International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 0701

Optimization analysis of demand response model based on resident heterogeneity

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ABSTRACT

Demand response (DR) has becomes one of the tools mostly used in adjusting users' electricity consumption pattern and behavior on the electricity market. In this paper, a single-objective optimization model with multiple constraints is established. Based on the electricity demand-price elasticity and the credit mechanism, further consider the impact of factors such as income, environmental awareness, family member and age, a more realistic subsidy mechanism is developed by taking into account the heterogeneity of users. The actual electricity load and price data are used for numerical simulation, and the results of economic index and load factor show that this model is more effective than the model which only considers the demand-price elasticity and the results show that the model is practical and effective.

Keywords: Demand response, Resident heterogeneity, Credit mechanism, Elasticity coefficient

NONMENCLATURE

Symbols	
α	weight of electricity cost index
$\beta_1/\beta_2/\beta_3$	weights of different factors
N	total number of users
T_1/T_2	peak/valley periods
$A(t)$	subsidy from service provider
$\varepsilon_c^P/\varepsilon_c^I/\varepsilon_c^F/\varepsilon_c^R/\varepsilon_c^A$	price/income/member/awareness/ age elasticity of demand
$\theta_c(t)$	willing index to change the habit of class c users at time t
$credit_c(t)$	credit of class c users at time t
$d_c(t)/d_{oc}(t)$	optimal/original load of class c users at time t
$O_c(t)$	degree of change for class c users at time t
$P_c(t)/P_{oc}(t)$	optimized/original price of class c users at time t
$P_c^{min}(t)/P_c^{max}(t)$	minimum /maximum price of class c users at time t
$I_c^{min}(t)/I_c^{max}(t)$	minimum /maximum income of class c users at time t
$R_c^{min}(t)/R_c^{max}(t)$	minimum /maximum awareness of class c users at time t
$F_c^{min}(t)/F_c^{max}(t)$	minimum /maximum population of class c users at time t
$A_c^{min}(t)/A_c^{max}(t)$	minimum /maximum age of class c users at time t
$S_c(t)$	subsidy of class c users at time t
Abbreviations	
DR	demand response
RTP	real-time pricing

1. INTRODUCTION

As an important way of supply-demand interaction, Demand Response (DR) is conducive to the coordination and optimization of electricity generation-side and demand-side resources. DR strategies are mainly divided into two types: the incentive-based programs and the price-based programs. Reasonable DR subsidies settlement way can effectively improve users involved in the potential of demand response. In the existed studies, scholars mainly study the impact of electricity price on users, while there are few studies on income and other factors. For instance, Moghaddam [1] based on the concept of demand elasticity and the consumer benefit function, has established the economic model of price/impulse response to load and calculated the

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elasticity of each demand response program. Sun et al. [2] proposed a new virtual real-time power pricing scheme based on the benefits of end users and the comfort level of users in view of the difficulties in real-time pricing and some defects of time-of-use pricing in China. Zhang [3] analyzed users under real-time pricing mode based on the demand-price elasticity and credit mechanism system. A detailed data set on appliance-level electricity consumption at the hourly level has been used in [4] to estimate the income elasticity of the hourly electricity consumption of appliances. In addition, electricity price is the primary factor that affects residents' electricity consumption. At the same time, residents' electricity consumption is also affected by their income level, and the number of member, age and environmental awareness of family will also have a certain impact on residents' electricity consumption.

This paper divides the impact of residents' heterogeneity on electricity consumption into three categories. The first is the direct impact of residents' electricity price fluctuations on household electricity consumption. In the stage of real-time pricing (RTP), the fluctuation of residents' electricity consumption is mainly affected by the fluctuation of market electricity price. The second is the impact of consumers' purchasing power on residents' electricity consumption. Existing studies have shown that the electricity consumption is also affected by the household economy level [5]. While the level of the family economy can be reflected by the income level of residents, the heterogeneity varies greatly in different industries, regions and income levels. The third is the impact of household electricity demand on electricity consumption. Different family size, age and environmental awareness of residents have a great impact on the electricity demand.

In this paper, based on the existing credit mechanism, we consider not only the price fluctuation factor, but also the impact of residents' income level, environmental awareness, the number of family member and age on electricity demand. Finally, actual load data are used for numerical simulation. The results show that this model is more practical and can provide a reference for the implementation of RTP plan and relevant policy makers.

2. MODEL

This paper aims to minimize all users' electricity cost and degree of change. In the following research work, one day is divided into 24 periods, that is, one hour for each period.

2.1 Object function

The comprehensive objective function of the model, given in formula (1), composed of two parts, namely, the users' cost function and degree of change function. The two parts are contradictory, so it is possible for users to find a balance between them. The objective function is as follows:

$$min\ F = \sum_{t=1}^{24}[\alpha \cdot C'(t) + (1-\alpha)\cdot\ O'(t)] \tag{1}$$

$$\begin{cases} C'(t) = \dfrac{C(t) - \min\limits_{1\le\tau\le24} C(\tau)}{\max\limits_{1\le\tau\le24} C(\tau) - \min\limits_{1\le\tau\le24} C(\tau)} \\ O'(t) = \dfrac{O(t) - \min\limits_{1\le\tau\le24} O(\tau)}{\max\limits_{1\le\tau\le24} O(\tau) - \min\limits_{1\le\tau\le24} O(\tau)} \end{cases} \tag{2}$$

where $C(t)$ and $O(t)$ represent the total electricity cost and degree of change for all users at time t, respectively, and α is a scalar in the range of [0,1]. $C^{'}(t)$ and $O'(t)$ are the normalization of $C(t)$ and $O(t)$, respectively.

2.1.1 Cost function

$$C(t) = \sum_{c=1}^{N} C_c(t) = \sum_{c=1}^{N}[P_c(t)d_c(t) - S_c(t)] \tag{3}$$

where $P_c(t)$ and $d_c(t)$ represent the optimized real-time electricity price and electricity demand of class c users at time t, respectively, and $S_c(t)$ is the subsidy of class c users given by the system. $C_c(t)$ represents the electricity cost of class c users at time t.

$$\begin{aligned} d_c(t) = d_{oc}(t)\cdot[1+\beta_1\cdot(\varepsilon_c^P(t,t)\cdot\lambda_c^P(t,t) \\ +\sum_{h\neq t}\varepsilon_c^P(t,h)\cdot\lambda_c^P(t,h)) + \beta_2\cdot\varepsilon_c^I(t)\cdot\lambda_c^I(t) \\ +\beta_3\cdot\left(\varepsilon_c^F(t)\cdot\lambda_c^F(t) + \varepsilon_c^A(t)\cdot\lambda_c^A(t) + \varepsilon_c^R(t)\cdot\lambda_c^R(t)\right)] \end{aligned} \tag{4}$$

where $\varepsilon_c^P(t,t)$ is the price self-elasticity and $\varepsilon_c^P(t,h)$ is the price crossing-elasticity.

$$\varepsilon_c^P(t,t) = \frac{P_c(t)\partial d_c(t)}{d_c(t)\partial P_c(t)},\ \varepsilon_c^P(t,h) = \frac{P_c(h)\partial d_c(t)}{d_c(t)\partial P_c(h)} \tag{5}$$

According to formula (5), the demand-income elasticity can be defined as $\varepsilon_c^I(t,t) = \frac{I_c(t)\partial d_c(t)}{d_c(t)\partial I_c(t)}$, similarly, $\varepsilon_c^F(t)$, $\varepsilon_c^A(t)$ and $\varepsilon_c^R(t)$ can be calculated. $\varepsilon_c^F(t)$, $\varepsilon_c^A(t)$ and $\varepsilon_c^R(t)$ are the family member, age and awareness elasticity, respectively.

$\lambda_c^P(t,t) = \frac{P_c(t)-P_{oc}(t)}{P_{oc}(t)}$, $\lambda_c^P(t,h) = \frac{P_c(h)-P_{oc}(h)}{P_{oc}(h)}$, $\lambda_c^I(t) = \frac{I_c(t)-I_{oc}(t)}{I_{oc}(t)}$, similarly, $\lambda_c^F(t)$, $\lambda_c^A(t)$ and $\lambda_c^R(t)$ can be calculated. $P_{oc}(t)$ is the original price, $I_c(t)$ and $I_{oc}(t)$ represent the optimized income and original income, respectively.

2.1.2 Credit function

Define the daily average demand at the initial state: $\overline{D} = \frac{\sum_{c=1}^{N}\sum_{t=1}^{T} d_{oc}(t)}{T}$, the peak periods as $T_1 = \{t|\sum_c d_{oc}(t) \geq \overline{D}\}$, and the valley periods as $T_2 = \{t|\sum_c d_{oc}(t) < \overline{D}\}$. $credit_c(t)$ represents the credit of class c users by reducing demand at peaks or increasing the demand at valleys [2]. In this paper, users who meet the conditions are rewarded, and those who do not meet the conditions are not punished.

$$credit_c(t) = \varphi \cdot \left(d_{oc}(t) - d_c(t)\right) \cdot \left(\sum_c d_c(t) - \overline{D}\right) \tag{6}$$

where the parameter φ is 0 or 1, it indicates a user does not attract credit or attracts credit ,respectively.

$A(t)$ represents the subsidy provided by the system at time t.

At peaks :

$$A(t) = \begin{cases} \mu_1 \sum_{c=1}^{N} p_c(t)\left(d_{oc}(t) - d_c(t)\right) & d_{oc}(t) > d_c(t) \\ 0 & d_{oc}(t) \leq d_c(t) \end{cases} \tag{7}$$

At valleys :

$$A(t) = \begin{cases} \mu_2 \sum_{c=1}^{N} p_c(t)\left(d_{oc}(t) - d_c(t)\right) & d_{oc}(t) < d_c(t) \\ 0 & d_{oc}(t) \geq d_c(t) \end{cases} \tag{8}$$

The subsidy of class c users at time t is given by formula (9):

$$S_c(t) = \frac{credit_c(t)}{\sum_{c=1}^{N} credit_c(t)} \cdot A(t) \tag{9}$$

2.1.3 Degree of change function

When a user participates in the DR program, it is necessary to change his existing electricity consumption pattern, which may affect his comfort. Thus, it is necessary to adopt an effective measure of the degree of change with electricity demand. The formula for the degree of change function is shown as follows [3]:

$$O(t) = \sum_{c=1}^{N} O_c(t) = \sum_{c=1}^{N}[\theta_c(t) \cdot (d_c(t) - d_{oc}(t))^2] \tag{10}$$

where $\theta_c(t)$ represents the willing index of class c users at time t. $O_c(t)$ represents the degree of change for class c users at time t.

2.2 Constraints

The constraints for the designed variables are outlined as follows:

$$P_c^{min}(t) \leq P_c(t) \leq P_c^{max}(t) \tag{11}$$

$$d_c^{min}(t) \leq d_c(t) \leq d_c^{max}(t) \tag{12}$$

$$I_c^{min}(t) \leq I_c(t) \leq I_c^{max}(t) \tag{13}$$

$$R_c^{min}(t) \leq R_c(t) \leq R_c^{max}(t) \tag{14}$$

$$F_c^{min}(t) \leq F_c(t) \leq F_c^{max}(t) \tag{15}$$

$$A_c^{min}(t) \leq A_c(t) \leq A_c^{max}(t) \tag{16}$$

$$\sum_{t=1}^{24}[P_c(t)d_c(t) - S_c(t)] \leq \sum_{t=1}^{24}[P_{oc}(t)d_{oc}(t)] \tag{17}$$

where $P_c^{min}(t)$ and $P_c^{max}(t)$ are the lower and upper bounds of price for class c users at time t. The load (demand) composed of shiftable load and non-shiftable load, it expected that users maintain their load within the acceptable range at each moment. Formula (12) represents the upper and lower bounds of load, formula (13) represents the upper and lower bounds of income, formula (14) represents the upper and lower bounds of environmental awareness, formula (15) represents the upper and lower bounds of the number of family member, and formula (16) represents the upper and lower bounds of family age.

3. NUMERICAL SIMULATION AND RESULTS

According to *Jiangsu Statistical Yearbook (2009-2014) [6]*, urban residents can be divided into the following seven levels on the basis of income: (a) the lowest income households, (b) the low income households, (c) the lower middle income households, (d) the middle income households, (e) the upper middle income households, (f) the high income households, and (g) the highest income households. Thus, we can calculate the electricity demand-income elasticity of urban residents at different income levels, and the results are shown in Table 1.

Table 1 Demand–income elasticity of residents at different income levels in Jiangsu province

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Elasticity	1.19	0.96	0.95	1.0	0.81	0.81	0.77

As can be seen from Table 1, with the increase of income, residents are less sensitive to the demand for electricity.

To further analyze the impact of environmental awareness, number of member and age of family on demand, a questionnaire survey is conducted. Based on the questionnaire, the residents' electricity demand-awareness elasticity, demand-family member elasticity and demand-age elasticity are shown in Tables 2-4, respectively.

Table 2 Demand-environmental awareness elasticity of residents in Jiangsu province

Awareness	1	2	3	4	5
Elasticity	0.51	0.49	0.25	0.75	-0.5

As can be seen from Table 2, the higher the environmental awareness, the less the elastic value.

Table 3 Demand-family member elasticity of residents in Jiangsu province

Member	1	2	3	4	5	6
Elasticity	0.82	0.74	-0.72	-0.12	-0.26	0.08

Table 4 Demand-age elasticity of residents in Jiangsu province

Age	under 18	18-25	26-30	31-40	41-50	51-60
Elasticity	0.68	5.8	-0.74	0.16	0.52	-0.34

In this paper, the model is a nonlinear optimization problem with constraints, Genetic Algorithm are used for optimization. In order to improve the efficiency of algorithm, the penalty function is considered. Meanwhile, seven groups of electricity consumption data are obtained from [7-9], corresponding to different income levels respectively. Class A users correspond to the lowest income households, and so on.

Four cases are studied to demonstrate the effectiveness of the proposed model.

Case 1: the base case. The credit mechanism model in reference [2] is adopted.

Case 2 (β_1=1, β_2=0, β_3=0): consider only price elasticity.

Case 3 (β_1=1/3, β_2=1/3, β_3=1/3): various factors with the same weight.

Case 4 (β_1=0.8, β_2=0.15, β_3=0.05): the unsteady price is deemed to the main factor affecting demand, meanwhile income is a crucial factor affecting demand, and the environmental awareness, member and age of family will make a difference.

Compared the results of the four cases, with the increase of the proportion of income factors and other factors, low-income families have greater demand fluctuations than high-income families, but the proportion can't be too big. Therefore, in order to reflect the heterogeneity of users, proper consideration of income and other factors is necessary. Fig.1 displays the optimal load and the original load of Case 4.

Table 5 Indicators comparison of the four different cases

	Cost(Yuan)			Load factor (%)		Peak to Valley(kwh)	
	Original	Optimal	reduction	Original	Optimal	Original	Optimal
Case1	38699.52	36843.04	1856.48	68.69%	69.29%	2444.10	2426.01
Case2	38699.52	36910.93	1788.59	68.69%	70.00%	2444.10	2304.44
Case3	38699.52	37268.72	1430.80	68.69%	69.33%	2444.10	2438.11
Case4	38699.52	36667.37	2032.15	68.69%	70.98%	2444.10	2265.46

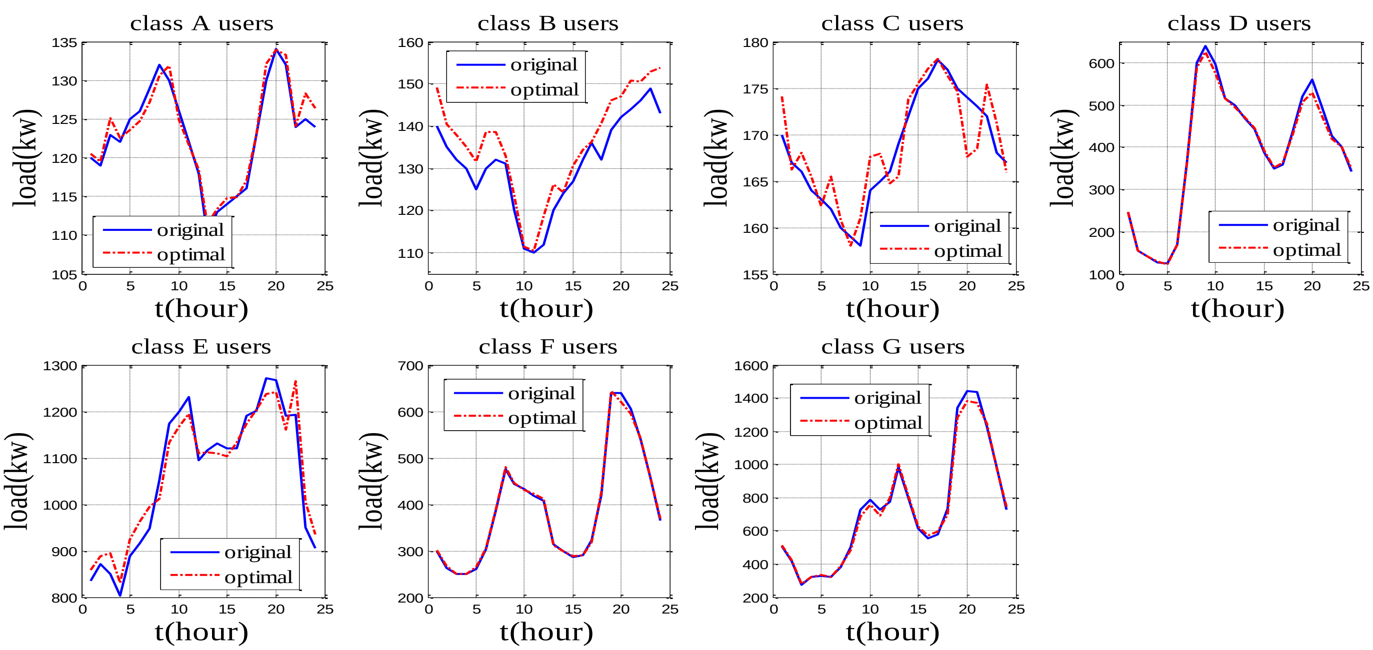

Fig.1. Optimized load curve and original load curve for Case 4 (β_1=0.8,β_2=0.15,β_3=0.05) .

The results for the total load and cost of four cases were shown in Fig.2 and Fig. 3, more details are shown in Table 5. It shows that users decrease load at peaks and increase load at valleys to enjoy credit incentives that goes with it. Compared the optimized load and cost on hourly basis for the four cases and conclude that, Case 4 had the best result.

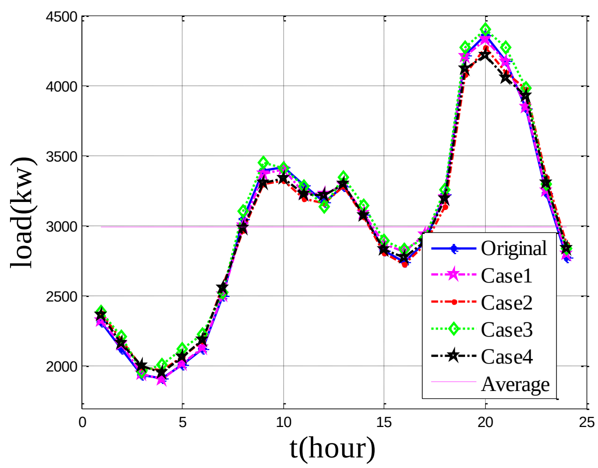

Fig.2. Four Cases distribution of optimal load compared with the original load

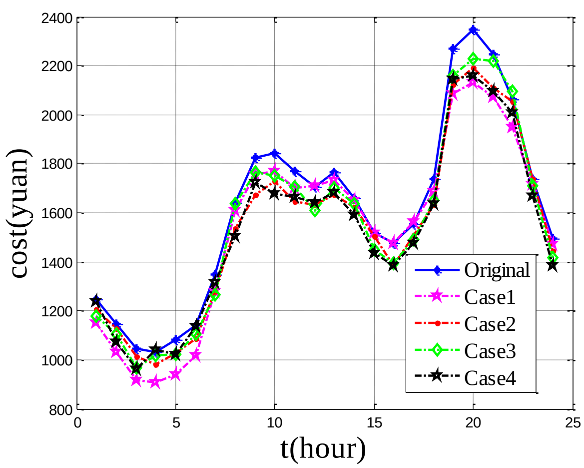

Fig.3. Four Cases distribution of optimal cost compared with the original cost

For the load factor, it is 68.69% in the original state, and 69.29%, 70.00%, 69.33% and 70.98% in four cases, respectively. The results show that the load factor has been increased in different cases, but the largest one is Case 4.

4. CONCLUSIONS

In this paper, an improved demand response model based on resident heterogeneity has been established. On the basis of the credit mechanism and demand-price elasticity, we considered the influence of income, environmental awareness, the number of member and age of family, and conducted simulation analysis with actual electricity data. The results show that reasonable consideration of income and other factors, different kinds of residents can better participate in demand response by combining their own characteristics. In Case 4, the cost was saved by 2032.15 yuan, the load factor has increased to 70.98%. The results of economic index and load factor show that this model is more effective than the model which only considers the demand-price elasticity. This paper takes full account of the impact of the residents' heterogeneity on the electricity consumption demand, which has important practical guiding significance for the exploration of real-time pricing strategy.

ACKNOWLEDGEMENT

This research was supported by National Nature Science Foundations of China (71774070 and 71690242).

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