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ORIGINAL PAPER

Optimal scheduling of household appliances for smart home energy management considering demand response

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Abstract As an important part of demand-side management, residential demand response (DR) can not only reduce consumer's electricity costs, but also improve the stability of power system operation. In this regard, this paper proposes an optimal scheduling model of household appliances for smart home energy management considering DR. The model includes electricity cost, incentive and inconvenience of consumers under time-of-use (TOU) electricity price. Further, this paper discusses the influence of inconvenience weighting factor on total costs. At the same time, the influence of incentive on optimization results is also analyzed. The simulation results show the effectiveness of the proposed model, which can reduce 34.71% of consumer's total costs. It also illustrates that the total costs will be raised with the increase in inconvenience weighting factor. Thus, consumers will choose whether to participate in DR programs according to their preferences. Moreover, the result demonstrates that incentives are conducive to shifting load and reducing the consumer's total energy costs. The presented study provides new insight for the applications of residential DR.

Keywords Demand response · Energy management · Household appliances · Scheduling

1 Introduction

Demand-side management (DSM) was first proposed by the American Electric Power Research Institute (EPRI) in 1980s, which changed the concept that the increasingly growing electricity demand can only be met through expanding power generation

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capability. DSM implies a new concept that achieves energy saving from demand side and regards energy use optimization as an alternative source for the supply side (Ardakani and Ardehali 2014). As an important form of DSM, demand response (DR) refers to market participation behavior that consumers take initiatives to change their original electricity consumption patterns in response to market price signals or incentives. DR has changed the previous situation that consumers do not have opportunities to participate in the operation of the power system. And it enables consumers to become important players in regulating market supply and demand (Heydarian-Forushani et al. 2015; Zhou and Yang 2015). DR can reduce electricity costs of consumers by promoting them to reduce power consumption in high-priced periods and increase the power consumption in low-priced periods. At the same time, DR is helpful to improve the stability of power system by reducing the occurrence probability and frequency of peak load (Moghaddam et al. 2011; Tsui and Chan 2012). Generally, the current DR programs are categorized as incentive-based and price-based programs (Ju et al. 2016; Zhou and Yang 2016). These two categories of DR programs are interconnected and can be designed to achieve complementary goals (Aalami et al. 2008).

Electricity consumption of a single household is much smaller than that of commercial and industry, so the initial research on residential DR programs is few (Liu et al. 2015; Rassia and Pardalos 2012; Xie and Pearman 2014; Zhou et al. 2016b). But with the growth of population and residents' disposable income, more and more household appliances are being used. The proportion of residential energy consumption has reached around 30–40% of the world's total energy consumption (Fan et al. 2015; Torriti 2014; Wu et al. 2014). The residential loads have the characteristics of seasonal and daily peak demand, which makes the utility companies to increase their generation capacity to meet these occasional peak demands. It brings huge cost burdens to the operation of power system (Song et al. 2016a, b). Nowadays, the emergence and development of smart home make it possible to schedule household load (Rassia and Pardalos 2014, 2015; Zhou et al. 2016a). Scheduling household load can achieve power supply and demand balance by changing the load curve shape. And it is helpful to improve energy efficiency and slow down the grid expansion (Sanjari et al. 2015). Thus, it is of great practical significance to carry out optimal scheduling of household appliances for smart home energy management.

Currently, researchers have identified the significance of optimal scheduling of household appliances and consequently have presented many strategies and policies for optimal scheduling of household appliances. Firstly, there are papers on modeling specific appliances. For instance, Li et al. (2011) separated appliances into four types, and the utility model and constraints of various types of appliances are considered. Shao et al. (2013) considered physical and operational characteristics of different load types, including space cooling/heating, water heating, clothes drying and electric vehicle (EV) loads. And the inconvenience of household appliances, such as electric water heater (EWH) and air conditioners, is considered in some studies (Ericson 2009; Zhang and Xia 2007). Then, some existing studies focused on the influence of electricity price on optimal scheduling of household appliances. Mohsenian-Rad and Leon-Garcia (2010) proposed a residential load control strategy in a real-time pricing tariff combined with inclining block rates, and proposed strategy is combined with price prediction capabilities. Derakhshan et al. (2016) presented an optimization model for consumption scheduling of residential consumers under different electricity price, including TOU price, real-time price, critical peak price and no tariff for pricing. Ji et al. (2014) proposed a residential DR controller to control heating, ventilating and air-conditioning (HVAC) systems based on dynamic pricing, which can curtail peak load and reduce electricity cost. In addition, some existing studies focused on the influence of incentive on optimal scheduling of household appliances. Mallette and Venkataramanan (2010) discussed the impact of incentives on the residential load control containing plug-in hybrid electric vehicle (PHEV). Farahani et al. (2012) used an exponential modeling of DLC programs as incentive-based DR programs, which is incorporated into the nonlinear behavioral characteristic of elastic loads to make the model more realistic.

This paper proposes an optimal scheduling model of household appliances considering DR, which comprehensively considers the electricity costs, incentive and inconvenience under TOU electricity price. This research is different from prior work in three ways that reflect its unique contributions. (1) The incentive for a certain period is generally fixed in the existing research works. It is not conducive to motivating consumers to shift more load from peak to valley time. Thus, the incentive is divided into several tiers according to the amount of shifted load during peak times in this study. (2) It will bring inconvenience to consumers when changing their original electricity consumption behaviors. But the influence of inconvenience level on consumers has not been explored in depth in existing studies. In this study, the influence of inconvenience level on the optimization results is discussed. Consumers can control how they favor the scheduling inconvenience over the cost by using the weighting factor. (3) Most existing studies only consider linear constraints in order to facilitate the calculation. In this study, nonlinear constraints are considered, such as continuous operation constraints, and it makes the scheduling model more reasonable.

The rest of this paper is organized as follows. Section 2 proposes the optimal scheduling model of household appliances considering DR. Then experimental setup is presented in Sect. 3. In Sect. 4, the results are analyzed, and the influences of inconvenience weighting factor and incentive on the results are discussed, respectively. Finally, conclusions are drawn in Sect. 5.

2 Model

This paper proposes an optimal scheduling model of household appliances for smart home energy management considering DR. The objective function of the proposed model is obtained by comprehensively considering the electricity cost, incentive and inconvenience. At the same time, the constraints of household appliances are considered in the model.

2.1 Objective function

2.1.1 The electricity cost

DR can reduce electricity cost of consumer by shifting load from peak to valley time. The electricity cost of consumer after participating in DR program is defined as follows.

$$C = \sum_{t=1}^{T} \sum_{i=1}^{N} P_i \cdot S_t \cdot k_{i,t}^{\mathrm{opt}} \cdot \Delta t \quad (1)$$

$$k_{i,t} = \begin{cases} 0 & \text{when } i\text{th appliance is off at } t\text{th period} \\ 1 & \text{when } i\text{th appliance is on at } t\text{th period} \end{cases} \quad (2)$$

where C is consumer's electricity cost. T is the total number of periods in scheduling cycle. t is the number of period. Δt is the length of each time period. N is the total number of appliances. i is the number of appliances. P_i is the rated power of the ith appliance. S_t is the electricity price in period t. $k_{i,t}^{\mathrm{opt}}$ is the new on/off status of ith appliance in period t, which is determined by Eq. (2). If the operation status of ith appliance is on in period t after optimization, then $k_{i,t}^{\mathrm{opt}}$ is equal to 1. If the operation status of ith appliance is off in period t after optimization, then $k_{i,t}^{\mathrm{opt}}$ is equal to 0.

2.1.2 Incentive

In order to promote consumers to shift load during peak times, the incentive is considered in the optimal scheduling model of household appliances. The incentive is divided into several tiers according to the amount of shifted load during peak times, which is defined as follows.

$$B = \sum_{t=1}^{T} \sum_{m=1}^{M} (a_{m,t} \cdot p_{m,t}) \Delta t \tag{3}$$

where B is the consumer's incentive. $a_{m,t}$ is the subsidized price of mth tier of incentive in period t. $p_{m,t}$ is the amount of shifted load of mth tier of incentive in period t. M is the total number of tiers of incentive.

Too few tiers of incentive are not conducive to stimulating the consumer's potential of shifting load from peak to valley time. But too many tiers of incentive will make it difficult for consumers to determine the amount of shifted load during peak times. Thus, the incentive is divided into three tiers in this paper ($M = 3$). Then Eq. (3) can be converted to

$$B = \sum_{t=1}^{T} (a_{1,t} \cdot p_{1,t} + a_{2,t} \cdot p_{2,t} + a_{3,t} \cdot p_{3,t}) \Delta t \tag{4}$$

where $p_{1,t}$, $p_{2,t}$ and $p_{3,t}$ are the shifted load corresponding three-tier incentive in period t respectively, and their sum is equal to Q_t. $a_{1,t}$, $a_{2,t}$ and $a_{3,t}$ are the subsidized price corresponding three-tier incentive in period t, respectively. For example, incentive is divided into three tiers by p_1 and p_2, i.e., $[0, p_1]$, $[p_1, p_2]$ and $[p_{2,} + \infty]$. If Q_t is bigger than p_1 and smaller than p_2, then $p_{1,t}$, $p_{2,t}$, $p_{3,t}$ are equal to p_1, $Q_t - p_1$, 0, respectively. So the incentive in period t is equal to $a_{1,t} * p_1 + a_{2,t} * (Q_t - p_1)$.

2.1.3 Inconvenience

The behavior of consumers to change the original electricity consumption patterns will bring inconvenience. The level of the inconvenience will affect consumers whether to participate in the DR programs. Thus, the inconvenience must be considered in the proposed model. We assume that the consumers' electricity consumption behavior is fixed, and advance or delay in the electricity consumption behavior will bring inconvenience to the consumers. In real life, inconvenience is related to the length of advance or delay time. Therefore, this article defines inconvenience as follows.

$$I = \sum_{i}^{N} \left| \sum_{t=1}^{T} t\left(k_{i,t}^{\mathrm{opt}} - k_{i,t}^{\mathrm{bl}}\right) \right| \tag{5}$$

where I is the inconvenience. $k_{i,t}^{\mathrm{bl}}$ is the consumer's baseline on/off status of ith appliance in period t, which is determined by Eq. (2). $\sum_{t=1}^{T} t\left(k_{i,t}^{\mathrm{opt}} - k_{i,t}^{\mathrm{bl}}\right)$ is the delay or advance time of ith appliance (positive value indicates delay, and negative value indicates advance). For example, we take one hour as a sampling time and a study period of 24 h. The running time intervals of dishwasher before and after optimization are 20:00–21:00 and 23:00–24:00, respectively. The running time of dishwasher is delayed for 3 h, and then inconvenience is equal to 3.

2.1.4 *Objective function*

The goal of each household to participate in load scheduling is to minimize its total cost subject to various consumption constraints. After comprehensively considering the electricity cost, incentive and inconvenience, the objective function of residential DR is defined as follows.

$$C_{\mathrm{total}} = C - B + \alpha I \tag{6}$$

where C_{total} is the total costs. α is the weighting factor, which reflects preference of consumers to participate in DR programs. The large weighting factor means shifting load will bring great inconvenience to consumers so that consumers are reluctant to participate in DR programs.

2.2 Constraints

2.2.1 *Energy consumption constraints*

The energy consumption after optimization should not be less than the energy consumption before optimization in order to satisfy consumer's normal life. This constraint is denoted as follows.

$$\sum_{\mathrm{start}_i}^{\mathrm{end}_i} k_{i,t}^{\mathrm{opt}} \geq N_i \tag{7}$$

where start_i and end_i are the start and end of the schedulable time interval of ith appliance. It means that appliances must be run at a certain time interval (Baboli et al. 2012; Rastegar et al. 2012). N_i is the time duration required to finish normal operation of ith appliance, which is represented by the total number of running time periods.

2.2.2 *Continuous operation constraints*

Some electrical appliances cannot be interrupted when running. Thus, continuous operation constraints of electrical appliances should be considered in the model except water pump of swimming pool, EWH and EV. This constraint is expressed as follows.

$$\sum_{\text{start}_i}^{\text{end}_i-(N_i-1)} k_{i,t}^{\text{opt}} \cdot k_{i,t+1}^{\text{opt}} \cdot k_{i,t+2}^{\text{opt}} \cdots k_{i,t+(N_i-1)}^{\text{opt}} \geq 1 \tag{8}$$

2.2.3 Running order constraints

In real life, some appliances must be run after the other. For example, the clothes dryer must be run after the washing machine. It is necessary to restrict running order of appliances. This constraint is denoted as follows.

$$\text{start}_u \geq \text{start}_v + N_v \tag{9}$$

where start_u and start_v are starting time of uth and vth appliance, respectively, $1 \leq u, v \leq N$. N_v is the time duration required to finish normal operation of vth appliance. It means that the starting time of uth appliance must be after the starting time of vth appliance plus its run time.

2.2.4 The constraint of incentive

$$\sum_{t=1}^{T} \sum_{m=1}^{M} (a_{m,t} \cdot p_{m,t})\, \Delta t \leq \text{UB} \tag{10}$$

where UB is the utility's total budget. Equation (10) ensures that the total incentive paid by the utility is less than or equal to the utility's budget.

2.2.5 Capacity constraints of EV battery

EV is considered in the model. The state of charge (SOC) of the battery refers to the ratio of the residual energy to the rated energy. In order to protect the battery of the EV, battery cannot be overcharged. This constraint is expressed as follows.

$$SOC_{EV} \leq SOC_{EV}^{\max} \tag{11}$$

where SOC_{EV} is the SOC of battery of EV and $\text{SOC}_{\text{EV}}^{\max}$ is the upper limit of SOC of EV.

3 Experimental setup

The household loads can be classified into two types. The first type is the shiftable load, which can be scheduled at different time periods. The shiftable load can be divided into interruptible load and non-interruptible load. For example, the EWH is the shiftable and interruptible load, but the washing machine is the shiftable and non-interruptible load. The second type is the non-shiftable load that must be operated during specific time periods, such as lighting and television. Therefore, only the shiftable load can be involved in the DR programs. In this paper, the eight appliances are selected in the optimal scheduling model in a smart home. The data of appliances are listed in Table 1, including power rating, time duration required to finish normal operation, starting and ending time of the schedulable time interval. The TOU electricity price is shown in Fig. 1. Peak times are 08:00–13:00 and 17:00–22:00. Valley times are 00:00–06:00. Other times of the day are flat times.

Table 1 Data of appliances

Appliance	Power rating/W	Duration N_i (min)	start_i and end_i
Washing machine	500	60	20:00–7:00
Tumble dryer	750	120	21:00–7:00
Dishwasher	800	60	13:00–17:00
		60	19:00–24:00
Water pump	1800	180	00:00–9:00
Microwave	1200	60	18:00–20:00
EWH	2000	120	3:00–8:00
		120	15:00–21:00
EV1	6000	300	19:00–7:00
EV2	7000	300	18:00–7:00

Three-tier incentive data are listed in Table 2. It is shown in Table 2 that there are no incentive data during valley times. The reason is that reducing valley load is meaningless for power system.

4 Results and discussion

4.1 Result analysis

The problem is formulated as mixed integer nonlinear programming (MINLP). It is solved by linear interactive and general optimizer (LINGO) software. LINGO is a comprehensive tool designed to make building and solving mathematical optimization models easier and more efficient, which has a good ability to solve the linear and nonlinear optimization problems. This paper sets the calculation cycle as one day, by setting 1 h as a calculation period, and then the whole day could be divided into 24 periods. The weighting factor of inconvenience is set to 0.2. The selection of inconvenience weighting factor will affect the optimization results. Thus, the influence of inconvenience weighting factor on optimization results will be discussed later in this paper. Household load before optimization is shown in Fig. 2. Household load after optimization at $\alpha = 0.2$ is shown in Fig. 3.

It is shown in Fig. 2 that household load mainly concentrated at 19–24 h before optimization. The electricity price is high at that time. After optimization, it is shown in Fig. 3 that load in high-priced time periods has been shifted to low-priced time periods for DR, i.e., at 3–6 h in the evening. Thus, DR plays a role of peak shaving and valley filling for the main power grid.

The running time intervals of household load before and after optimization at $\alpha = 0.2$ are listed in Table 3. It is shown in Table 3 that the running time interval of washing machine before and after optimization is 20–21 h and 21–22 h, respectively. For the second appliance, the running time intervals of tumble dryer before and after optimization are 21–23 h and 22–24 h, respectively. The tumble dryer was operated after washing machine, which satisfies the running order constraints. In addition, it can be seen that the running times of washing machine and tumble dryer are consecutive. The reason is that they must satisfy the continuous operation constraints. As for water pump, EWH and EV, they do not need to satisfy the continuous operation constraints because they are continuous on/off appliance.

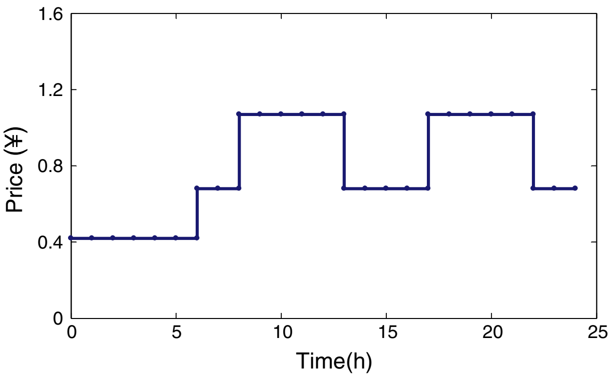

Fig. 1 TOU electricity price

Table 2 Three-tier incentive data

Type	First tier		Second tier		Third tier
	p_1 kWh	Price ¥/kWh	p_2 kWh	Price ¥/kWh	Price ¥/kWh
Peak	3	0.2	6	0.35	0.4
Flat	5	0.1	10	0.15	0.2
Valley	–	–	–	–	–

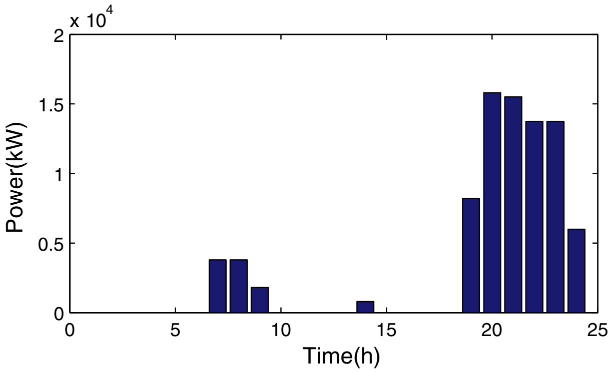

Fig. 2 Household load before optimization

The switching status of high-cost appliances before and after optimization at $\alpha = 0.2$ is shown in Fig. 4. The reason of high cost is their long running time and high-rated power. For example, running time of both EV1 and EV2 is 5 h, which is longer than other appliances. Meanwhile, the rated power of EV1 and EV2 is 6 and 7 kW, respectively, which is greater than the general electrical appliances. In order to reduce costs, more high-cost appliances should be incorporated into the DR programs.

The simulation results show that the total costs before optimization are ¥78.0455. And the total costs after optimization with $\alpha = 0.2$ are ¥50.955. The total costs are reduced by 34.71% through the DR. The results show the correctness and effectiveness of the proposed model. In fact, the amount of saving will be influenced by the inconvenience weighting factor and the incentive. Thus, the influence of inconvenience and incentive on optimization results will be discussed later.

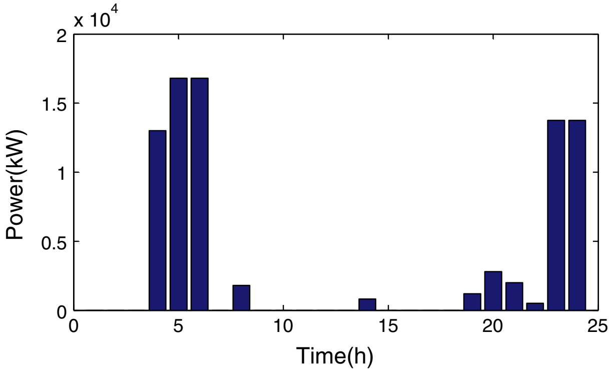

Fig. 3 Household load after optimization

Table 3 Running time intervals of household load before and after optimization

Appliance	Running time interval before optimization	Running time interval after optimization
Washing machine	20:00–21:00	21:00–22:00
Tumble dryer	21:00–23:00	22:00–24:00
Dishwasher	13:00–14:00	13:00–14:00
	19:00–20:00	19:00–20:00
Water pump	6:00–9:00	04:00–06:00 07:00–08:00
Microwave	18:00–19:00	18:00–19:00
EWH	6:00–8:00	04:00–06:00
	19:00–21:00	19:00–21:00
EV1	19:00–24:00	03:00–06:00 22:00–24:00
EV2	18:00–23:00	03:00–06:00 22:00–24:00

4.2 The influence of inconvenience weighting factor

The inconvenience level of consumer is depended on the weighting factor α. The influence of inconvenience level on consumers' electricity consumption behavior is not discussed in depth in the current study. Therefore, it is necessary to discuss the influence of weighting factor on the results. Household load after optimization at different weighting factor is shown in Fig. 5. Total costs and inconvenience at different weighting factors are listed in Table 4.

According to Figs. 1 and 5, it is shown that the shifted load from peak times (19–22 h) to valley times (1–6 h) becomes less with the increase in weighting factor α. The reason is that the weighting factor reflects consumer's preference. The smaller weighting factor means lower penalty on inconvenience, so that consumers are willing to shift more load in order to reduce the total costs.

It is shown in Table 4 that the inconvenience decreases with the increase in weighting factor. But the total costs increases with the increase in weighting factor. The reason is that

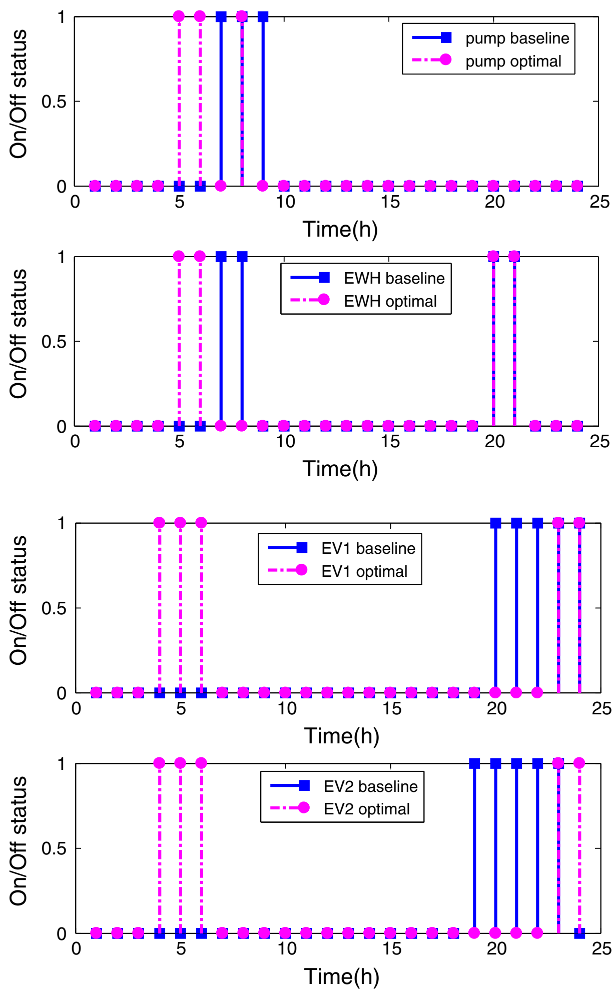

Fig. 4 Switching status of high-cost appliances before and after optimization

the high weighting factor means a high penalty on inconvenience. To reduce the penalty on inconvenience, consumers are not willing to shift peak load when their weighting factor is high. The decrease in shifted load leads to the increase in total costs. Thus, weighting factor is a trade-off between the total costs and the inconvenience.

According to Table 4, the total costs and inconvenience remain constant when the α is larger than or equal to 1. The reason is that the penalty on inconvenience is very high when α is larger than or equal to 1. Consumers are not willing to shift peak load. Thus, the total costs and inconvenience remain constant.

4.3 The influence of the incentive

In this paper, we discuss the results of residential DR considering the incentive and inconvenience. The incentive is divided into several tiers according to the amount of shifted load during peak times in this paper, which is different from previous studies and conducive to motivating consumers to shift load from peak to valley time. Whether

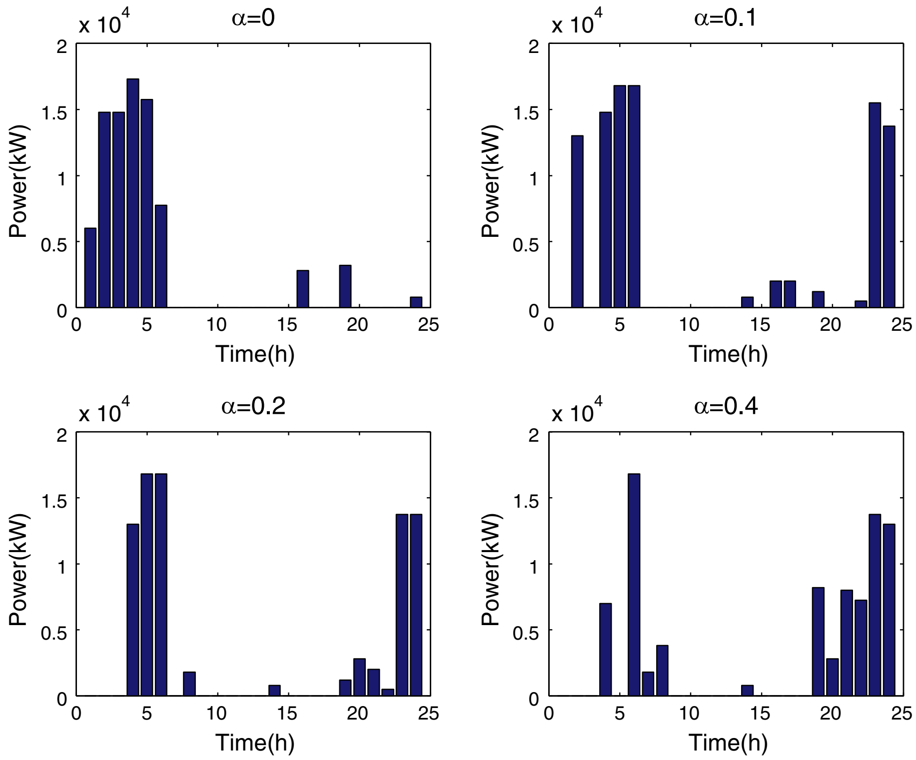

Fig. 5 Household load after optimization at different weighting factor

Table 4 Total costs and inconvenience at different weighting factors

α	Total costs (¥)	Inconvenience (*I*)
0	17.16	264
0.1	36.845	160
0.2	50.955	103
0.4	70.7155	48
1	78.0455	0
5	78.0455	0
10	78.0455	0

consumers participate in the DR programs will be affected by the incentive. Thus, it is necessary to discuss the influence of incentive on the results. Total costs and inconvenience at different weighting factors without incentive are listed in Table 5. Cost comparisons between incentive and no incentive are shown in Fig. 6. Inconvenience comparisons between incentive and no incentive are shown in Fig. 7.

It is shown in Table 5 that the inconvenience decreases with the increase in weighting factor. And the total costs increases with the increase in weighting factor. The reason is same as optimal scheduling model of household appliances considering the incentive. It is shown in Fig. 6 that the total costs with incentive are smaller than those without incentive at different inconvenience weighting factor. It means incentives are conducive to reducing

Table 5 Total costs and inconvenience at different weighting factors without incentive

α	Total costs (¥)	Inconvenience (*I*)
0	37.96	264
0.1	56.367	114
0.2	67.515	100
0.4	77.8575	2
1	78.0455	0
5	78.0455	0
10	78.0455	0

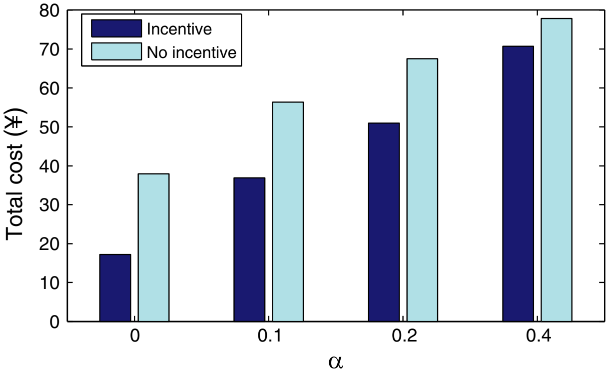

Fig. 6 Cost comparisons between incentive and no incentive

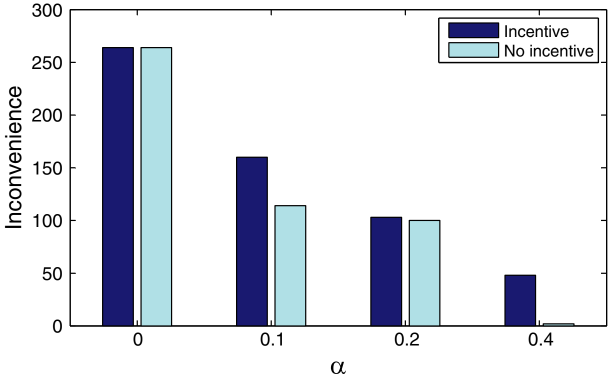

Fig. 7 Inconvenience comparisons between incentive and no incentive

the consumer's total costs. Meanwhile, Fig. 6 shows that the gap between total costs with incentive and without incentive will be smaller with the increase in weighting factor. The reason is that shifting load will bring great penalty on inconvenience to consumers when inconvenience weighting factor is large enough. Consumers are not willing to shift load. The total costs with incentive or without incentive will be the same as before the implementation of DR.

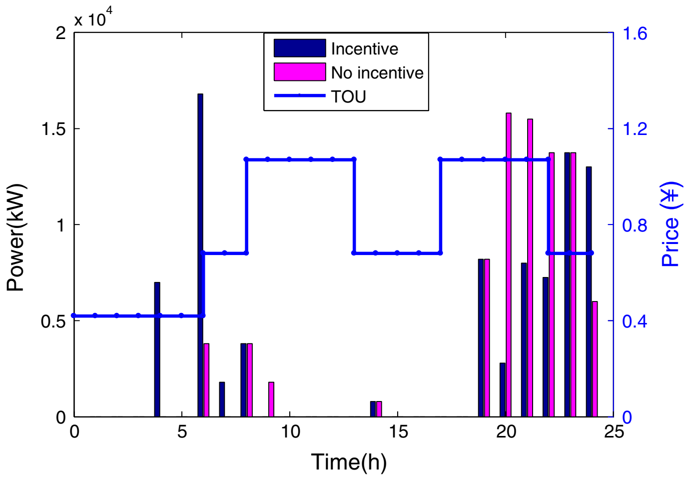

Fig. 8 Household load comparisons between incentive and no incentive

It is shown in Fig. 7 that the inconvenience of consumer considering incentive is larger than that without considering incentive when α is larger than 0. It demonstrates that incentives are conducive to shifting load. For example, Fig. 8 shows the household load comparisons between incentive and no incentive at $\alpha = 0.4$. According to Fig. 8, more loads are shifted from high-priced periods (19–22 h) to low-priced periods (1–6 h) when considering incentive. It illustrates that consumers are more willing to shift peak load in order to reduce the total costs under the incentive.

5 Conclusions

This paper proposes an optimal scheduling model of household appliances for smart home energy management considering DR. The electricity cost, incentive and inconvenience of consumers under TOU electricity price are considered in the model. The results show that the consumer will shift load from peak times to valley times in response to the electricity prices and incentive. Consumer will reduce 34.71% of the total costs when inconvenience weighting factor $\alpha = 0.2$. The influence of inconvenience weighting factor on optimization results is considered in this paper. It illustrates that the weighting factor is a trade-off between the total costs and the inconvenience. Consumers will choose whether to participate in DR according to their preferences. Meanwhile, the influence of incentive on optimization results is also considered in this paper. The results demonstrate that the incentives are conducive to shifting load and reducing the consumer's total costs.

In this paper, we discuss the DR application of one household in one day. Future work will consider more households and longer study period. Meanwhile, with the increase in the number of households, the inconvenience level of households may be different. It will bring difficulties to energy management of smart home. Thus, optimal scheduling problem of multi-household needs to be further studied. In addition, this article considers electrical appliances of fixed operating power. But some household appliances are regulating appliances, whose consumption level can be determined through the energy management procedure, such as air conditioner. This type of appliances will be considered in the further research.

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