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Optimal Control of Intelligent Electricity Consumption for Residential Customers Considering Demand Response

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Abstract

The increasing power demand and the widening peak-valley differences bring more challenges to the power system. Moreover, the home energy management system (HEMS) becomes an effective way for residential customers to participate in demand response (DR). This paper classifies the smart appliances of residential customers and analyzes the electrical characteristics. An optimal control model is proposed to minimize customers' cost and decrease the peak-valley differences by day-ahead electricity prices and real-time incentive signals, whereas comfort is not affected. Several cases are studied to prove the effectiveness of the proposed method.

Keywords: HEMS; intelligent electricity consumption; demand response; optimal control

1. Introduction

With the development of socio-economic and industrial, the power demand and the peak-valley differences are increasing rapidly [1]. Moreover, the renewable energy power generations will bring randomness and uncontrollability to the power system [2]. In order not to startup and shutdown conventional generators (e.g. thermal power units)

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repeatedly, demand response (DR) has become an essential way to reduce the peak-valley differences, improve resource utilization and strengthen the reliability of power system [3].

Implementation of electricity management for residential customers is an important way for demand side management (DSM). In recent years, the smart sockets, smart meters, intelligent control terminals and smart appliances are gaining popularity among residential customers. HEMS is used to optimize the operation scheduling of smart appliances by electricity prices and control signals without affecting customers' comfort, which contributes to the reduction of customers' electricity cost and system's peak loads [4-5]. Some studies have been carried out on HEMS. Most of them focus on the single or multi-objective optimizations which minimize electricity costs or peak-valley differences under variable price mechanisms [4-11]. However, the rapid responses of HEMS in the grid emergency are not involved in the studies.

This paper classifies the smart appliances of residential customers and analyzes the intelligent power characteristics. An optimal control model considering customers' cost and comfort requirements is proposed under day-ahead electricity prices. HEMS will adjust the model parameters after receiving the real-time incentive signals. Several cases are studied to prove the proposed method.

Nomenclature

N	interval number of a day	a	smart appliance
t_0	length of each interval	i	interval
Q , q	electricity consumption	t_{start} / t_{end}	actual start interval/stop interval
ρ	day-ahead electricity price	T_{sig}	release time of incentive signal
T_{start} / T_{end}	allowed start interval/stop interval	N_{sig}	required continue intervals
T	minimum runtime for a work	t_{res}	response interval
T_{off}	maximum length of interrupt time	N_{res}	continue intervals of response
N_{off}	maximum number of interrupt times	R	reserve capacity

2. Intelligent power characteristics

2.1. Intelligent power model

Divide one day into N intervals, then the length of each interval is $t_0 = 1440 / N(\text{min})$. A large value of N may improve the accuracy of the model in theory, but the amount of computations will also increase. This paper assumes that the continuous operation time of each appliance is an integer multiple of t_0, otherwise it will be replaced by the nearest integer value according to the rounding principle. Furthermore, t_0 should match up to the change cycle of real-time electricity price T_{price} , usually $T_{price} = t_0$.

It is assumed that the electricity consumption of the smart appliance a is Q_a per hour. The consumption of a in each interval can be expressed as

$$q_{a,i} = \frac{24 \times Q_a}{N} \times \lambda_{a,i} \tag{1}$$

The 0-1 variable $\lambda_{a,i}$ describes the operating status of a in interval i . $\lambda_{a,\mathrm{i}} = 0/1$ means a is shutdown/running in interval i . The total electricity consumption in i is Q_i , which can be expressed as

$$Q_i = \sum_{a \in A} q_{a,i} \tag{2}$$

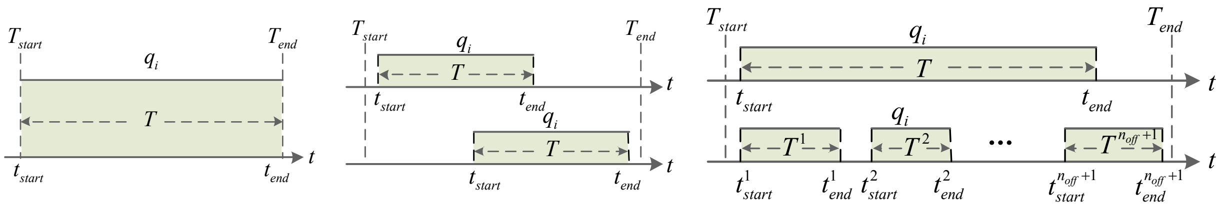
2.2. Classification of smart appliances

According to the characteristics of smart appliances and the customer's electricity usages, the smart appliances can be divided into three categories [11]. The Electrical characteristics are shown in Figure 1.

a. Uncontrolled load (UL): The appliances don't have the ability to participate in DR, such as lights and refrigerators, whose operation time is fixed and cannot be interrupted.

b. Transferable load (TL): The operation time can be adjusted within some time extensions. However, any interruptions are not allowed when the appliances running to avoid discomfort or losses.

c. Interruptible load (IL): The start-top status of the appliances is allowed to be controlled by HEMS. It will restore the original operating state at the end of an interval.



(a) (b) (c)

Fig. 1. Electrical characteristics of (a) UL; (b) TL; (c) IL.

3. Optimal control model of HEMS

3.1. HEMS

The structure of HEMS is shown in Figure 2. The controllers receive the electricity prices or incentive signals and periodically output commands with the cycle $T_{con} = t_0$. Customers are allowed to set the electrical parameters based on different seasons and working/non-working days on controller panel. Whether to participate in the next day's incentive control can also be chosen a day in advance.

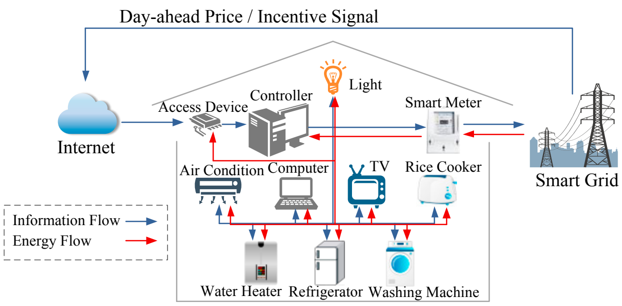


Fig. 2. Structure of HEMS.

3.2. Optimal model by day-ahead electricity prices

According to the day-ahead price, HEMS controllers perform the optimal algorithm within the adjustable range of customer's electrical parameters to arrange the working status of smart appliances. Minimize the electricity cost without affecting customers' comfort. The objective function is

$$Cost = \min \sum_{i=1}^{N} (\rho_i Q_i(\rho_i)) \tag{3}$$

To meet the customer's comfort requirements, the appliance a can only run in intervals $\left[T_{start,a}, T_{end,a}\right]$. A smaller interval range indicates a higher requirement for comfort. The optimize control constraints for each category of appliances are as follows.

a. UL a_1

$$\begin{cases} t_{end,a_1} - t_{start,a_1} + 1 = T_{a_1} \\ T_{start,a_1} = t_{start,a_1} < t_{end,a_1} = T_{end,a_1} \\ N_{off,a_1} = 0 \end{cases} \tag{4}$$

b. TL a_2: The equality constraints are same to formula (4), the inequality constraint is

$$T_{start,a_2} < t_{start,a_2} < t_{end,a_2} < T_{end,a_2} \tag{5}$$

c. IL a_3: Frequent start/stop or long-time standby will impact appliances life. Therefore, the maximum number of interrupt times and the maximum length of interrupt time should be limited.

$$\begin{cases} \sum_{k=1}^{n_{off,a_3}+1} (t^k_{end,a_3} - t^k_{start,a_3} + 1) = T_{a_3} \\ T_{start,a_3} \le t^1_{start,a_3} < t^{n_{off,a_3}+1}_{end,a_3} \le T_{end,a_3} \\ t^k_{start,a_3} < t^k_{end,a_3} \\ t^{k+1}_{start,a_3} \le t^k_{end,a_3} + T_{off,a_3} \\ 0 \le n_{off,a_3} \le N_{off,a_3} \\ 1 \le k \le n_{off,a_3} + 1 \end{cases} \tag{6}$$

3.3. Optimal model by incentive mechanisms

If HEMS receives an incentive signal asks for reserve capacity R at T_{sig} and continue N_{sig} intervals, the controller will output a command at the beginning of the next adjacent interval t_{res} and continue N_{res}.

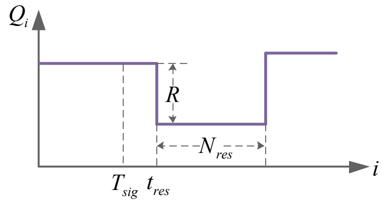


Fig. 3. Response characteristics to incentive signal.

Adapt the constraint conditions on the basis of the optimal models in Section 3.2.

$$\begin{cases} Q_{T_{sig}} - Q_i \ge R \qquad (t_{res} \le i \le t_{res} + N_{res}) \\ T_{res} \le t_{res} \le T_{res} + t_0 \\ N_{res} \ge N_{sig} \end{cases} \tag{7}$$

4. Case and discussions

4.1. Data initialization

In order to verify the practicality of the optimal models, this paper designs some electrical parameters of a residential customer on summer working day (Table 1). The day-ahead electricity price is shown in Figure 4. $N = 96$ and $t_0 = 15\,\text{min}$. In this paper, genetic algorithm is used to solve the optimal models [12-13]. The algorithm parameters are as follows: the population number is 200, the maximum number of iterations is 400, the crossover probability is 0.90 and the mutation probability is 0.20.

Table 1. Smart appliances power data.

No.	Appliances	T_{start}	T_{end}	T	N_{off}	T_{off}	Q_a $(kW{\cdot}h)$
1	Light (UL)	73	92	20	0	0	0.05
2	Water Heater (IL)	17	32	4	2	8	2.00
		65	90	6	2	8	
3	Rice Cooker (TL)	37	50	3	0	0	0.65
		53	72	3	0	0	
4	Washing Machine (TL)	53	88	4	0	0	0.35
5	TV (IL)	73	92	10	1	2	0.15
6	Computer (TL)	77	94	8	0	0	0.20
7	Refrigerator (UL)	1	96	96	0	0	0.07
8	EV (IL)	1, 75	30, 96	24	3	6	2.00

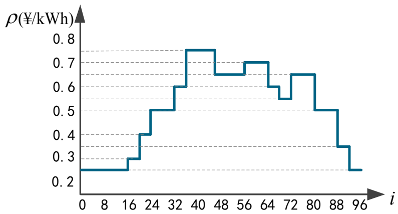
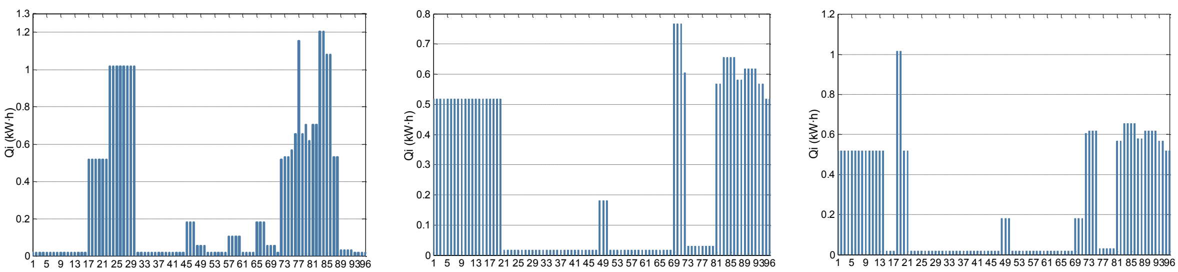


Fig. 4. Day-ahead electricity price.

4.2. Results and discussions

It is assumed that the controller receives the incentives at 3:15 a.m. and 4:50 p.m., $N_{sig} = 3$, $R = 0.50kWh$ The customer's electricity curves and costs in various mechanisms are shown in Figure 5.



(a) electricity cost = ¥ 13.89 (b) electricity cost = ¥ 8.96 (c) electricity cost = ¥ 9.65

Fig. 5. Electricity curves and costs in various mechanisms (a) random consumption; (b) day-ahead price; (c) incentive mechanism.

The results indicate that: The peak load and the electricity cost of day-ahead electricity price is obviously lower than random consumption, which prove that the optimal models can reduce the pressure of the grid and enhance the economy of electricity consumption effectively. After receiving the incentive signal, the load reduce in intervals 15~17 and intervals 69~71 while the cost is a little higher than price mechanism. To encourage residents to actively response the incentive mechanism, the grid companies need to subsidize to the customers who have responded successfully.

5. Conclusions

This paper classifies the smart appliances of residential customers and analyzes the intelligent power characteristics. An optimal control model to minimize customers' cost is proposed under day-ahead electricity prices. HEMS will adjust the model parameters after receiving the real-time incentive signals to cut down power loads. The cases illustrate that HEMS is able to reduce electricity costs and peak-valley differences without affecting the customers' comfort, and provide reserve capacity for the grid.

Acknowledgements

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Biography

Xinyao Qu received the B.Eng. degree from the College of Electrical Engineering in Zhejiang University in 2015. She is currently pursuing master degree in Zhejiang University. Her main research direction is demand response.