Consumer Psychology Based Optimal Portfolio Design for Demand Response Aggregators

Yunwei Shen, Yang Li, Qiwei Zhang, Fangxing Li, and Zhe Wang

Abstract—**Demand response (DR) has received much attention for its ability to balance the changing power supply and demand with flexibility. DR aggregators play an important role in aggregating flexible loads that are too small to participate in electricity markets. In this work, a DR operation framework is presented to enable local management of customers to participate in electricity market. A novel optimization model is proposed for the DR aggregator with multiple objectives. On one hand, it attempts to obtain the optimal design of different DR contracts as well as the portfolio management so that the DR aggregator can maximize its profit. On the other hand, the customers' welfare should be maximized to incentivize users to enroll in DR programs which ensure the effective and flexible load control. The consumer psychology is introduced to model the consumers' behavior during contract signing. Several simulation studies are performed to demonstrate the feasibility of the proposed model. The results illustrate that the proposed model can ensure the profit of the DR aggregator whereas the customers' welfare is considered.**

Index Terms—**Demand response (DR), aggregator, contract, consumer psychology, multi-objective problem, Pareto optimization.**

I. Introduction

WITH the growing concern about reducing greenhouse gas emission to achieve a sustainable and environment-friendly energy system, renewable energy sources (RESs) have drawn lots of attention all over the world [1]. The increasing penetration of RESs has posed significant challenges to the operation of power systems [2], [3] due to the inherent characteristics of RESs, which requires a more flexible and effective way to maintain the balance between supply and demand [4]. Demand response (DR) can deal with peak demand, provide reserves, and improve the system reliability, which is a cost-effective technique to add more flexibility to the grid [5]-[9]. In addition, the development of the communication infrastructure, advanced metering equipment and automatic control technologies enable more involvement of DR resources to provide system services [10], [11]. A DR aggregator plays a vital role in the interaction between the electric utility and flexible customers. DR aggregators can contribute to achieving peak load reduction by offering aggregated DR service and help retail customers adjust their electricity consumption behaviors as well as allow them to participate in electricity markets [12].

Many works have been done from different aspects to explore the operation of the DR aggregator. In [13], a reward-based residential DR scheme is proposed to achieve peak shaving and to improve the feeder voltage profile under different spatial distributions of residential loads. A price-based economic DR model is proposed in [14], which considers customer response to prices, customer energy pattern and aggregated load dynamics. A hierarchical market model for the interaction of the utility operator, aggregators and customers is introduced in [15], in which a multi-objective problem is formulated to maximize the benefits of independent system operator (ISO), the aggregator, and customers. Usually, the load aggregators sign contract agreement with the participating customers which details their responsibility. In [16], an optimization model for the DR aggregator is proposed to determine the optimal schedule of DR contracts and maximize the payoff in the day-ahead (DA) electricity market. In [17], a bi-level optimization model is proposed to determine the optimal portfolio of the DR resources for the participation of the aggregator in bulk electricity markets.

The aforementioned studies explore the implementation of DR aggregators effectively, but neglect customers' comfort. Considering customer preferences, an analytical method to control thermostatically controlled loads (TCLs) is proposed in [18] to ensure users' satisfaction. A hierarchical and distributed control strategy for TCLs is proposed in [19], in which the target assignment is self-regulated. In [20], an incentive-based DR model is proposed to maximize the benefit of electricity retailers which considers customers' behaviors during peak and valley time. A time-geographic diary approach is proposed and a software called VISUAL-TimePAcTS/energy use is designed in [21] to visualize electricity consumption patterns in a household. A modification

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Y. Shen and Y. Li (corresponding author) are with the School of Electrical Engineering, Southeast University, Nanjing 210096, China, and Y. Shen is also with the Department of Electrical Engineering and Computer Science, The University of Tennessee, Knoxville, TN 37996, USA (e-mail: shenywee@seu.edu.cn; li_yang@seu.edu.cn).

Q. Zhang and F. Li are with the Department of Electrical Engineering and Computer Science, The University of Tennessee, Knoxville, TN 37996, USA (e-mail: qzhang41@vols.utk.edu; fli6@utk.edu).

Z. Wang is with State Grid Shanghai Municipal Electric Power Company, Shanghai 200122, China (e-mail: wang.z@sh.sgcc.com.cn).

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of a concept for peer-to-peer learning about residential energy solutions is evaluated in [22] through a collective "energy walk". The satisficing theory is applied in [23] to model consumers' behaviors. The consumers' welfare must be greater than or equal to an aspiration level.

This paper proposes a novel multi-objective optimization model for the aggregator to determine the contract details for the DR services provided by end-users as well as the optimal portfolio of DR contracts. The DR aggregator participates in the DA market with the objective of maximizing its profit and the customers' welfare. In particular, the main contributions of this work are as follows:

1) A DR aggregator operation framework dealing with the interaction between the aggregator and customers is proposed, as well as the contract design which considers the interests from both the DR aggregator and the consumers.

2) A multi-objective model for the aggregator is formulated to maximize both the profit and the customers' welfare, which encourages the positive enrollment of potential DR resources.

3) Consumers' behaviors based on the consumer psychology are modeled considering customer preferences.

4) The design of three different DR contracts and the optimal portfolio of DR resources are described.

5) A comprehensive analysis for several case studies is conducted, which demonstrates the feasibility of the model and the flexibility provided by DR contracts that enables the aggregator to participate in the electricity market.

The rest of this paper is organized as follows. Section II presents the overall hierarchy of DR aggregator participation in the DA market and the details of prevailing contracts that the DR aggregator signs with customers. A mathematical model is formulated and explained in Section III. Section IV describes the problem reformulation and optimization algorithm. In Section V, case studies and simulation results are discussed. Finally, the conclusion and future work are discussed in Section VI.

II. Operation Model of DR Aggregator

In this paper, the DR aggregator provides DR services to ISO by offering customers a set of contracts in the DA market. The aggregator is considered as a price-taker entity.

A. Operation Framework of DR Aggregator

The DR aggregator provides a comprehensive customer service like an integrated energy service provider, because it is hard for customers to evaluate their DR potentials. The DR aggregator can perform an overall data mining of users' behaviors based on the technical models and the social-behavioral survey results [2], [24]-[26]. It is assumed that the customers have an overall understanding of their electricity consumption and DR capacity based on the performance evaluation service provided by the DR aggregator.

In practice, DR aggregators can assemble a number of flexible customers into an aggregation to participate in the DA market with considerable weight. Figure 1 shows the operation framework of the DR aggregator.

The DR aggregator offers multiple DR contracts, which are load curtailment (LC), load shifting (LS) and flexible charging load (FCL) to encourage residential customers to actively join in DR programs. These contracts are settled well in advance and allow the aggregator to control the customers' loads under certain authority. Customers sign the contracts to receive incentives for their DR capacity. As a result, the customer preference can be obtained and the potential customers can be located when the DR contracts are signed. The DR aggregator participates in the DA market to submit DR bids according to customers' DR contracts and receives penalties for false bidding if the real DR services provided by the aggregator are less than the bidding amount. In real time, customers can choose to shift a certain proportion of the contract amount and they will receive penalties for any performance failure. Basically, the DR aggregator earns profit hourly once the market is cleared. The purpose of the aggregator is to design the DR contracts and monitor customers' actual response to maximize the total profits.

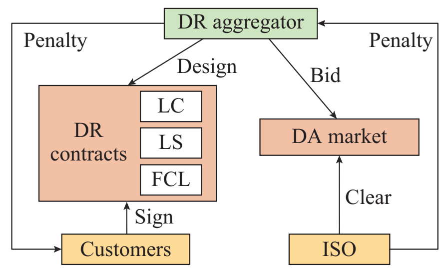

Fig. 1. Operation framework of DR aggregator.

B. DR Contracts

The DR aggregator can accumulate multiple customers with similar characteristics of electricity consumption into a cluster under the same DR contract. This would significantly simplify the design of DR contracts. In this work, the DR aggregator can make the best use of the flexibility of its customers by scheduling three types of DR contracts, the details of which are described below.

1) LC

LC contract indicates the conventional load curtailment strategy. Customers participating in LC contracts agree to reduce a certain amount of their electricity consumptions during the scheduled time window and do not shift their loads to any other period. Suitable loads for LC contracts are lights, air-conditioners, water heaters, and non-essential applications.

2) LS

Loads participating in LS contracts can be partially rescheduled during the scheduled time window and shifted to off-peak hours. Suitable loads for LS contracts are air-conditioners, washing machines, and laundry dryers.

3) FCL

Customers participating in FCL contracts can choose a preferred schedulable duration from the predetermined time window to reduce a certain amount of their electricity consumptions. The schedulable duration can be continuous or discrete. If the specified duration is equal to the time window set by the aggregator, the FCL contract is the same as the LC contract. For example, if the load control time window planned by the aggregator is from 08:00 a.m. to 12:00 p. m. and the preferred schedulable duration of one customer is 2 hours, this customer can be enrolled in the DR program in any 2 hours from 08:00 a.m. to 12:00 p.m.. Suitable loads for FCL contracts are pool filters, plug-in electric vehicles and high efficiency particulate air (HEPA) filters.

III. Problem Formulation

The operation of the DR aggregator is to design and dispatch the DR contracts, which optimize its own profit. To achieve this, the DR aggregator needs to account for the customers' satisfaction because the more customers are enrolled in DR events, the more revenues the aggregator can gain from the DA market. This problem can be formulated as a multi-objective optimization model in which both the profit of the DR aggregator and the customers' welfare are maximized.

A. Profit of DR Aggregator

The DR aggregator profits by bidding DR capacity in the DA market and paying the customers based on the DR contracts. The objective of the DR aggregator is to maximize its profit R as shown in (1), which is subjected to (2)-(4) and the contract constraints in the profit model of the DR aggregator.

$$\max R=\sum_{t\in T}\left(L_t^{bid}\rho_t^{da}-\sum C_{t,k_1}^{lc}-\sum C_{t,k_2}^{ls}-\sum C_{t,k_3}^{fcl}-Pen_t^A+Pen_t^C\right) \tag{1}$$

$$0\le L_t^{bid}\le \sum q_{t,k_1}^{lc}+\sum q_{t,k_2}^{ls}+\sum q_{t,k_3}^{fcl} \quad \forall t\in T \tag{2}$$

$$Pen_t^A=\varepsilon_t^A\left[L_t^{bid}-\left(\sum q_{t,k_1}^{lc,R}+\sum q_{t,k_2}^{ls,R}+\sum q_{t,k_3}^{fcl,R}\right)\right] \quad \forall t\in T \tag{3}$$

$$Pen_t^C=Pen_t^{lc}+Pen_t^{ls}+Pen_t^{fcl} \quad \forall t\in T \tag{4}$$

where subscripts k_1, k_2, k_3 are the customer types, $k_1\in K^{lc}$, $k_2\in K^{ls}$, $k_3\in K^{fcl}$, and K^{lc}, K^{ls}, K^{fcl} are the total numbers of LC, LS, FCL contracts, respectively; T is the set of simulation time slots; L^{bid} is the bid of the aggregator for offering DR service in DA market; ρ^{da} is the electricity price of DA market; C^{lc}, C^{ls} and C^{fcl} are the total costs of LC, LS and FCL contracts, respectively; Pen^A is the penalty to the aggregator; Pen^C is the penalty to the customers; Pen^{lc}, Pen^{ls} and Pen^{fcl} are the penalties to the customers enrolled in LC, LS and FCL contracts, respectively; q^{lc}, q^{ls} and q^{fcl} are the allowed dispatch capacities of LC, LS and FCL contracts, respectively; $q^{lc,R}$, $q^{ls,R}$ and $q^{fcl,R}$ are the real dispatch power of LC, LS and FCL contracts, respectively; and ε^A is the penalty coefficient to the aggregator.

The objective function (1) represents the payoff of the DR aggregator. The income consists of two parts: the revenue for bidding in the DA market and the penalty to customers for their inadequate response. The expenditure is the total cost of paying the customers for their response based on the contracts and the penalty from ISO for the false bidding. The decision variables are the unit price of LC contract ρ^{lc}, the unit price of LS contract ρ^{ls} and the allowed dispatch capacity of FCL contract q^{fcl}. According to (2), it is ensured that the bidding amount in the DA market does not exceed the total amount of load reduction capacity in the contracts. To ensure fair competition on the market, the DR aggregator will be penalized by the ISO if the real DR service provided by the aggregator is less than the bidding amount. It is assumed that the DR aggregator is equipped with interval meters recording electricity usage which must be sufficient to provide the ISO with hourly, one-minute, or real-time load data as applicable to the wholesale market [27]. As a result, a penalty function (3) is introduced. Similarly, customers will also be penalized for inadequate response as shown in (4), which will be discussed in Section III-B.

The contract constraints in the profit model of the DR aggregator are specifically elaborated in this paper. The execution of LC, LS and FCL contracts are presented in detail as follows.

1) The LC contract can be modeled as:

$$C_{t,k_1}^{lc}=q_{t,k_1}^{lc}\rho_{t,k_1}^{lc} \quad \forall t\in\psi_{lc},\forall k_1 \tag{5}$$

$$\rho_{t,k_1}^{lc,\min}\le\rho_{t,k_1}^{lc}\le\rho_{t,k_1}^{lc,\max} \quad \forall t\in\psi_{lc},\forall k_1 \tag{6}$$

where ψ_{lc} is the scheduling hour for the LC contract.

The cost of LC contract is determined by (5). The maximum and minimum values of the unit price of LC contract are limited by (6).

2) The LS contract can be modeled as:

$$C_{t,k_2}^{ls}=q_{t,k_2}^{ls}\rho_{t,k_2}^{ls} \quad \forall t\in\psi_{ls,p},\forall k_2 \tag{7}$$

$$\rho_{t,k_2}^{ls,\min}\le\rho_{t,k_2}^{ls}\le\rho_{t,k_2}^{ls,\max} \quad \forall t\in\psi_{ls,p},\forall k_2 \tag{8}$$

Under LS contract, customers allow the aggregator to shift their loads from period $\psi_{ls,p}$ to period $\psi_{ls,v}$.

3) The FCL contract has a fixed schedulable duration Td, which represents the total hours of load dispatch. Thus, the FCL contract can be modeled as:

$$C_{t,k_3}^{fcl}=\rho^{fcl}q_{t,k_3}^{fcl} \quad \forall t\in T,\forall k_3 \tag{9}$$

$$\sum_{t\in T}v_{t,k_3}^{fcl}=Td_{k_3} \quad \forall k_3 \tag{10}$$

$$v_{t,k_3}^{fcl}\in\{0,1\} \quad \forall t\in T,\forall k_3 \tag{11}$$

$$q_{t,k_3}^{fcl,\min}v_t^{fcl}\le q_{t,k_3}^{fcl}\le q_{t,k_3}^{fcl,\max}v_t^{fcl} \quad \forall t\in T,\forall k_3 \tag{12}$$

where ρ^{fcl} is the unit price of FCL contract, which is fixed and determined by the aggregator; and v^{fcl} is the binary variable that indicates the status of FCL contract.

The cost of FCL contract is given by (9). The dispatch period of the FCL contract is set to be within the schedulable duration Td by (10) and (11). The maximum and minimum dispatch power provided by the customers in FCL contract is limited by (12).

B. Customers' Welfare

The DR aggregator can obtain comprehensive information about users' electricity consumption and DR capacity by equipping local smart meters. In the long run, the DR aggregator negotiates the details of the DR contracts with customers to encourage them to enter into the DR program. The objective of the customers is to maximize their welfare as shown in (13), which is subjected to (14)-(19) and the contract constraints in the customers' welfare model.

$$\max S=\sum_{t\in T}\left(\sum_{k_1\in K^{lc}}C_{t,k_1}^{lc}+\sum_{k_2\in K^{ls}}C_{t,k_2}^{ls}+\sum_{k_3\in K^{fcl}}C_{t,k_3}^{fcl}-Pen_t^{lc}-Pen_t^{ls}-Pen_t^{fcl}-\sum_{k_1\in K^{lc}}Dis_{k_1}^{lc}-\sum_{k_2\in K^{ls}}Dis_{k_2}^{ls}-\sum_{k_3\in K^{fcl}}Dis_{k_3}^{fcl}\right) \tag{13}$$

$$Pen_t^{lc}=\varepsilon_t^{lc}\sum_{k_1\in K^{lc}}\left(q_{t,k_1}^{lc}-q_{t,k_1}^{lc,R}\right)\quad \forall t\in\psi_{lc} \tag{14}$$

$$Pen_t^{ls}=\varepsilon_t^{ls}\sum_{k_2\in K^{ls}}\left(q_{t,k_2}^{ls}-q_{t,k_2}^{ls,R}\right)\quad \forall t\in\psi_{ls,p} \tag{15}$$

$$Pen_t^{fcl}=\varepsilon_t^{fcl}\sum_{k_3\in K^{fcl}}\left(q_{t,k_3}^{fcl}-q_{t,k_3}^{fcl,R}\right)\quad \forall t\in T \tag{16}$$

$$Dis_{k_1}^{lc}=\mu_{k_1}^{lc}\left(q_{t,k_1}^{lc,R}\right)^2\quad \forall t\in\psi_{lc},\forall k_1 \tag{17}$$

$$Dis_{k_2}^{ls}=\mu_{k_2}^{ls}\left(q_{t,k_2}^{lc,R}\right)^2\quad \forall t\in\psi_{ls,p},\forall k_2 \tag{18}$$

$$Dis_{k_3}^{fcl}=\mu_{k_3}^{fcl}\left(q_{t,k_3}^{fcl,R}\right)^2\quad \forall t\in T,\forall k_3 \tag{19}$$

where Dis^{lc}, Dis^{ls} and Dis^{fcl} are the dissatisfactions of customers caused by LC, LS and FCL contracts, respectively; μ^{lc}, μ^{ls} and μ^{fcl} are the dissatisfactory coefficients of customers in LC, LS and FCL contracts, respectively; and ε^{lc}, ε^{ls} and ε^{fcl} are the penalty coefficients. The penalties to customers in LC, LS and FCL contracts are given by (14), (15) and (16), respectively. Obviously, it will cause inconvenience on the customers' daily life when they provide DR service through the contracts. Customer dissatisfaction should be considered in their welfare model, and it depends on the real dispatch power. The dissatisfaction function of the customers in LC, LS and FCL contracts can be modeled by quadratic equations [15] which are given by (17), (18) and (19), respectively.

In this paper, the consumer psychology [28]-[31] is applied to describe the consumers' behavior. It is assumed that the allowed dispatch capacities of LC and LS contracts are determined by customers, which follow the consumer psychology. As shown in Fig. 2, ρ_i is the unit price for load dispatch in the DR contract and q_i is the allowed dispatch capacity [31]. There exists a lower limit of the incentive to each customer. When the unit price for load reduction is less than the lower limit a_i, the customer does not sign the contract because the incentive is too small. This region is called the insensitive area. When the unit price continues to increase and exceeds a_i, the customer is willing to enroll in the DR contract and the allowed dispatch power is approximately proportional to the unit price offered by the aggregator [24]. This region is called the responsive area. The gradient γ_i in the responsive area represents the sensitivity of the customer to the price offered in the DR contract. Meanwhile, there exists an upper limit of the response capacity which means after the unit price reaches the saturation stimulus value b_i, regardless how high the unit price is, the response remains the same because the customer does not want to further compromise their comfort levels. This region is called the saturation area.

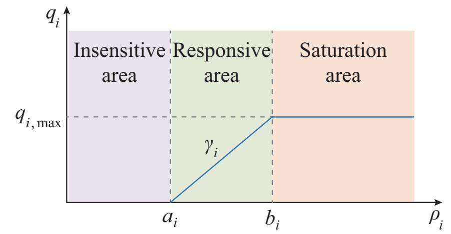

Fig. 2. Relationship between allowed dispatch capacity and unit price based on consumer psychology.

Then, the relationship between the allowed dispatch capacity q_i in the contract and the unit price ρ_i can be described as follows.

$$q_i=\begin{cases}0 & 0\le\rho_i<a_i\\ \gamma_i(\rho_i-a_i) & a_i\le\rho_i<b_i\\ q_{i,\max} & \rho_i\ge b_i\end{cases} \tag{20}$$

In addition, considering customer preferences, it is assumed that the actual dispatch load in the real-time stage can be a portion of the allowed dispatch capacity in the contract and the portion follows the normal distribution. However, the customers will be penalized for their failure of performance.

The contract constraints in the customers' welfare model are specifically elaborated as follows.

1) The allowed dispatch capacity in LC contract is given by (21) based on the consumer psychology. According to (22), the actual dispatch load in the real-time stage is part of the allowed dispatch capacity in the contract and the portion α^{lc} follows the normal distribution.

$$q_{t,k_1}^{lc}=\begin{cases}0 & 0\le\rho_{t,k_1}^{lc}<a_{k_1}^{lc},\forall t\in\psi_{lc},\forall k_1\\ \gamma_{k_1}^{lc}(\rho_{t,k_1}^{lc}-a_{k_1}^{lc}) & a_{k_1}^{lc}\le\rho_{t,k_1}^{lc}<b_{k_1}^{lc},\forall t\in\psi_{lc},\forall k_1\\ \gamma_{k_1}^{lc}(b_{k_1}^{lc}-a_{k_1}^{lc}) & \rho_{t,k_1}^{lc}\ge b_{k_1}^{lc},\forall t\in\psi_{lc},\forall k_1\end{cases} \tag{21}$$

$$q_{t,k_1}^{lc,R}=\alpha_{t,k_1}^{lc}q_{t,k_1}^{lc}\quad \forall t\in\psi_{lc},\forall k_1 \tag{22}$$

where a^{lc} and b^{lc} are the upper limit and the lower limit of the incentive in LC contract, respectively; and γ^{lc} is the gradient.

2) The execution of LS contract can be modeled as follows.

$$q_{t,k_2}^{ls}=\begin{cases}0 & 0\le\rho_{t,k_2}^{ls}<a_{k_2}^{ls},\forall t\in\psi_{ls,p},\forall k_2\\ \gamma_{k_2}^{ls}(\rho_{t,k_2}^{ls}-a_{k_2}^{ls}) & a_{k_2}^{ls}\le\rho_{t,k_2}^{ls}<b_{k_2}^{ls},\forall t\in\psi_{ls,p},\forall k_2\\ \gamma_{k_2}^{ls}(b_{k_2}^{ls}-a_{k_2}^{ls}) & \rho_{t,k_2}^{ls}\ge b_{k_2}^{ls},\forall t\in\psi_{ls,p},\forall k_2\end{cases} \tag{23}$$

$$q_{t,k_2}^{ls,R}=\alpha_{t,k_2}^{ls}q_{t,k_2}^{ls}\quad \forall t\in\psi_{ls,p},\forall k_2 \tag{24}$$

where a^{ls} and b^{ls} are the upper limit and the lower limit of the incentive in LS contract, respectively; and γ^{ls} is the gradient. Under LS contract, customers allow the aggregator to shift their loads from period $\psi_{ls,p}$ to period $\psi_{ls,v}$.

3) The allowed dispatch capacity of FCL contract is within the limitation offered by the customer, which is given by (11) and (12). Since the schedulable duration is flexible, the customers enrolled in the FCL contract give full authority to

the DR aggregator to control their loads. Thus, the actual dispatched load in the real-time stage is exactly the same as the capacity in the FCL contract, which is given by (25). As the dispatch duration is relatively small and flexible, the dissatisfaction caused by the FCL contract can be ignored, as shown in (26).

$$q^{fcl,R}_{t,k_3} = q^{fcl}_{t,k_3} \quad \forall t, k_3 \tag{25}$$

$$Dis^{fcl}_{k_3} = 0 \tag{26}$$

IV. Simulation Procedure

A. Model Reformulation

According to the above problem formulation, it is clear that the consumer psychology will pose piecewise linear constraints, which is a common issue for most of the optimization algorithms. In this paper, the piecewise constraints are dealt with by introducing extra 0-1 integer variables. Equations (21)-(24) can be reformulated as shown in (27)-(36).

$$\begin{aligned} q^{lc}_{t,k_1} = {} & 0 \times \eta^1_{t,k_1} + \gamma^{lc}_{k_1} \rho^{lc}_{t,k_1} - \eta^2_{t,k_1} \gamma^{lc}_{k_1} a^{lc}_{k_1} + \\ & \eta^3_{t,k_1} \gamma^{lc}_{k_1} (b^{lc}_{k_1} - a^{lc}_{k_1}) \quad \forall t \in \psi_{lc}, \forall k_1 \end{aligned} \tag{27}$$

$$\eta^1_{t,k_1} + \eta^2_{t,k_1} + \eta^3_{t,k_1} = 1 \quad \forall t \in \psi_{lc}, \forall k_1 \tag{28}$$

$$(\eta^2_{t,k_1} - M\eta^3_{t,k_1}) a^{lc}_{k_1} \le \rho^{lc}_{t,k_1} \le b^{lc}_{k_1} (\eta^2_{t,k_1} - M\eta^3_{t,k_1}) \quad \forall t \in \psi_{lc}, \forall k_1 \tag{29}$$

$$\rho^{lc}_{t,k_1} \ge \eta^3_{t,k_1} b^{lc}_{k_1} \quad \forall t \in \psi_{lc}, \forall k_1 \tag{30}$$

$$q^{lc,R}_{t,k_1} = \partial^{lc}_{t,k_1} q^{lc}_{t,k_1} \quad \forall t \in \psi_{lc}, \forall k_1 \tag{31}$$

$$\begin{aligned} q^{ls}_{t,k_2} = {} & 0 \times \eta^1_{t,k_2} + \gamma^{ls}_{k_2} \rho^{ls}_{t,k_2} - \eta^2_{t,k_2} \gamma^{ls}_{k_2} a^{ls}_{k_2} + \\ & \eta^3_{t,k_2} \gamma^{ls}_{k_2} (b^{ls}_{k_2} - a^{ls}_{k_2}) \quad \forall t \in \psi_{ls,p}, \forall k_2 \end{aligned} \tag{32}$$

$$\eta^1_{t,k_2} + \eta^2_{t,k_2} + \eta^3_{t,k_2} = 1 \quad \forall t \in \psi_{ls,p}, \forall k_2 \tag{33}$$

$$(\eta^2_{t,k_2} - M\eta^3_{t,k_2}) a^{ls}_{k_2} \le \rho^{ls}_{t,k_2} \le b^{ls}_{k_2} (\eta^2_{t,k_2} - M\eta^3_{t,k_2}) \quad \forall t \in \psi_{ls,p}, \forall k_2 \tag{34}$$

$$\rho^{ls}_{t,k_2} \ge \eta^3_{t,k_2} b^{ls}_{k_2} \quad \forall t \in \psi_{ls,p}, \forall k_2 \tag{35}$$

$$q^{ls,R}_{t,k_2} = \partial^{ls}_{t,k_2} q^{ls}_{t,k_2} \quad \forall t \in \psi_{ls,p}, \forall k_2 \tag{36}$$

where η^1_{t,k_1}, η^2_{t,k_1}, η^3_{t,k_1}, η^1_{t,k_2}, η^2_{t,k_2}, η^3_{t,k_2} are the new introduced binary variables which indicate each segment of the piecewise function; and M is a self-defined large number. Constraints (27), (32) ensure that q^{lc}_{t,k_1} and q^{ls}_{t,k_2} can be situated in only one segment of the piecewise function. Constraints (29), (34) confine ρ^{lc}_{t,k_1} and ρ^{ls}_{t,k_2} within a_i and b_i in the responsive area. These two constraints will be non-binding by the use of M in the saturation area. Constraints (30), (35) enable ρ^{lc}_{t,k_1} and ρ^{ls}_{t,k_2} to be larger than b_i in the saturation area. The equivalency of (20)-(24) and (27)-(36) can be easily demonstrated by enumerating all the binary variables introduced.

B. Obtain Pareto Front Using Non-dominated Sorting Genetic Algorithm II (NSGA-II)

After the reformulation, the proposed problem becomes a multi-objective integer optimization model. The Pareto front can present the trade-offs between each objective [32]. Conventional scalarization methods like the weighted sum method may fail due to non-convexity. Equations (7) and (9) will lead traditional integer programming methods like branch and bound to infeasible regions. Therefore, the NSGA-II is applied to obtain the Pareto front for its efficiency and ease of implementation [33]. Each solution in the Pareto front solution set has its own advantages over the others. However, some solutions are prone to benefit one particular objective. According to (37)-(41), an optimal solution P^* can be obtained to guarantee fairness, where P is a solution from the solution set Sol [15], [34].

$$P^* = \arg \max_{P \in Sol} \min \left(\frac{R^{\max} - R(P)}{R^{\max} - R^{\min}}, \frac{S^{\max} - S(P)}{S^{\max} - S^{\min}} \right) \tag{37}$$

$$R^{\max} = \max_{P \in Sol} R(P) \tag{38}$$

$$R^{\min} = \min_{P \in Sol} R(P) \tag{39}$$

$$S^{\max} = \max_{P \in Sol} S(P) \tag{40}$$

$$S^{\min} = \min_{P \in Sol} S(P) \tag{41}$$

V. Simulation Results

In this section, several case studies are presented. This paper aims to show how the DR aggregator participates in the DA market based on the multi-objective optimization model while considering the customers' welfare reflected as DR contracts. The price forecasting approach is considered out of the scope of this paper [16], [17], [23], [35]. In terms of the DA market prices, the historical data from PJM in 2017 is used in the model [36], as shown in Fig. 3.

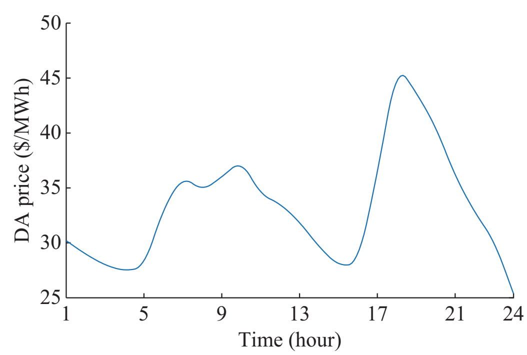

Fig. 3. DA expected price for DR aggregator.

For simulation purpose, customers are aggregated into several typical representative consumer types. It is assumed that customers of the same type respond to the incentives from the aggregator in the same way. The proposed multi-objective problem for the DR aggregator is implemented in MATLAB 2014 and runs in a computer with an Intel i7-3720 processor and 8 GB RAM.

A. Base Case

The number of customer types in the three contracts k_1, k_2 and k_3 are 3, 3, 1, respectively. The allowed dispatch capacities of LC and LS contracts of different types of customers are shown in Fig. 4. The real response coefficients α^{lc} and

α^{ls} follow the normal distribution as shown in Fig. 5. In terms of the FCL contract, the maximum dispatch power $q^{fcl,\max}$ is 85 MW and the schedulable duration Td is 3 hours. The unit price of the FCL contract is 17 \$/MW. The penalty coefficients to the aggregator and customers are 5 and 3, respectively. The dissatisfaction coefficient of customers is 0.1 [15].

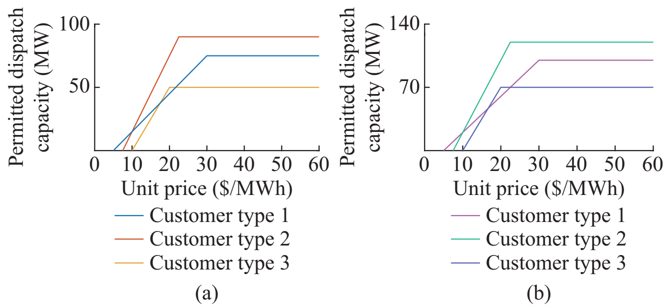

Fig. 4. Consumer psychology curves of different customer types in LC and LS contracts. (a) Customer response in LC contract. (b) Customer response in LS contract.

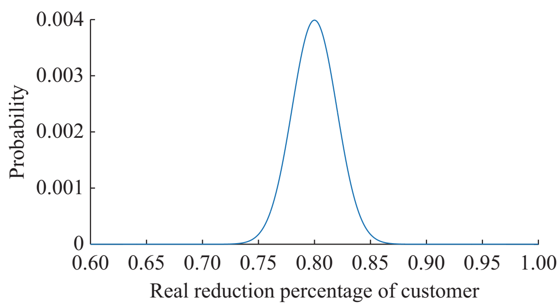

Fig. 5. Distribution of real response coefficient of customer.

Using the NSGA-II, the Pareto front for the DA market model can be generated. Figure 6 gives an example of the Pareto front. It explains the interaction between the two objectives. An optimal solution p^* can be chosen based on (37)-(41) to ensure fairness. As shown in Fig. 6, the selected optimal solution is located in the center of the Pareto front graphically, which means that a fair design can be achieved through the proposed multi-objective model.

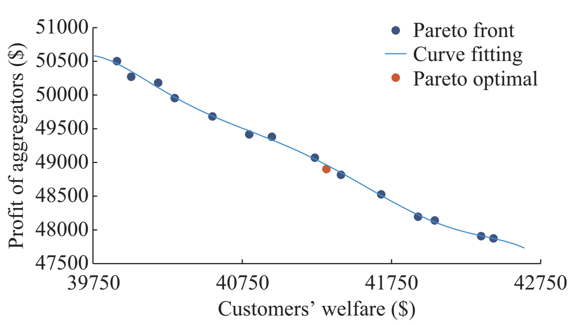

Fig. 6. Example of Pareto front.

The optimal schedules for the three DR contracts are shown in Fig. 7 as well as the hourly DA market prices. The daily optimal profit of the DR aggregator is \$41358.65 and customers' welfare is \$48902.13. None of the contracts are scheduled at hours 1-6, 8-9, 11-16 and 22-24, when the DA market price is relatively small and the DR aggregator does not bid DR services in the market. The scheduled quantity of the LS contract is larger than the others at hours 7, 17 and 20, since the unit price of the LS contract is higher than that of the others. Although the unit price of the LC contract is higher than that of the LS contract, the scheduled quantity is smaller because the customers in the LS contract are set to be more sensitive to price incentives. The FCL contract is scheduled at hours 10, 19 and 21 owing to the limit of 3-hour schedulable duration.

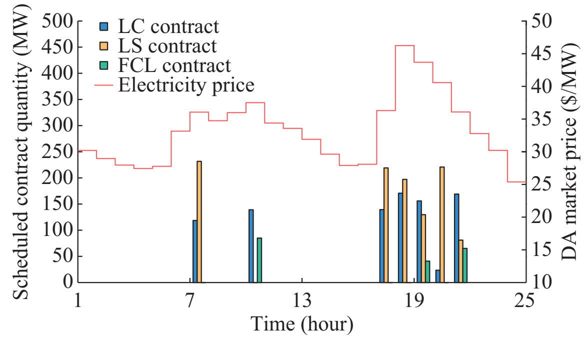

Fig. 7. Optimal schedules of three DR contracts.

B. Impact of Bidding Strategy of DA Aggregator

In the proposed model, it is assumed that the DR aggregator has full information about the DA market. It can predict the demand balance and DA prices with high accuracy to make a proper bidding strategy. The impact of the bidding strategy of DR aggregator is investigated. The other parameters such as the DA prices and the response of customers remain the same as in the base case. The data of different bidding strategies are presented in Table I. At the rest hours which are not listed in Table I, the bidding amounts are zero.

TABLE I
BIDDING AMOUNT OF DIFFERENT HOURS

Time (hour)	Bidding amount (MW)		
	Base case	Case 1	Case 2
7	438	396	318
10	256	552	435
17	441	478	453
18	463	350	149
19	401	431	590
20	301	343	571
21	383	441	105

The optimal schedules for DR contracts in cases 1 and 2 are shown in Fig. 8 and Fig. 9, respectively. In case 1, the daily optimal profit of the DR aggregator and the customers' welfare are \$42683.94 and \$55567.79, respectively, while those in case 2 are \$39658.23 and \$48534.44, respectively. With different bidding strategies, the composition of contracts changes significantly. For example, at hour 18, the bidding amount of the DR aggregator in the base case is 463 MW while it is 350 MW in case 1 and 149 MW in case 2.

Compared with the base case, the scheduled amount of LS contracts increases greatly and the FCL contract is put into use in case 1 while only the LS contract is scheduled at that time.

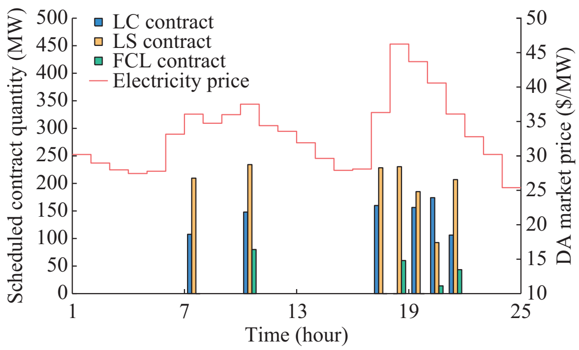

Fig. 8. Optimal schedules of three DR contracts in case 1.

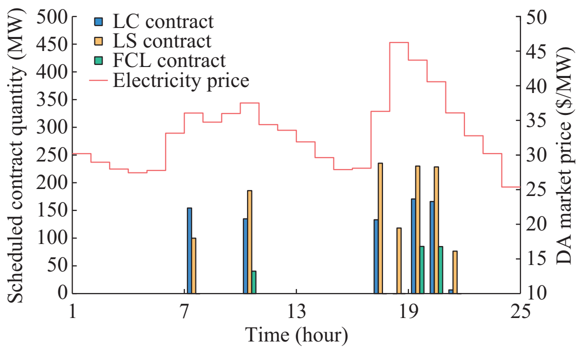

Fig. 9. Optimal schedules of three DR contracts in case 2.

C. Impact of Sensitivity of Customer Response

The impact of the sensitivity of customer response is investigated. In case 3, customers are set to be more sensitive to the price incentives than they are in the base case, which means the slopes of the consumer psychology curves are larger; while in case 4, customers are set to be less sensitive to the price incentives than in the base case. The allowed dispatch capacities of LC and LS contracts of different customer types in case 3 and case 4 are shown in Fig. 10. The other parameters such as the DA prices and the bidding strategy of the DR aggregator remain the same as in the base case.

The optimal unit prices of the DR contracts in the base case, case 3 and case 4 are listed in Table II. In case 3, at hours 10, 17-19 and 21, the unit prices of the LC contract are lower than those in the base case since customers are more sensitive to the pricing and they respond with less incentive. Similarly, the unit prices of the LS contract at hours 7, 17-20 are smaller than those in the base case. The exceptions at the rest hours exist because the aggregator needs to reach the bidding amount as well as consider the customers' welfare. By contrast, in case 4, at hours 7, 17 and 20, the unit prices of the LC contract are higher than those in the base case, while at hours 7, 10 and 17-19, the unit prices of the LS contract are higher than those in the base case. This is because customers are less sensitive to the pricing and they need more incentives for the DR service. The unit prices in case 4 reach the maximum value 30 $/MW several times because the limit of customer response is at 30 $/MW.

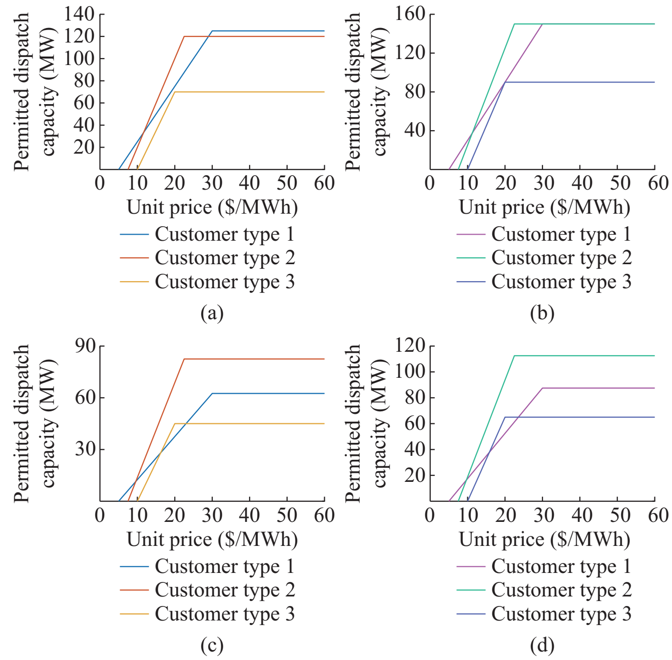

Fig. 10. Consumer psychology curves of different customer types in LC and LS contracts of case 3 and case 4. (a) Customer response in LC contract of case 3. (b) Customer response in LS contract in case 3. (c) Customer response in LC contract of case 4. (b) Customer response in LS contract in case 4.

TABLE II
UNIT PRICES OF DR CONTRACTS

Time (hour)	Unit price of base case ($/MW)			Unit price of case 3 ($/MW)			Unit price of case 4 ($/MW)		
	LC	LS	FCL	LC	LS	FCL	LC	LS	FCL
7	18.4	29.9	17	29.5	12.7	17	22.4	30.0	17
10	20.1	0.0	17	0.0	14.9	17	12.5	14.4	17
17	20.2	25.0	17	12.6	22.4	17	24.2	30.0	17
18	30.0	21.6	17	12.5	21.5	17	30.0	26.0	17
19	23.9	16.5	17	22.9	13.0	17	21.1	19.5	17
20	9.9	25.6	17	12.1	16.3	17	17.2	18.6	17
21	30.0	13.3	17	10.9	19.5	17	30.0	15.5	17

In case 3, the daily optimal profit of the DR aggregator and the customers' welfare are $36562.23 and $51892.05, respectively, while those in case 4 are $40719.36 and $ 49916.45, respectively. The profit of the DR aggregator in case 3 increases because customers are willing to reduce their load with less incentive which is also the reason for the decrease of customers' welfare. Similarly, the customers' welfare increases in case 4 because there is greater incentive.

Customers respond to the price incentive with different sensitivities, thus affecting the composition of the scheduled contracts. The optimal schedules for the three DR contracts of cases 3 and case 4 are shown in Fig. 11 and Fig. 12, respectively. Compared with the base case, in case 3, at hours 7 and 19, the scheduled amount of LC contracts increases and at hours 17, 18 and 21, the scheduled amount of LS contracts increases greatly. The FCL contract is put into use at hours 18 and 21. In case 4, at hour 10, the scheduled amount of LC contracts increases and at hours 19 and 21, the scheduled amount of LS contracts increases as well. The changes in the sensitivity of customer response influence the detailed pricing and the scheduling of the DR contract, but it is very complicated because many factors related to the profit of both the aggregator and customers are considered in the proposed model.

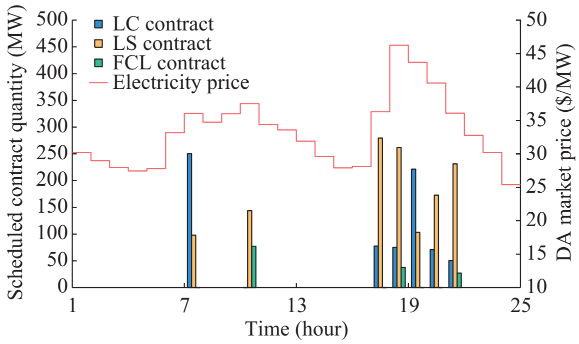

Fig. 11. Optimal schedules of three DR contracts in case 3.

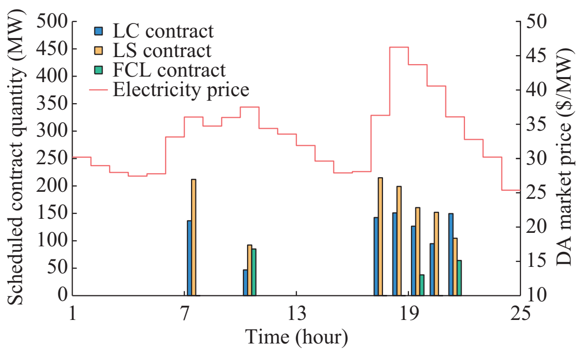

Fig. 12. Optimal schedules of three DR contracts in case 4.

VI. Conclusion

This paper proposes an optimization model for DR aggregators to determine the optimal contract strategy for maximizing their profit and customers' welfare. In this model, three types of DR contracts, namely LC contracts, LS contracts and FCL contracts, are considered for customers. In terms of the responsive load, consumer behaviors are innovatively modeled through the consumer psychology in order to reveal the relationship between the incentives and the expected customer response. Besides, the actual response of customers is represented by stochastic programming. The proposed model is a multi-objective integer-programming model, which is solvable for an evolutionary algorithm after reformulating. It can be implemented to provide guidelines for the aggregators to design the DR contracts when participating in the energy markets. Several case studies are performed to investigate the feasibility and practicability of the proposed model. The results demonstrate that the proposed model is able to yield enough revenues for the DR aggregator while the customers' welfare is also ensured.

In future study, more details of the DR contracts such as energy storage will be considered. Also, in order to broaden the application of this work, the participation in real-time markets will be introduced into the proposed model. Finally, future work might also explore other alternative ways to model consumers' behaviors of different consumer types.

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Yunwei Shen received the B.S. degree from Southeast University, Nanjing, China, in 2014. She is currently pursuing Ph.D. degree at Southeast University. Her research interests include demand response, system frequency regulation and electricity market.

Yang Li received the B.S., M.S. and Ph.D. degrees from Southeast University, Nanjing, China, in 1982, 1992, and 2002, respectively. Currently, he is a Professor at Southeast University. His research interests include demand side management, power system operation and power market.

Qiwei Zhang received the B. S. degree from North China Electric Power University, Beijing, China, in 2016, and the M.S. degree from The University of Tennessee, Knoxville, USA, in 2018. He is currently pursuing a Ph.D. degree from The University of Tennessee. His research interests include electricity market and cyber attack.

Fangxing Li also known as Fran Li, received the B.S.E.E. and M.S.E.E. degrees in electrical engineering from Southeast University, Nanjing, China, in 1994 and 1997, respectively, and the Ph.D. degree in electrical engineering from Virginia Polytechnic Institute and State University, Blacksburg, USA, in 2001. Currently, he is the James McConnell Professor at The University of Tennessee, Knoxville, USA. His research interests include renewable energy integration, demand response, power markets, power system control, and power system computing.

Zhe Wang received the B.S. degree in electrical engineering & automation from Shanghai University of Electric Power, Shanghai, China, in 2011, the M. S. degree in electronic & electrical engineering from the University of Strathclyde, Glasgow, UK in 2012, and the Ph.D. degree in electrical engineering from Southeast University, Nanjing, China, in 2017. He now works for the State Grid Shanghai Municipal Electric Power Company, Shanghai, China. His current research interests include the electricity market and demand side management.