A Comprehensive Demand Response Strategy Considering Household Comfort and Economy

Xiheng Sun
Department of Electrical Engineering
Guangdong University of Technology
Guangzhou, China
2112004465@mail2.gdut.edu.cn

Chun Sing Lai
Department of Electronic and Electrical Engineering
Brunel University London
Uxbridge, UK
chunsing.lai@brunel.ac.uk

Zhanlian Li
Department of Electrical Engineering
Guangdong University of Technology
Guangzhou, China
1112104006@mail2.gdut.edu.cn

Haoliang Yuan
Department of Electrical Engineering
Guangdong University of Technology
Guangzhou, China
haoliangyuan@gdut.edu.cn

Loi Lei Lai
Department of Electrical Engineering
Guangdong University of Technology
Guangzhou, China
l.l.lai@gdut.edu.cn

Zhenhao Li
Guangdong Power Grid Co., Ltd，
Qingyuan Power Supply Bureau
Qingyuan, China
lizhenhao@qy.gd.csg.cn

***Abstract*—With the emerging smart grid technology, communication between residential customers and load aggregator (LA) is becoming more common which facilitates the implementation of incentive-based demand response (IBDR). As a type of IBDR, load shedding plays a potential role in reducing supply cost and improving extra revenue in electric utilities sector as well as increasing the energy efficiency and economic income in residential side. In this paper, a residential welfare model based on utility function is proposed, by considering the electricity consumption preferences to analyze the welfare of users after participating in IBDR which includes comfort loss and incentives. Subsequently, a comprehensive IBDR strategy is presented considering household comfort and economy. The purpose of this strategy is to maximize the revenue of load aggregators while increasing the welfare of residential sector in IBDR event.**

***Keywords*—demand response, utility function, incentive, residential consumption behavior**

I. INTRODUCTION

Due to the shortage of fossil fuels and the increasing energy demand, the penetration rate of renewable energy resources in the power system is getting higher rapidly, which causes the uncertainty of output power and affects the stability of the electricity system. To solve this problem, in addition to strengthening the management of renewable energy [1], it is necessary to make good use of demand-side resources.

The response resource of residential part is potential and becomes increasingly popular [2,3,4]. The authors in [2] regard the residential users' air conditioners as virtual energy storage systems, and proposed a hierarchical dispatch strategy for coordinating groups of virtual energy storage systems to regulate voltage due to high photovoltaic penetration. In [3], a novel consensus-driven distributed control strategy is proposed to coordinate virtual energy storage systems, such as residential households with air conditioners, to avoid the violation of voltage and loading which are part of the main power quality issues in the distribution network. When it regarded electric vehicles as a demand-side resource, the proposed novel blockchain-based energy trading mechanism in [4] for electric vehicles in the power market. The application of demand-side resources in these articles can be seen as an extension of demand response.

As one of the most commonly used tools to utilize demand-side resources, demand response can enhance the living quality of individual residential consumers [5] and have a beneficial environmental effect on society [6] by modifying customers' power usage and time periods [7], which can be divided into price-based and incentive-based.

Price-based demand response (PBDR) can change the load curve of individual residential customers by setting retail tariffs. After the implementation of PBDR, the new tariff will cause a significant number customers to shift a large amount of peak load to off-peak periods, leading the power system to confront a new supply-demand balance problem [8]. Incentive-based demand response (IBDR) based on load shedding is seen as having more potential which avoid the above problems.

It is necessary to study the electricity consumption behavior of residents for the implement of IBDR program. Some researchers have focused on residential home appliances to model residential consumers' electricity consumption behavior [9,10]. In [11], the authors leverage artificial intelligence to learn customers' electricity consumption behavior in response to electricity prices. And some researchers believe that residential users decide their behavior according to the welfare they get from electricity consumption, and leverage utility function to model the user's welfare [12]. The authors in [13] leverage multi-attribute utility functions considering cost and convenience factors to model electricity consumption behavior.

By summarizing the existing research results, it is found that there are mature optimization scheduling methods for integrating user-side resources. There are also theoretical models and relatively complete evaluation methods for cutting capacity potential. However, there is still a lack of IBDR optimization strategies to improve the economic benefits of load aggregator (LA) considering the residential user's comfort loss, economic income and electricity consumption preferences.

In this paper, the utility theory and the concept of elasticity are applied to model the customer's electricity consumption behavior at each time slot in the whole day. On the basis of that, the residential welfare model in IBDR event based on load shedding is established. Considering the welfare model, the customers are divided into three categories. And then, the demand response optimizing strategy considering users' preference is proposed to maximize the revenue of LA. The main contribution of this paper is the comprehensive consideration consisting of comfort loss, economic income and users' preference in IBDR program to establish IBDR optimization strategy.

The remaining parts of the paper are as follows. Section II describe the background of the problem. In Section III customer welfare model and the objective functions are described. The numerical results and analysis are elaborated in Section IV. Section V summarizes and concludes the paper.

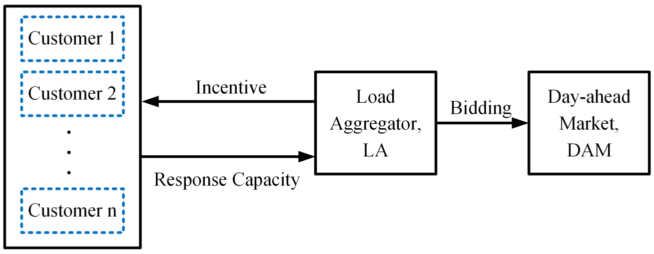

Fig. 1. Profit framework of LA in DAM

II. PROBLEM STATEMENT

A. *Profit Model of LA in Day-ahead Market*

In some power markets, such as the PJM market in the U.S., load retailers are assigned a certain amount of electrical capacity based on their peak capacity to ensure the safety and stability of the system. If the demand exceeds this set capacity, the load retailer has to pay additional charges. Therefore, the load retailers need to purchase electricity from day-ahead market (DAM) when their demand exceeds the set capacity. When there is increasing demand in the market and insufficient supply, the price in DAM rises.

At this point, LA can act as the representative of the consumers to aggregate the demand-side resources from residential customers to participate in the DAM and make profits as shown in Fig.1. There are two common types of IBDR signal for residential users: 1) a signal which informs the duration of IBDR event and the amount of kWh to be reduced; 2) a signal which informs the duration of IBDR event and let the subscribers decide how much they are willing to cut. We focus on the second type IBDR signals to understand the residential consumption behavior and know how incentive rate influence users' electricity consumption during the IBDR event.

B. *Customer Model*

Residential electricity consumption is mainly determined by the utility of electricity and the cost of electricity purchase. From residential customers' perspective, altering load is not desirable which cause the loss of comfort when they take part in IBDR program. Therefore, incentive compensation is necessary to make up for the user's comfort loss. During the IBDR event, users' consumption behavior is affected not only by the utility of electricity and the cost of electricity purchase, by also by incentive compensation. When the user receives the second IBDR signal, the user will decide the electricity consumption (load reduction) to maximize the benefit based on the information in the signal included baseline and incentive price.

Each consumer has his/her own electricity preferences, and the feeling of the comfort loss caused by altering load is different from diverse users. Therefore, each residential user decides their own electricity consumption according to their own preferences and electricity tariff for the reason that electric energy could bring equivalent benefits such as comfort, health and convenience [13]. Considering household comfort and economy, LA needs to classify householders according to the feeling of the loss of comfort and design incentive rate accordingly. Although quantifying these losses (satisfaction) and classifying users into different groups might be difficult, it is necessary for LA to develop the optimal bidding strategy considering the customers' electricity preferences. The concept of utility function could be adopted in this paper, and the customers are classified into economy-demanding customers (EDCs), standard customers (SCs) and comfortable-demanding customers (CDCs).

III. PROBLEM FORMULATION

A. *Residential Customer Welfare Model*

Utility function theory with a long history of growth is suitable to quantify these benefits in order to analyze residential electricity consumption behaviors. As a special commodity, electricity can also bring economic utility to users, which reflects in the power consumption brings convenience, comfort and economic output to the user. The economic utility obtained through electricity consumption is defined in this paper as the electricity economic utility.. This section will establish the welfare model before IBDR and demonstrate the solving process of model parameters.

Electricity economic utility model can be established with exponential function establish electricity economic utility model which can be formulated as [14]:

$$U(D,k)=1-e^{-k\cdot D},\quad k>0, U\in[0,1] \tag{1}$$

Where D is the power consumption and k is the comfort coefficient, and different users have various values. CDCs with high comfort requirement will have a higher k while EDCs focused on economic income which has a lower k .

The welfare model before IBDR program can be expressed as follows:

$$W^0(D,k)=K\cdot U(D,k)-P\cdot D \tag{2}$$

Where, P is the retail price which is fixed. K is the converted coefficient in order to transform the abstract concept of utility into money which is able to compare to the electricity cost. The utility in this paper is the total satisfaction or benefit derived from consuming electricity.

The key to calculate the welfare value is to obtain the converted coefficient K . Under the assumption that customers are rational individuals, the users will maximize the welfare at each moment of electricity consumption. The maximization of welfare can be obtained by the following equation:

$$\frac{\partial W^0(D,k)}{\partial D}=K\cdot\frac{\partial U(D,k)}{\partial D}-P=0 \tag{3}$$

Supposing that the initial demand is D_0 and the original price is P_0. Considering (1) and (3), the converted coefficient K would be as:

$$K = \frac{P_0}{\left.\dfrac{\partial U(D,k)}{\partial D}\right|_{D=D_0}} = \frac{P_0}{k}\cdot e^{k\cdot D_0} \tag{4}$$

Considering (3) and (4), the electricity load before IBDR would be as:

$$D = D_0 - \frac{1}{k}\cdot \ln(\frac{P}{P_0}) \tag{5}$$

Equation (5) indicates that customers will control their consumption in order to maximize welfare in the case of electricity price fluctuations. Users will increase (decreases) their demand when price is decreasing (increasing). According to it, the concept of electricity elasticity is introduced here, that is, a normalized measure of the sensitivity of customer demand in change of electricity price [15]. Electricity elasticity, ε , can be formulated as:

$$\varepsilon = \frac{\partial D}{\partial P}\cdot\frac{P_0}{D_0} \tag{6}$$

Considering (5) and (6), the comfort coefficient can be calculated by elasticity original demand and price which can expressed as:

$$k = -\frac{1}{\varepsilon\cdot D_0} \tag{7}$$

According to (7), it indicates that the users' comfort coefficient decreases with the increase in the absolute value of elasticity. In other words, the more users attach importance to comfort, the less load consumption can be reduced by the increase of unit electricity price, and the more difficult it is for users to adjust their electricity consumption by changing the electricity price.

B. Residential Customer Welfare Model in IBDR event

In this section, a residential customer welfare model is developed to analyze the change of users' welfare when householder participate in IBDR event. The customers receive incentive compensation when loads are shedding at the special period set by LA. The additional welfare with IBDR is formulated as follows:

$$W_{i,t}^{0}(D_{0,i,t},k_{i,t}) = K_{i,t}\cdot U(D_{0,i,t},k_{i,t}) - P\cdot D_{0,i,t} \tag{8}$$

$$W_{i,t}^{DR}(D_{i,t},k_{i,t}) = K_{i,t}\cdot U(D_{i,t},k_{i,t}) - P\cdot D_{i,t} + P_{i,t}^{inc}\cdot \Delta D_{i,t} \tag{9}$$

$$\begin{aligned}\Delta W_{i,t}^{DR} &= W_{i,t}^{DR} - W_{i,t}^{0}\\ &= K_{i,t}\cdot \Delta U^{DR} + P\cdot \Delta D_{i,t} + P_{i,t}^{inc}\cdot \Delta D_{i,t}\end{aligned} \tag{10}$$

The relevant variables in (10) could also be formulated as follows:

$$\Delta U^{DR} = U(D_{i,t}) - U(D_{0,i,t}) = e^{-k_{i,t}\cdot D_{0,i,t}} - e^{-k_{i,t}\cdot D_{i,t}} \tag{11}$$

$$\Delta D_{i,t} = D_{0,i,t} - D_{i,t} \tag{12}$$

Where, i , t , $P_{i,t}^{inc}$, $D_{0,i,t}$ and $D_{i,t}$ are index for the household, index for the time slot, incentive price, baseline load in peak time and actual load in peak time respectively.

The residential customers consume electricity aiming to maximize their welfare during the IBDR period. Therefore, there are two constraints from customers' behavior that LA needs to satisfy: individual rationality constraint and incentive compatibility constraint. The former means that users will participate in IBDR event only when the welfare after participation are greater than the benefits before participation, which can be written as:

$$\Delta W_{i,t}^{DR} > 0 \tag{13}$$

The incentive compatibility constraint refers to the fact that, given both the baseline and incentive rate, the customer always chooses the electricity consumption that maximizes his or her welfare, which can be obtained by taking the derivative of (9):

$$\frac{\partial W_{i,t}^{DR}(D_{i,t},k_{i,t})}{\partial D_{i,t}} = K_{i,t}\cdot\frac{\partial U(D_{i,t},k_{i,t})}{\partial D_{i,t}} - P - P_{i,t}^{inc} = 0 \tag{14}$$

$$D_{i,t} = -\frac{1}{k_{i,t}}\cdot \ln\left(\frac{P+P_{i,t}^{inc}}{K_{i,t}\cdot k_{i,t}}\right) \tag{15}$$

C. Objective Function

The residential customers will be classified into different categories according to their own consumption preference. The comfort coefficient in every time slot in an IBDR day can be calculated by LA from historical and forecasted data. By analyzing (11) it indicates that different k causes various loss of electricity economic utility. In LA's perspective, various price should be applied to diverse customers in order to make up utility loss and increase the users' enthusiasm to participate in the IBDR program in the long-term.

In this section, the objective function of the proposed strategy considering users' consumption preference to maximize LA's benefit will be formulated as follows:

$$\begin{aligned}\max B^{LA} = \sum_{t\in N_T}[&P_{DAM,t}\cdot(\Delta D_t^{ECO} + \Delta D_t^{STA} + \Delta D_t^{COM})\\ &-(inc_t^{ECO} + inc_t^{STA} + inc_t^{COM})]\end{aligned} \tag{16}$$

Where, the whole day is equally divided into 48 segments, and the interval of each part is 30 minutes, and N_t is the set for IBDR execution time slots. ΔD_t^{ECO} , ΔD_t^{STA} and ΔD_t^{COM} are the aggregated cutting capacity from EDCs, SCs and CDCs, respectively. inc_t^{ECO} , inc_t^{STA} and inc_t^{com} are the incentives to pay EDCs, SCs and CDCs, respectively. $P_{DAM,t}$ is the wholesale price in DAM.

The relevant variables in (15) are further given as:

$$\Delta D_t^{ECO} = \sum_{i\in N^{ECO}} r_{i,t}^{ECO}\cdot \Delta D_{i,t}^{ECO} \qquad \forall t\in N_t \tag{17}$$

$$\Delta D_t^{STA} = \sum_{i\in N^{STA}} r_{i,t}^{STA}\cdot \Delta D_{i,t}^{STA} \qquad \forall t\in N_t \tag{18}$$

$$\Delta D_t^{COM} = \sum_{i\in N^{COM}} r_{i,t}^{COM}\cdot \Delta D_{i,t}^{COM} \qquad \forall t\in N_t \tag{19}$$

$$inc_t^{ECO} = \sum_{i\in N^{ECO}} r_{i,t}^{ECO}\cdot P_{i,t}^{ECO,inc}\cdot \Delta D_{i,t}^{ECO} \qquad \forall t\in N_t \tag{20}$$

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$$inc_t^{STA} = \sum_{i\in N^{STA}} r_{i,t}^{STA}\cdot P_{i,t}^{STA,inc}\cdot \Delta D_{i,t}^{STA} \qquad \forall t\in N_t \tag{21}$$

$$inc_t^{COM} = \sum_{i\in N^{COM}} r_{i,t}^{COM}\cdot P_{i,t}^{COM,inc}\cdot \Delta D_{i,t}^{COM} \qquad \forall t\in N_t \tag{22}$$

Where, i , N^{COM} , N^{STA} and N^{ECO} are the index of customers, the set of CDCs, SCs and EDCs respectively. $P_{i,t}^{COM,inc}$, $P_{i,t}^{STA,inc}$ and $P_{i,t}^{ECO,inc}$ are the incentive rate of CDCs, SCs and EDCs respectively. $r_{i,t}^{COM}$ are the execution state of IBDR as a binary variable, 1 is ON and 0 is OFF, which can be extended to $r_{i,t}^{STA}$ and $r_{i,t}^{ECO}$.

Since the constraints from EDCs and SCs are similar to that from CDCs, to avoid repetition, only the individual rationality constraint and incentive compatibility constraint from CDCs are formulated as follows:

$$\Delta W_{i,t}^{CDC,DR} > 0 \tag{23}$$

$$D_{i,t}^{CDC} = -\frac{1}{k_{i,t}^{CDC}}\cdot \ln\left(\frac{P+P_{i,t}^{inc,CDC}}{K_{i,t}^{CDC}\cdot k_{i,t}^{CDC}}\right) \tag{24}$$

Equation (23) states that CDCs will participate in IBDR event only when the welfare after participation are greater than the benefits before participation, and the (24) describes that CDCs decide electricity consumption to maximize their welfare according to the IBDR signal.

IV. CASE STUDY AND RESULTS

In order to verify the effectiveness of the proposed strategy for optimal LA's benefit and analyze the additional welfare of different customers, MATLAB is used for the numerical simulation, and the optimization model was solved by utilizing CPLEX solver in YALMIP toolbox. The experimental data at the Austin, Texas, USA provided by Pecan Street Dataport include the residential load data [16]. The corresponding price information comes from Austin energy [17]. In this section, LA aggregates 72 household consumers in the data set to bid in power market. EDCs, SCs and CDCs account for one third each, and their elasticity is taken as $\varepsilon^{ECO} = -0.9$, $\varepsilon^{SC} = -0.6$ and $\varepsilon^{COM} = -0.3$, respectively. The maximum shedding ratio is taken as $\alpha = 0.2$ assuming both types of users have the same reduction potential. Taking a typical day with high DAM price in summer as an example, the effectiveness of the proposed strategy is discussed by utilizing the following experimental results. In the summer, IBDR is implemented from 13:30 to 18:30 daily for a total of five hours.

To the effectiveness of the proposed strategy and enable a comparison, the following scenarios were defined:

- Scenario 1: As the comparison simulation, the proposed strategy is not used in this scenario. LA will treat all users as SCs regardless of their electricity consumption preferences and give the same incentive rate to them.
- Scenario 2: The proposed strategy is used in this scenario considering the users' preferences. LA will give the different incentive rate to various subscribers according to their type.

A. *Sensitivity Analysis*

Considering the preferences of different types of users, a sensitivtity analysis is performed to investigate the impact of incentive rate on reduced capacity of electricity compared to baseline. The corresponding results are shown in Fig.2, it denotes the sensitivity analysis of the reduced capacity. The incentive rate is varing from 0 \$ to 0.1 \$, while the cutting capacity of different types of users is varing from 0 kWh to 260 kWh.

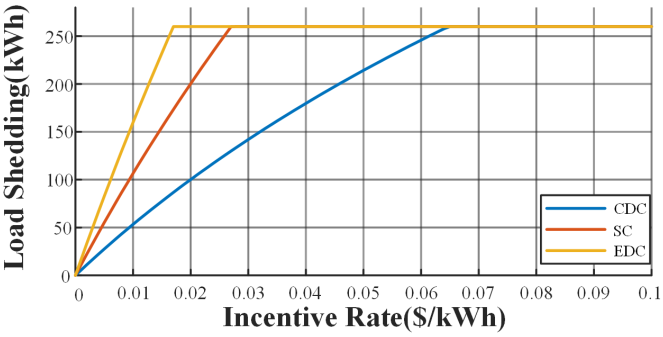

Fig. 2. Sensitivity analysis of reduced capacity to incentive rate.

It can be observed that from Fig. 2 that EDCs are the most sensitive to incentive rate, followed by SCs then CDCs. For each increase in the unit of incentive rate, EDCs cut the most load. The reduced capacity of EDCs reachs the upper limit when the incentive rate is 0.017 \$, while t hese of CDCs reachs the cap when the incentitive rate is 0.065 \$. In the same case, SUs reaches its maximum load reduction at an incentive price of 0.027 \$ and will no longer reduced more electricity demand. From the LA's perspective, higher incentive sensitivity means lower incentive compensation. In the scheduling order, the LA should first schedule the EDCs with the highest incentive sensitivity, followed by the SCs and finally the CDCs.

TABLE I. COMPARISON OF INCENTIVE RATE AND CUTTING CAPACITY

Variables	**Scenario 1**		
	EDCs	***SUs***	***CDCs***
Incentive rate (\$/kWh)	0.027	0.027	0.027
Cutting capacity (kWh)	217.17	217.17	108.59
Variables	**Scenario 2**		
	EDCs	***SUs***	***CDCs***
Incentive rate (\$/kWh)	0.017	0.027	0.065
Cutting capacity (kWh)	217.17	217.17	217.17

B. *LA Benefit*

This section will analyze the LA's benefit in the two scenarios. Load shedding for three types of users in the two scenarios and DAM price are shown in Fig. 3. It can be seen from the figure that the DAM price is relatively high from 13:30 to 18:30 while the load consumption is also high in Fig.3. Based on the proposed strategy, LA needs to invoke the reducible load capacity on the residential side to maximize its benefit when the market electricity price is high.

In Scenario 1, although LA offers the same incentive price to all users, they have different sensitivity to the incentive rate due to their different preferences for electricity consumption, which leads to different electricity consumption behaviors. As we can see from Table I, the cutting capacity of CDCs is 108.59 kWh. As CDCs is not sensitive to the incentive, they are more inclined to ensure their own electricity economic utility and reduce the cutting their demand compared with SCs and EDCs for the same incentive price. Due to the limit of load shedding cap, the cutting capacity of EDCs is 217.17 kWh, and the amount of load shedding cannot be further increased.

TABLE II. THE COMPONENTS OF CUSTOMERS' WELFARE

Type of Users	**Scenario 1**			
	Utility cost ($)	***Electricity cost savings ($)***	***Incentive ($)***	***Additional welfare ($)***
EDCs	16.61	14.83	5.87	4.09
SUs	17.60	14.83	5.87	3.10
CDCs	8.80	7.42	2.93	1.55
Type of Users	**Scenario 2**			
	Utility cost ($)	***Electricity cost savings ($)***	***Incentive ($)***	***Additional welfare ($)***
EDCs	16.61	14.83	3.69	1.91
SUs	17.60	14.83	5.87	3.10
CDCs	21.09	14.83	14.06	7.80

In Scenario 2, LA calculates incentive rate for different users according to their power consumption preferences, and their cutting capacity reach their maximum at the action of these incentive price. In this case, LA issues the incentive rate that will invoke all of the potential user's cutting capacity due to the higher upstream market price. This allows users to cut the electricity demand as much as possible and LA can maximize their profits by bidding in DAM.

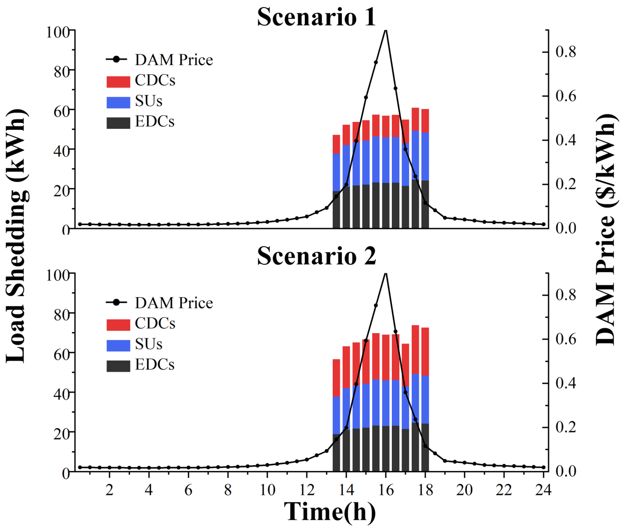

Fig. 3. Load shedding in two scenarios.

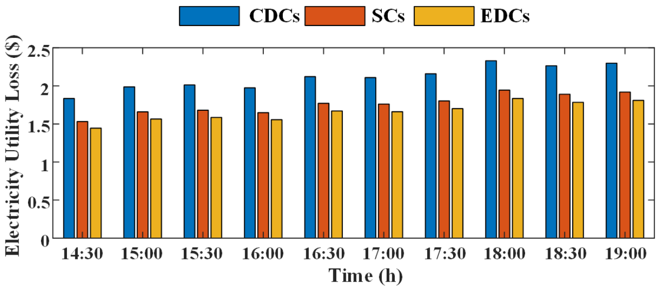

Fig. 4. Electricity economic utility loss in Scenario 2.

TABLE III. THE COMPONENTS OF LA'S BENEFIT

Type of Users	**Scenario 1**		
	Revenue ($)	***Incentive ($)***	***Benefit ($)***
EDCs	71.94	5.87	66.07
SUs	71.94	5.87	66.07
CDCs	35.97	2.93	33.04
Total	179.85	14.67	165.18
Type of Users	**Scenario 2**		
	Revenue ($)	***Incentive ($)***	***Benefit ($)***
EDCs	71.94	3.69	68.25
SUs	71.94	5.87	66.07
CDCs	71.94	14.06	57.88
Total	215.82	23.62	192.20

The details of the benefit generated to LA by different users in the two scenarios are shown in Table II. The LA's benefit is derived from the revenue in the DAM minus incentive compensation to subscribers as shown in (16). In Scenario 1, as LA sets the same incentive rate regardless of users' electricity consumption preferences, CDCs cannot be fully mobilized to participate in IBDR, resulting in small cutting capacity. In Scenario 1, the LA's benefit generated by the CDCS is 33.04 $, and in Scenario 2 it is 57.88 $. For EDCs users, since the reduction amount has reached the peak when the incentive price is 0.017 $/kWh, increasing the incentive price to 0.027 $/kWh in Scenario 1 can no longer increase the reduction amount, but will lead to an increase in the incentive compensation of LA. The incentive compensation of LA to EDCs is 5.87 $ in scenario 1 and 3.69 $ in scenario 2. To sum up, the total LA's benefit generated by all consumers in Scenario 2 is 192.2$, a 16.36% improvement over Scenario 1.

C. *Customer Welfare*

As shown in (10), the customer welfare model includes three parts: electricity economic utility loss, electricity cost savings and incentive compensation. The details of additional benefits of different residential consumers in the two scenarios are shown in Table III.

Electricity economic utility is used to describe the psychological feelings caused by electricity consumption or the feelings by changing the original electricity pattern. The which loss of different householders as shown in Fig.4. It can be observed that electricity economic utility loss of the CDCs is larger than that of EDCs and SUs. Therefore, LA needs to give CDCs a larger incentive rate to encourage them to cut the electricity consumption, so that the incentive compensation they get can make up for the loss of utility and meet the individual rationality constraint. The reason is that LA does not consider electricity consumption preference and sent CDCs a higher incentive price, which leads to them preferring to guarantee their own utility of electricity consumption and reduces the enthusiasm to participate in IBDR event.

As shown in Table III, the electricity economic utility loss of CDCs is few in scenario 1, while the electricity purchase cost savings and incentive compensation are not high. Although the electricity economic utility loss is higher in Scenario 2, the overall welfare is higher than in scenario 1 due to the more incentive compensation and electricity cost savings. In scenario 1, LA assigns all users as SUs for economic scheduling, and SUs users' welfare is consistent with scenario 2. For EDCs, they receive more incentive compensation in Scenario 1, but there is no increase in load shedding, which leads to an increase in incentive cost for LA.

Comparing the customer welfare in Scenario 1 and Scenario 2, it can be seen that the proposed optimization strategy considering the customer's electricity consumption preference can set the incentive price for different customers with alignment, which can improve the LA's revenue and save the incentive cost, and make the incentive compensation for customers more fair.

V. CONCLUSION

In this paper, we analyze residential electricity consumption behavior based on utility function. The electricity economic utility which represents the total satisfaction or benefit derived from consuming electricity is measured by money. Results show that CDCs have higher electricity economic utility loss than SUs and EDCs with the same electricity consumption. The proposed strategy for IBDR considering customer electricity consumption preference could effectively enhance LA's benefit and increase the welfare of residential sector in IBDR program.

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