this paper.

The contributions can be summarized as follows:

(1) In order to reduce the risk of the profit loss caused by price volatility when the LA bids in the wholesale market, DRP implementation is taken into account in this paper, which also brings a new business model for the LA. The results show that all entities in the electricity market enable to obtain benefits through the implementation of DRP.

(2) An optimal bidding strategy for the LA is proposed, which is formulated as a mixed integer linear programming (MILP) model that can be solved efficiently.

(3) A quantitative compensation mechanism is designed for the LA to induce its customers to participate in the DRP without significantly compromising their consumption level.

The rest of this paper is organized as follows. Section II constructs a framework of the LA bidding problem. Case studies are presented in Section III followed by a discussion in Section IV. In section V, we conclude and outline the further implication of our work.

II. Framework of the LA Bidding Problem

In this section, an optimal bidding model for the LA is proposed firstly, which takes the implementation of DRP in to account and help the LA to reduce the risk of profit loss caused by price volatility. Secondly, the quantitative compensation mechanism design is introduced. Fig. 1 schematically shows the structure and mechanism of the electricity market. When the power system is likely to face the extreme load peaks, an ISO/RTO will send a DR instruction to the LA day ahead, and the LA will respond to the instruction via rescheduling customers' load patterns (i.e., curtail load during DR event hours or shift load from peak/high-price hours to off-peak/low-price hours) for maximizing its additional profit when it bids in day-ahead (DA) market. With the implementation of the DRP, the LA is able to get the reward from the ISO/RTO for providing the DR service. After DR event, the LA is supposed to compensate to its customers for their DR resource supply.

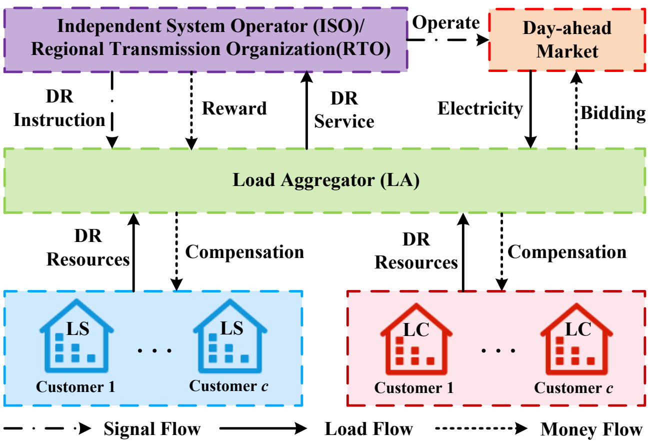

Fig. 1 The structure and mechanism of the electricity market

A. Bidding Without DR

The CBL is defined as the amount of electricity that customers would have consumed in the absence of DR event, therefore, the LA is supposed to purchase the amount of the electricity bid_t^{NDR} at timeslot t in the DA market if there is no DR event. bid_t^{NDR} and the total profit of the LA TP^{NDR} can be calculated by formulas (1)-(4).

$$bid_t^{\mathrm{NDR}} = \sum_{c \in \boldsymbol{C}} d_{c,t}^{\mathrm{base}}, \forall t \in \boldsymbol{T} \tag{1}$$

$$R^{\mathrm{NDR}} = \gamma \cdot \sum_{t \in \boldsymbol{T}} bid_t^{\mathrm{NDR}} \tag{2}$$

$$M^{\mathrm{NDR}} = \sum_{t \in \boldsymbol{T}} bid_t^{\mathrm{NDR}} \cdot \pi_t^{\mathrm{DA}} \tag{3}$$

$$TP^{\mathrm{NDR}} = R^{\mathrm{NDR}} - M^{\mathrm{NDR}} = \sum_{t \in \boldsymbol{T}} bid_t^{\mathrm{NDR}} \cdot \left(\gamma - \pi_t^{\mathrm{DA}}\right) \tag{4}$$

Implicitly, equation (4) indicates that if the WMPs are higher than the fixed price charged to its customers, the LA will lose money with a high probability, which, especially, happens when there are unexpected demand peaks in the power system causing extreme price spikes.

B. Bidding With DR

In order to avoid the demand peaks that threaten the safety of the power system and cause price spike in the wholesale market, the ISO/RTO will send a DR instruction to the LA who has signed the DR contracts with its customers for load shifting (LS) or load curtailment (LC) [34]. By rescheduling its customers' load, the LA is able to meet the DR requirement of ISO/RTO and augment demand bidding with DR. This strategy is also referred to as DR-aided demand bidding [35]. The bidding process is shown in Fig.2 schematically.

Specifically, the LS contract and LC contract are described as follows:

1) Load shifting (LS): In the LS contracts, the LA is capable to shift the predetermined load quantity of each customer at timeslot t. For example, the LA can control the electrical vehicles or energy storage system charging during a specific period. The illustration of different shifting strategies is shown in Fig. 3 where the value 1 at each timeslot indicates that the load is shifted, 0 otherwise. Although there are lots of shifting strategies (i.e., $\mathbf{C}_{24}^{5} = 42504$), the LA would like to shift load from peak/high-price hours to off-peak/low-price hours to reduce the cost of electricity procurement while satisfying the DR requirement of ISO/RTO.

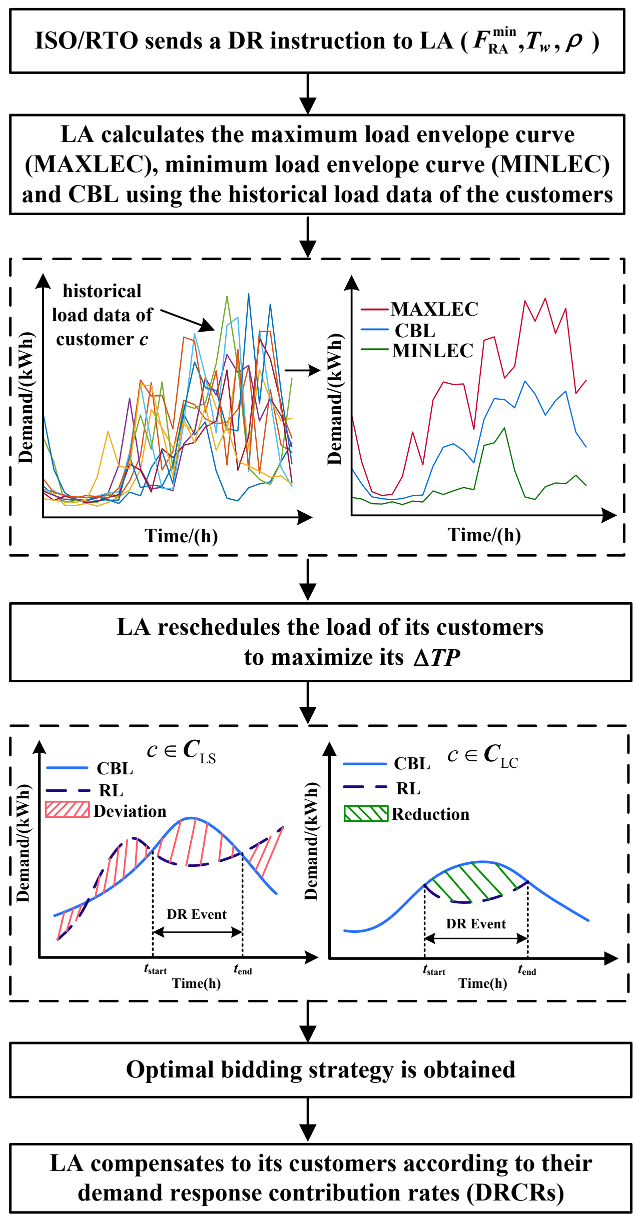

Fig. 2. Bidding process of LA

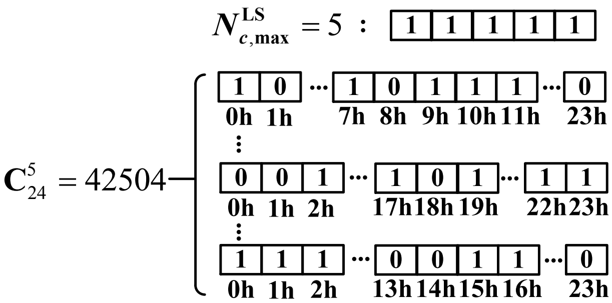

Fig. 3 Illustration of different load shifting strategies

The proposed model for the LS contracts is presented by (5)-(11). Equation (5) indicates that the rescheduled load $d_{c,t}^{\mathrm{LS}}$ depends on the decision binary variable $u_{c,t}^{\mathrm{LS}}$. $d_{c,t}^{\max}$ represents the maximum demand load of customer c at timeslot t over the past n days. The vector $\boldsymbol{d}_{c}^{\max}=[\,d_{c,0}^{\max},\ldots,d_{c,23}^{\max}\,]$ can be drawn as maximum load envelope curve (MAXLEC). Equation (6) ensures that the shifting times equal to the time limitation $N_{c,\max}^{\mathrm{LS}}$, while (7) shows the total amount of electricity usage won't be changed in LS contracts. The aggregated demand load is presented in (8). The revenue of selling the electricity, the cost of the electricity procurement and the total profit obtained are denoted by (9)-(11), respectively.

$$\begin{cases} d_{c,t}^{\mathrm{base}} \le d_{c,t}^{\mathrm{LS}} \le d_{c,t}^{\max}, u_{c,t}^{\mathrm{LS}}=0, \forall c\in \boldsymbol{C}_{\mathrm{LS}}, \forall t\in \boldsymbol{T} \\ d_{c,t}^{\mathrm{LS}} = d_{c,t}^{\mathrm{base}} - q_{c,t}^{\mathrm{LS}}, u_{c,t}^{\mathrm{LS}}=1, \forall c\in \boldsymbol{C}_{\mathrm{LS}}, \forall t\in \boldsymbol{T} \end{cases} \tag{5}$$

$$\sum_{t\in \boldsymbol{T}} u_{c,t}^{\mathrm{LS}} = N_{c,\max}^{\mathrm{LS}}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \tag{6}$$

$$\sum_{t\in \boldsymbol{T}} d_{c,t}^{\mathrm{LS}} = \sum_{t\in \boldsymbol{T}} d_{c,t}^{\mathrm{base}}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \tag{7}$$

$$bid_{t}^{\mathrm{LS}} = \sum_{c\in \boldsymbol{C}_{\mathrm{LS}}} d_{c,t}^{\mathrm{LS}}, \forall t\in \boldsymbol{T} \tag{8}$$

$$R^{\mathrm{LS}} = \gamma \cdot \sum_{t\in \boldsymbol{T}} bid_{t}^{\mathrm{LS}} \tag{9}$$

$$M^{\mathrm{LS}} = \sum_{t\in \boldsymbol{T}} bid_{t}^{\mathrm{LS}} \cdot \pi_{t}^{\mathrm{DA}} \tag{10}$$

$$TP^{\mathrm{LS}} = R^{\mathrm{LS}} - M^{\mathrm{LS}} = \sum_{t\in \boldsymbol{T}} bid_{t}^{\mathrm{LS}} \cdot \left(\gamma - \pi_{t}^{\mathrm{DA}}\right) \tag{11}$$

1) Load Curtailment (LC): In the LC contracts, the LA is able to curtail its customers' load during the period of DR event without shifting the load to any other time period. For example, some appliances would be turned off such as lights and the thermostat in the customers' premises.

The proposed formulation for LC contracts is given as follows:

$$\begin{cases} d_{c,t}^{\mathrm{LC}} = d_{c,t}^{\mathrm{base}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}}, \forall t\in \boldsymbol{T}\setminus \boldsymbol{T_w} \\ d_{c,t}^{\mathrm{LC}} = d_{c,t}^{\mathrm{base}} - F_{c,t}^{\mathrm{LC}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}}, \forall t\in \boldsymbol{T_w} \\ d_{c,t}^{\min} \le d_{c,t}^{\mathrm{LC}} \le d_{c,t}^{\mathrm{base}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}}, \forall t\in \boldsymbol{T} \end{cases} \tag{12}$$

$$F_{c,t}^{\mathrm{LC}} = \begin{cases} 0, u_{c,t}^{\mathrm{LC}} = 0, \forall c\in \boldsymbol{C}_{\mathrm{LC}}, \forall t\in \boldsymbol{T_w} \\ q_{c,t}^{\mathrm{LC}} = \eta_{c,t}^{\mathrm{LC}} \cdot d_{c,t}^{\mathrm{base}}, u_{c,t}^{\mathrm{LC}} = 1, \forall c\in \boldsymbol{C}_{\mathrm{LC}}, \forall t\in \boldsymbol{T_w} \end{cases} \tag{13}$$

$$bid_{t}^{\mathrm{LC}} = \sum_{c\in \boldsymbol{C}_{\mathrm{LC}}} d_{c,t}^{\mathrm{LC}}, \forall t\in \boldsymbol{T} \tag{14}$$

$$R^{\mathrm{LC}} = \gamma \cdot \sum_{t\in \boldsymbol{T}} bid_{t}^{\mathrm{LC}} \tag{15}$$

$$M^{\mathrm{LC}} = \sum_{t\in \boldsymbol{T}} bid_{t}^{\mathrm{LC}} \cdot \pi_{t}^{\mathrm{DA}} \tag{16}$$

$$TP^{\mathrm{LC}} = R^{\mathrm{LC}} - M^{\mathrm{LC}} = \sum_{t\in \boldsymbol{T}} bid_{t}^{\mathrm{LC}} \cdot \left(\gamma - \pi_{t}^{\mathrm{DA}}\right) \tag{17}$$

Equation (12) presents the rescheduled load $d_{c,t}^{\mathrm{LC}}$ during different time periods, while $d_{c,t}^{\min}$ represent the minimum demand load of customer c at timeslot t over the past n days. The vectors $\boldsymbol{d}_{c}^{\min}=[\,d_{c,0}^{\min},\ldots,d_{c,23}^{\min}\,]$ can be drawn as minimum load envelope curve (MINLEC). Equation (13) presents the calculation of the flexibility of the customer c at timeslot t, which depends on the decision binary variable $u_{c,t}^{\mathrm{LC}}$. The aggregated demand load is presented in (14). The revenue of selling the electricity, the cost of the electricity procurement and the total profit obtained are denoted by (15)-(17), respectively.

2) DR reward (DRR): With the implementation of the DRP, the LA is able to get the reward from the ISO/RTO, which is calculated in (18).

$$\begin{aligned} F_{\mathrm{RA}}^{\mathrm{A}} &= \sum_{t\in \boldsymbol{T_w}} F_{\mathrm{RA},t}^{\mathrm{A}} \\ &= \sum_{t\in \boldsymbol{T_w}} \left(\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}} \left(d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LS}}\right) + \sum_{c\in \boldsymbol{C}_{\mathrm{LC}}} F_{c,t}^{\mathrm{LC}} \right) \\ DRR &= \sum_{t\in \boldsymbol{T_w}} \rho_t \cdot F_{\mathrm{RA},t}^{\mathrm{A}} \end{aligned} \tag{18}$$

Therefore, the total expected profit of the LA obtained with the implementation of DRP during the bidding process is given by (19):

$$\begin{aligned} TP^{\mathrm{DR}} &= TP^{\mathrm{LS}} + TP^{\mathrm{LC}} + DRR \\ &= \sum_{t\in \boldsymbol{T}} \left(bid_{t}^{\mathrm{LS}} + bid_{t}^{\mathrm{LC}}\right) \cdot \left(\gamma - \pi_{t}^{\mathrm{DA}}\right) + \\ &\quad \sum_{t\in \boldsymbol{T_w}} \rho_t \cdot \left(\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}} \left(d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LS}}\right) + \sum_{c\in \boldsymbol{C}_{\mathrm{LC}}} F_{c,t}^{\mathrm{LC}} \right) \end{aligned} \tag{19}$$

C. Optimal Bidding Model

In general, the settlement of the compensation to customers is executed after the DR event, which depends on the additional profit ΔTP [2]. Moreover, ΔTP also has an impact on the net additional profit of the LA directly. Accordingly, the LA aims to maximize the additional profit ΔTP. The optimal bidding model can be formulated as a mixed integer linear programming (MILP) problem given by (20)-(22):

$$\max \quad \Delta TP = TP^{\mathrm{DR}} - TP^{\mathrm{NDR}} = \sum_{t\in \boldsymbol{T}_w}\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}}\left(d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LS}}\right)\cdot \rho_t + \sum_{t\in \boldsymbol{T}}\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}}\left(d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LS}}\right)\cdot \pi_t^{\mathrm{DA}} + \sum_{t\in \boldsymbol{T}_w}\sum_{c\in \boldsymbol{C}_{\mathrm{LC}}}\left(d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LC}}\right)\cdot\left(\pi_t^{\mathrm{DA}} - \gamma + \rho_t\right) \tag{20}$$

$$\textit{s.t.} \quad \sum_{t\in \boldsymbol{T}_w}\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}}\left(d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LS}}\right) + \sum_{t\in \boldsymbol{T}_w}\sum_{c\in \boldsymbol{C}_{\mathrm{LC}}} F_{c,t}^{\mathrm{LC}} \geq F_{\mathrm{RA}}^{\min} \tag{21}$$

$$\text{(5)-(7), (12)-(13)} \tag{22}$$

Equation (21) satisfies the DR requirement for load reduction. It should be noticed that the constraints (5)-(7) and (12)-(13) are still supposed to be held.

D. Compensation Mechanism

With the participation of the customers in the DRP, the LA is able to get the reward from the ISO/RTO and make the optimal bidding strategy to maximize its additional profit when it bids in day-ahead market. Thus, a rational compensation mechanism for customers is supposed to be made, which is given by (23)-(28):

$$\begin{cases} DRCR_c^{\mathrm{LS}} = \omega_1\cdot\alpha_c^{\mathrm{LS}} + \omega_2\cdot\beta_c^{\mathrm{LS}}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \\ DRCR_c^{\mathrm{LC}} = \omega_1\cdot\alpha_c^{\mathrm{LC}} + \omega_2\cdot\beta_c^{\mathrm{LC}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}} \\ \omega_1 + \omega_2 = 1 \end{cases} \tag{23}$$

$$\begin{cases} CPSC_c^{\mathrm{LS}} = \lambda^{\mathrm{LS}}\cdot\Delta TP.DRCR_c^{\mathrm{LS}} \\ \qquad = \lambda^{\mathrm{LS}}\cdot\Delta TP\cdot\omega_1\cdot\alpha_c^{\mathrm{LS}} + \lambda^{\mathrm{LS}}\cdot\Delta TP\cdot\omega_2\cdot\beta_c^{\mathrm{LS}} \\ \qquad = IC_c^{\mathrm{LS}} + OC_c^{\mathrm{LS}}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \\ CPSC_c^{\mathrm{LC}} = \lambda^{\mathrm{LC}}\cdot\Delta TP.DRCR_c^{\mathrm{LC}} \\ \qquad = \lambda^{\mathrm{LC}}\cdot\Delta TP\cdot\omega_1\cdot\alpha_c^{\mathrm{LC}} + \lambda^{\mathrm{LC}}\cdot\Delta TP\cdot\omega_2\cdot\beta_c^{\mathrm{LC}} \\ \qquad = IC_c^{\mathrm{LC}} + OC_c^{\mathrm{LC}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}} \end{cases} \tag{24}$$

$$\begin{cases} \alpha_c^{\mathrm{LS}} = \dfrac{\sum_{t\in \boldsymbol{T}} q_{c,t}^{\mathrm{LS}}}{\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}}\sum_{t\in \boldsymbol{T}} q_{c,t}^{\mathrm{LS}}}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \\ \alpha_c^{\mathrm{LC}} = \dfrac{\sum_{t\in \boldsymbol{T}} q_{c,t}^{\mathrm{LC}}}{\sum_{c\in \boldsymbol{C}_{\mathrm{LC}}}\sum_{t\in \boldsymbol{T}} q_{c,t}^{\mathrm{LC}}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}} \end{cases} \tag{25}$$

$$\begin{cases} \beta_c^{\mathrm{LS}} = \dfrac{DVA_c}{\sum_{c\in \boldsymbol{C}_{\mathrm{LS}}} DVA_c}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \\ \beta_c^{\mathrm{LC}} = \dfrac{RDA_c}{\sum_{c\in \boldsymbol{C}_{\mathrm{LC}}} RDA_c}, \forall c\in \boldsymbol{C}_{\mathrm{LC}} \end{cases} \tag{26}$$

$$\begin{cases} DVA_c = \sum_{t\in \boldsymbol{T}} \dfrac{\left|d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LS}}\right|}{d_{c,t}^{\mathrm{base}}}, \forall c\in \boldsymbol{C}_{\mathrm{LS}} \\ RDA_c = \sum_{t\in \boldsymbol{T}_w} d_{c,t}^{\mathrm{base}} - d_{c,t}^{\mathrm{LC}}, \forall c\in \boldsymbol{C}_{\mathrm{LC}} \end{cases} \tag{27}$$

$$NAP = (1 - \lambda^{\mathrm{LS}} - \lambda^{\mathrm{LC}})\cdot\Delta TP \tag{28}$$

For the sake of simplicity, the superscript (i.e., LS or LC) of each index is omitted. $DRCR_c$ is an index called DR contribution rate (DRCR) to represent each customer's contribution to the DRP in (23). Equation (24) indicates the compensation to the customers which encompasses the initial cost IC_c and operation cost OC_c. λ is the proportion of the profit that the LA would like to share with its customers, which varies with LA's motivation. The LA sets a larger λ to incentive the customers to participate in DRP, or the LA set a lower λ to increase its net additional profit. α_c and β_c are the potential DR capability rate and operation cost rate, respectively, which can be calculated by utilizing (25)-(27). The net additional profit of the LA is denoted in (28).

III. CASE STUDY

In this section, a case study is presented to verify the effectiveness of the proposed optimal bidding strategy. The, rescheduled load profile, compensation to each DRP participant and other results are illustrated in this section.

A. Dataset and Parameter Settings

The data set used in our research is imported by the customers who had an end point monitor installed by the New Thames Valley Vision (NTVV) project [36]. The data set starts when the monitors were installed between February and March 2013 and ends in November 2014.There are 208 customers with a full year load data in the data set. We finally selected 90 customers (i.e. 45 LS customers and 45 LC customers) so that the results can be highlighted. The CBL estimation method applied in this section is High6of10 [32]. The key parameter settings are given in TABLE I.

TABLE I. SUMMARY OF KEY PARAMETERS

Parameter	Value	Parameter	Value
$F_{\mathrm{RA}}^{\min}$	40000 (kWh)	λ_{LS}	0.3
t_{start}	13h	λ_{LC}	0.4
t_{end}	16h	ω_1, ω_2	0.3,0.7
γ	0.04 (\$/kWh)	ρ_t	{0.01,0.015, 0.02,0.018}

B. Results and Analysis

With the implementation of the DRP, the LA is able to optimize its bidding strategy as shown in Fig. 4. Obviously, the LA shifts the load from high-WMP hours (i.e., 13h-20h) to low-MWP hours (i.e., 0h-7h and 21h-23h), which reduces the cost of the electricity procurement. Fig. 5 shows the load reduction during the DR event, which indicates that the rescheduled load satisfies the requirement of the ISO/RTO. The compensation of the whole LS customers is presented in Fig. 6. It should be noticed that customer 6 (C6) accounts for the biggest proportion of the total compensation while customer 31 (C31) occupies the smallest part, which can be illustrated in Fig. 7. The degree of the deviation between the CBL and the rescheduled load of these two customers is totally different, which implies that greater degree of deviation gives rise to more compensation. The load deviation of all LS customers is displayed in Fig. 8. The negative deviation suggests that the load at this timeslot is shifted to other timeslots. On the contrary, the positive deviation means that the load form other timeslots are shifted to this timeslot. It should be noticed that most LS customers would like to shift their loads from high-WMP hours (i.e., 13h-20h) to low-MWP hours (i.e., 0h-7h and 21h-23h), which verifies the bidding strategy in Fig. 4. The load reduction of all LC customers is given in Fig. 9. As the

Fig. 9 shows, in order to maximize the ΔTP and satisfy the DR requirement of ISO/RTO, most LC customers would like to curtail their loads during 14h-16h since the differences between the DR price ρ_t and WMP π_t^{DA} in this period are all larger than 13h. The relationship between compensation of each LC customer and their DRCR is depicted in Fig. 10. Some comparison results of implementing DRP or not are shown in TABLE II.

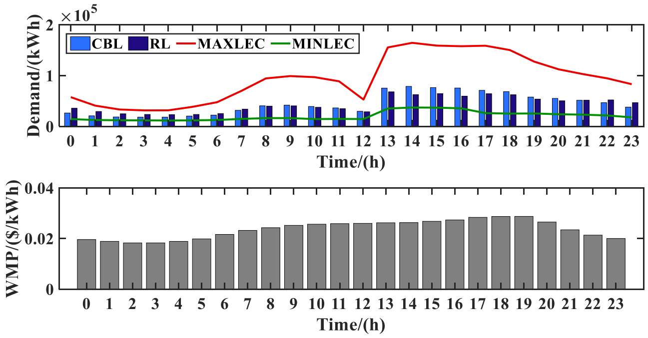

Fig. 4 The bidding strategy for LA

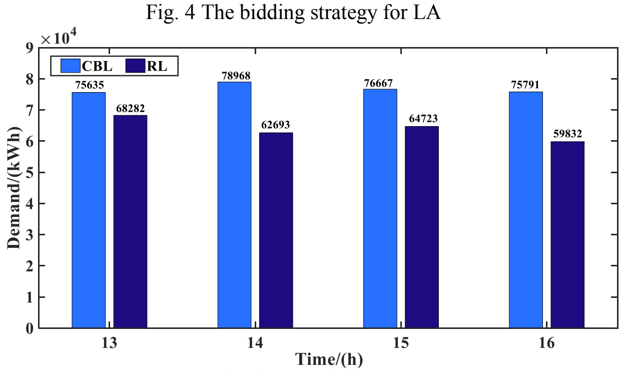

Fig. 5. Load reduction during DR event

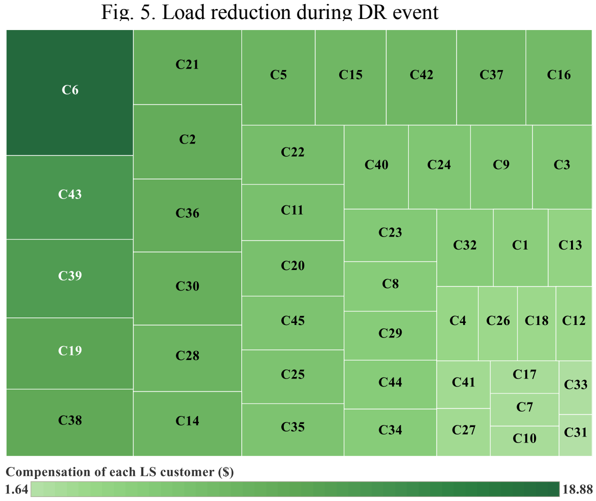

Fig. 6 Compensation of all LS customers

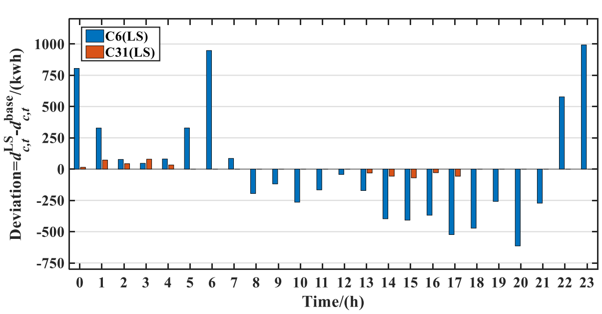

Fig. 7 Load deviation of customer 6 and customer 31

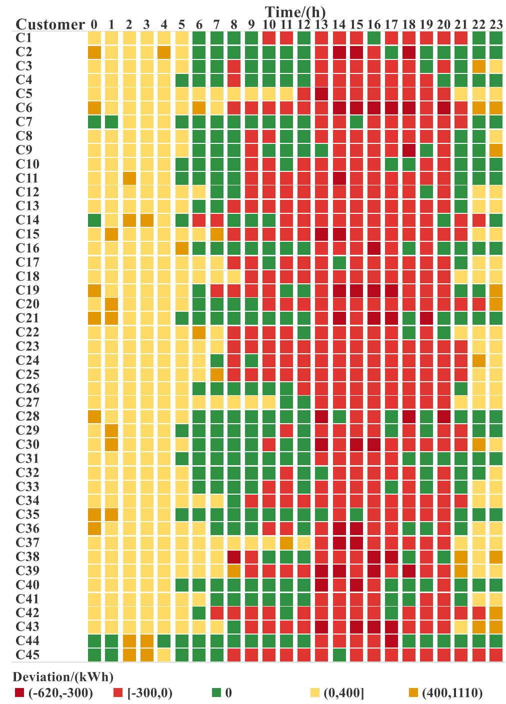

Fig. 8 Load deviation of all LS customers

Fig. 9 Load reduction of all LC customers

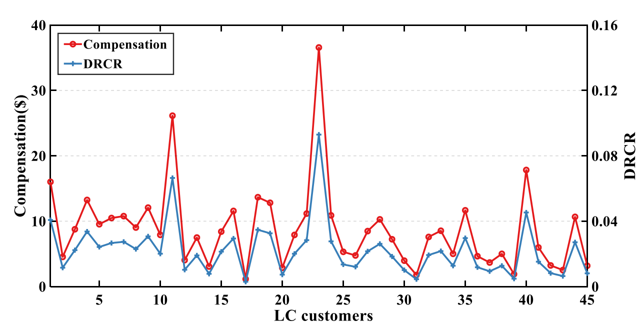

Fig. 10 Compensation and DRCR of all LC customers

TABLE II. COMPARISON BETWEEN SITUASTIONS WITH DR & WITHOUT DR

Indexes	ΔTP ($)	CPSC($)	NAP($)	$F_{\mathrm{RA}}^{\mathrm{A}}$ (kWh)
Without DR	—	—	—	0
With DR	983.4	688.4	295	51531

IV. DISCUSSION

Two main factors would have significant impacts on both the bidding strategy of the LA and some important indexes. One is the CBL estimation method since different estimated CBL will be obtained by utilizing different estimation methods. The other one is the DA price, especially when price spike occurs.

A. The Impact of CBL Estimation Methods

In this section, four CBL estimation methods are used to explore their impacts on the bidding strategy, including High6of10, Low6of10, Mid6of10 and exponential moving average (EMA) [32]. Fig. 11 and Fig. 12 present the estimated CBL and optimal bidding strategies under the four CBL estimation methods, respectively. Some important indexes are given in TABLE III. As these results show, different bidding strategies and indexes are obtained by using different CBL estimation methods. Obviously, the EMA method shows the best performance among these methods.

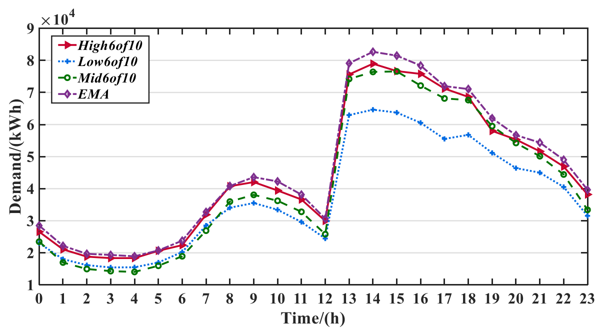

Fig.11 Estimated CBL under different CBL estimation methods

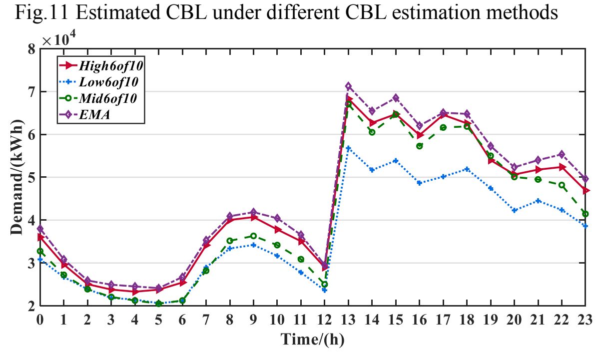

Fig.12 Bidding strategies under different CBL estimation methods

TABLE III. INDEXES UNDER DIFFERENT CBL ESTIMATION METHODS

Indexes	Baseline Estimation methods			
	High 6 of 10	Low 6 of 10	Mid 6 of 10	EMA
ΔTP ($)	983.4	847.4	989.8	**1045.8**
CPSC($)	688.4	593.2	692.9	**732.1**
NAP($)	295.5	254.2	296.9	**313.7**
$F_{\mathrm{RA}}^{\mathrm{A}}$ (kWh)	51531	40905	50060	**54434**

B. The Impact of Price Spike

As the Fig. 13 shows, two different price spike scenarios are investigated in this section. Scenario 1 has two price spike periods (i.e., 6h-10h and 17h-20h) whereas scenario 2 only has one price spike period (i.e., 12h-17h). Compared with the WMP shown in Fig. 4, the price at each timeslot in these two scenarios are all higher. The bidding strategies under these two price spike scenarios are illustrated in Fig. 14. Some important indexes are given in TABLE IV. It should be noticed that price spike will lead to larger ΔTP since the LA may lose money when there is no DRP implementation. Thus, it is pivotal to carry out the proposed optimal bidding strategy when price spike occurs.

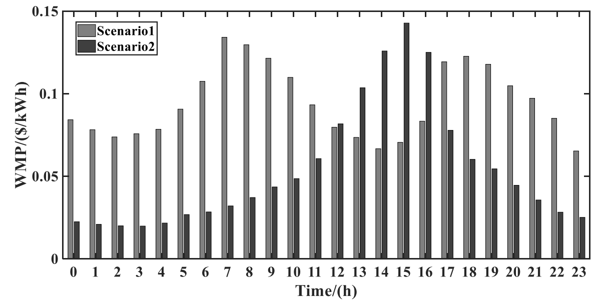

Fig.13 Different price spike scenarios

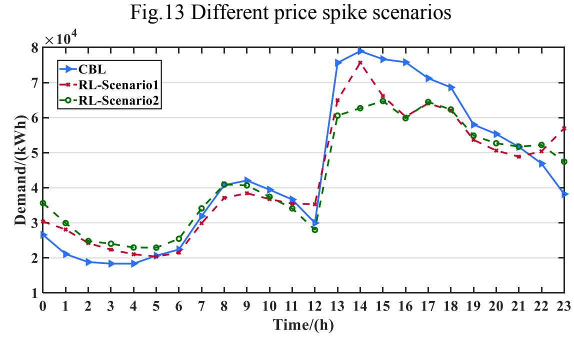

Fig. 14 Bidding strategies under different price spike scenarios

TABLE IV. INDEXES UNDER DIFFERENT PRICE SPIKE SCENARIOS

Price Spike Scenarios	Indexes			
	ΔTP ($)	CPSC($)	NAP($)	$F_{\mathrm{RA}}^{\mathrm{A}}$ (kWh)
Scenario1	3429.3	2400.5	1028.8	40000
Scenario2	7387.3	5171.1	2216.2	59243

V. CONCLUSION

This paper proposed an optimal bidding strategy for LA in DA market engaging the DRP, which considered the uncertainty of WMP. Moreover, a quantitative compensation mechanism design is investigated in this paper. The results of the case study show that all of the entities in the market will get the benefits during the DR events, which means this work is valuable for all of them. The LA is able to make more economical bidding strategy to obtain net additional profit. Customers are eligible to get compensation for participating in the DRP without significantly compromising their consumption level. Meanwhile, the ISO/RTO benefits because the peak load of the system during the DR event is reduced. In the future, the optimal bidding strategy utilizing in pre-emptive markets [37] considering the interaction between different DR aggregators [38] and under the time of use DR program [39], [40] should be addressed.

ACKNOWLEDGMENT

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