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Residential Power Scheduling Based on Cost Efficiency for Demand Response in Smart Grid

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ABSTRACT Residential power scheduling for demand response in a smart grid is a complex task. The traditional methods aim to minimize consumption costs and maximize consumption payoffs. In this paper, a power scheduling algorithm based on cost efficiency for smart homes is proposed to improve consumers' consumption efficiency and satisfaction. In this proposed method, a definition of cost efficiency for residential power scheduling is introduced. Consumers' consumption costs are modelled based on electricity payments and users' discomfort. A pair of parameters for a trade-off between users' discomfort and their electricity payment is designed to model cost efficiency based on the consumer's preference. A power scheduling algorithm based on cost efficiency is developed by adopting a fractional programming approach. Four consumption models are analysed and discussed. The results show that this proposed method can effectively improve consumers' consumption efficiency and satisfaction while saving costs. It is shown that discomfort and additional payment can impact consumers' consumption behaviour and smooth their consumption profile curves.

INDEX TERMS Residential power scheduling, cost efficiency, discomfort cost, electricity payment cost, smart home.

I. INTRODUCTION

The concept of a smart grid focuses on the enhancement of the energy efficiency of the power grid [1], [2]. A common solution is the development of demand-side management (DSM), which makes the demand profile match the supply [3]. Demand response (DR) is one of the most widely used DSM activities [4]. It is a procedure used to influence electricity users' consumption habits through responses to electricity prices or incentives. With the development of the social economy, lifestyles have changed dramatically, the demand for residential electricity has been increasing. Residential load management will play a greater role in DSM and is quite challenging [5]. In recent decades, an increasing number of DR programmes for residential load management have been developed, such as control-mechanism-based DR methods which help reduce loads during peak-demand hours through centralized or distributed schemes [6], motivations-based DR methods, which reduce or shift consumer power demands through pricing-mechanisms-based [7] or incentive-based DRs [8], decision-variable-based DR methods, which manage electricity user loads through task scheduling [9] or energy-management-based DRs [10]. These DR programmes aim to change the load structure and the activation time of loads in an in-home environment to balance consumers' load demands at different times [11]. An appropriate programme of residential load management can be used to achieve the scheduling of residential users' electrical appliances effectively. In DR programmes, the pricing-mechanisms-based and energy-management-based DRs are usually more suited for residential consumers [12]. These DR programmes are adopted by energy suppliers to influence consumer behaviour and smooth their demand curves.

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For pricing-mechanisms-based DR programmes, the power suppliers provide varied prices to consumers during different periods [13]. After receiving the price signal, customers tend to consume less electricity when the programmes charge high prices. Recently, a number of pricing schemes for DSM have been developed. The most traditional pricing schemes are based on flat pricing, which is fixed during a period, such as a season [14]. For example, Doostizadeh and Ghasemi [15] proposed a day-ahead electricity pricing model for DSM, where the users who participate in the scheme reduce their electricity consumption by using less electricity in a day. Another kind of pricing scheme based on flat pricing is time-of-use (TOU) pricing, which uses fixed prices for different days of the week or different hours in a day [16]. A simulation of household behaviour showed that users are attracted by off-peak prices and will avoid peak prices. However, the reductions in their electricity bills are limited [17]. Similar to TOU, critical peak pricing charges fixed prices during different periods, although prices can change when the system is in an emergency period [18]. When this occurs, the participant customers are notified of the new energy price, usually a day in advance. Although the loads are significantly reduced during emergency periods, users are not economically efficient. Popular DR schemes are day-ahead bidding (DAB) pricing [19] and real-time (RT) pricing [20]. The former scheme divides a day into various periods in which electricity prices are different. Based on historical data, electricity prices are determined, and the price signal is given to the users one day in advance. The participating consumers respond to the price signal and upload their hourly consumption demands to bid for electric energy. The DR programmes based on DABP aim to shift the consumers' demand away from peak periods and create a maximum payoff for energy suppliers [21]. However, the latter scheme maximizes customer participation. Electricity prices are different during the different periods throughout the day and are announced before the start of each period [22]. The consumers that participate in these programmes install an energy management controller (EMC) in their premises, and their electricity consumption is based on their preferences [23]. This kind of DR programme can result in high reductions in electricity consumption. However, as most household consumers do not concern themselves with systematic electricity decisions, the implementation of it in the residential domain has had little success.

For energy-management-based DR programmes, a reduction in consumers' electricity usage is achieved through curtailing their loads under a certain pricing model [24]. The common practices aim to trigger fewer loads or schedule some specific electrical appliances into the off-peak periods to reduce the total electricity usage when the system is stressed [25]. For example, Ahmadi *et al*. [26] developed a mixed-integer linear programming model for a solar-powered stochastic operation to capture thermal load uncertainties in a smart home, which significantly achieved an energy cost-saving and provided a decrease in the peak electricity demand. Astriani *et al*. [27] proposed an additional controls method that managed the consumed power effectively on the demand side by coordinating the output power within islanded microgrids. Recently, there have been many works focusing on dispatch models for smart homes and residential buildings, taking different energy sources and responsive loads into consideration, while also tackling different objectives such as cost and comfort. For example, Anvari-Moghaddam *et al*. [28] proposed a multi-agent-based energy management solution that could provide optimal control for integrated homes/buildings and microgrid systems using various renewable energy resources (RESs) and controllable loads. Jiang *et al*. developed a load scheduling algorithm based on cost efficiency and consumer preference for managing residential electrical appliances, which achieved the desired trade-off between economic efficiency and consumer preference [29]. Anvari-Moghaddam *et al*. developed a multiobjective mixed-integer nonlinear programming model [30] and a residential energy management algorithm based on cost-effectiveness and comfort awareness [31], respectively. The two methods consider a meaningful balance between energy savings and a comfortable lifestyle for the management of energy in smart homes. Latifi *et al*. proposed a distributed-game theoretic demand response with multi-class appliance controls in a smart grid to maximize consumer satisfaction levels [32]. These energy-management-based DR programmes aim to reduce total electricity consumption through the curtailment of consumer loads or the alteration of load activation time when the system experiences a peak period. However, customer satisfaction based on the user comfort and preference, along with a reduction in electricity consumption, is still a drawback to existing DR programmes for DSM.

To answer the above questions, this paper proposes a novel algorithm for residential demand management based on cost efficiency in a smart grid to improve consumers' consumption efficiency and satisfaction. In the proposed DR programme, the consumption cost is composed of the electricity payment cost and the discomfort cost, both of which are influenced by consumer preference. Cost efficiency can be calculated by the ratio of the user's total consumption benefit to their total consumption cost. A novel power scheduling algorithm based on cost efficiency is established. The algorithm is optimized by designing a pair of modulation parameters for constraining consumer preference. Different consumption models can be modelled by turning the parameters value in the cost efficiency. A series of experiments are conducted on different consumption models. The results show that the proposed method can effectively affect consumers' behaviour and improve their satisfaction, smoothing their consumption profile curves.

The contributions of our method are summarized as follows:

1) A novel algorithm for residential power scheduling based on cost efficiency is designed to schedule consumers' electricity appliances. The proposed algorithm considers not only consumers' electricity payments but also their comfort. The simulation result shows that the proposed algorithm is effective in reducing electricity consumption and that it can

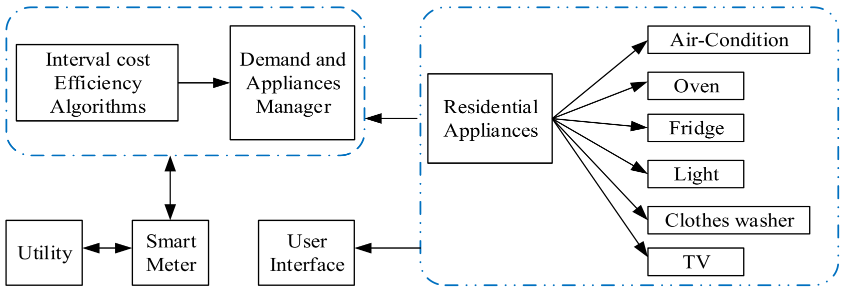

FIGURE 1. Consumption scenario of proposed residential power scheduling.

help consumers obtain maximal consumption benefits while saving costs.

2) A consumer's consumption cost is established by calculating their electricity payment cost and discomfort cost. A pair of modulation parameters are designed, and their values reflect consumer preference. Through tuning the parameter value, consumer consumption efficiency and satisfaction can be better understood, which could be for changing consumers' consumption behaviour.

3) Cost efficiency is modelled by the ratio of the user's total consumption benefits to their total consumption costs. Different consumption models can be modelled by tuning the parameter value in the cost efficiency. The simulation results show that a consumer's consumption preference determines their consumption model and that different consumption models achieve different consumption efficiencies. A consumer's consumption satisfaction level depends on their consumption preference.

This paper is organized as follows. The problem is described and formulated in section 2. In section 3, the consumption behavior is modeled. In section 4, the load scheduling based on the proposed algorithm is analyzed. In section 5, the simulation results are analyzed and discussed. In section 6, the research work of this paper is summarized.

II. PROBLEM DESCRIPTION AND FORMULATION

A. PROBLEM DESCRIPTION

In a smart grid, residential power management plays an important role in demand-side energy management. In this section, a residential consumption scenario (shown in Figure 1) for the application of the proposed power scheduling algorithm is described first. As shown in Figure 1, in an intelligent power system, the proposed residential power scheduling algorithm based on cost efficiency is applied to manage demand and appliances. In this study, the residential appliances include schedulable appliances (e.g., air conditioners) and non-schedulable appliances (e.g., refrigerators). The electrical appliances used in this paper are air conditioners (AC), ovens, refrigerators, lighting, clothes washers (CWs) and TVs. These appliances are classified into two types. Appliances in the first group, with fixed powers, start to work continuously at a flexible time. Appliances in the second group, with flexible powers, start to work continuously at the predefined time.

All the aforementioned appliances are effectively monitored and managed automatically by a smart metre. The smart metre utilizes a user interface to exchange measurements and control information between the power service provider (e.g., utility) and the residential customers. Despite power lines joins up with the user interface, the access of a two-way communication exists between the utility and residential customers. The communication conditions for applying the proposed power scheduling algorithm can be guaranteed by ensuring that the existing communication networks exchange the information.

B. PROBLEM FORMULATION

In [21], cost efficiency is defined as the ratio of the utility of the customer's electricity consumption and the customer's total electricity costs. The author chose cost efficiency to manage residential power consumption. Mathematically, the process of cost efficiency is presented as follows:

$$\text{C.E.} = \frac{Utility}{Cost} \tag{1}$$

where *Utility* is the user's electricity consumption utility, and *Cost* is the electricity cost. The results showed that cost efficiency can effectively measure consumer economic efficiency.

Traditional residential demand scheduling programmes for demand-side management consider the electricity payment as the electricity cost (the monetary cost). A reduction in electricity consumption leads to decreases in consumers' electricity bills through the scheduling of electrical appliances. In [21], only the electricity payment is taken into account to calculate the cost efficiency. However, an electrical appliance should be shifted in a scheduling horizon that includes time and power ranges. The task for the operation of an appliance is delayed or fulfilled with the dissatisfied power that results in consumers' discomfort. For instance, when the scheduling time horizon for a CW is 6 pm-8 am, the user chooses to make the CW start working the next day at 7 am and stop working at 8 am. The user may select to delay the operation of the CW to another time in its scheduling range because of lower electricity prices. Similar to the above example, the user may choose to shift the lighting power from 0.6 kWh to 0.3 kWh to reduce electricity consumption. An operation such as that can result in customer discomfort. Thus, in a practical application, user comfort is also considered.

Given these two considerations, including electricity payment and customer comfort, the total consumption cost should be composed of the monetary cost and the discomfort cost. In addition, the discomfort cost is associated with a reduction in monetary cost, caused by the scheduling of electrical appliances at set points that deviate from normal power use times. As a result, the significance of the monetary cost and the discomfort cost in the total consumption cost relies on consumer preference. Let μ_1 denote the user's preference for the electricity payment while μ_2 denotes the user's discomfort preference. The total consumption cost can be defined as follows:

$$TC = \mu_1 Pay + \mu_2 DC \tag{2}$$

where Pay denotes the total electricity payment, DC denotes the total discomfort cost that is expressed in exactly the same unit with Pay due to it can be mapped into a monetary cost by the approach in the following Section III. B, μ_1 is a weight that measures consumer preference for the electricity payment, μ_2 is a weight that measures consumer preference for the discomfort cost, and $\mu_1 + \mu_2 = 1$. When the user has a complete preference for the electricity payment, $\mu_1 = 1$, $\mu_2 = 0$. In contrast, when the user has a complete preference for the discomfort cost, $\mu_1 = 0, \mu_2 = 1$. Except for those two extreme cases, μ_1 and μ_2 are constrained by $0 < \mu_1 < 1, 0 < \mu_2 < 1$ and $\mu_1 + \mu_2 = 1$. Hence, the total consumption cost TC varies in the set point of different interval distributions. The optimization problem of Eq. (1) can be converted into modelling cost efficiency based on consumer preference as follows:

$$\text{C.E.} = \frac{Utility}{\mu_1 Pay + \mu_2 DC} \tag{3}$$

Cost efficiency based on consumer preference, as in Eq. (3), is sensitive to the schedule of the electrical appliances because the slightly scheduling of the appliances changes the consumer's electricity payment and affects their comfort and consumption utility. In this paper, in order to reduce a user's electricity consumption and maximize their consumption efficiency, we chose it as the optimization objective to derive the following.

1) Model consumption behaviour based on cost efficiency.
2) Study different residential consumption models based on consumer preferences.
3) Improve consumer satisfaction through trade-offs between their electricity payment and discomfort.
4) Maximize consumer consumption efficiencies through the maximization of cost efficiency.

III. MODELLING CONSUMPTION BEHAVIOUR

A. ELECTRICITY PAYMENT COST

In this section, the consumption behaviour of a smart home is described, and the pricing mechanism for electricity consumption is built on the foundation of TOU pricing, DAB pricing and RT pricing. The users respond to a price signal to decide how to manage their electrical appliances. Let the electricity price at the $t \in T$ time slot be P_t, where T is the operation cycle of the system, and $T = \{1, 2, \ldots, 24\}$. The residential electrical appliances are $A = \{A_1, A_2\}$, where A_1 is the aforementioned first type of appliance and A_2 is the second type of appliance. Thus, one of the appliances a works at t time to consume electrical energy x_a^t. The user's consumption load in time slot t is defined as

$$L_t = \sum_{a \in A} \sum_{t \in T} x_a^t \tag{4}$$

If TOU pricing is used in the DR, the electricity payment cost Pay^T can be given by

$$Pay_t^T = P_t L_t \tag{5}$$

In the day-ahead bidding, the future pricing is given to consumers ahead of time, and the customers of the smart house upload the day-ahead consumption load $\hat{L}_t$ to bid for the electricity [21]. Let $[D_{min}^b,\ D_{max}^b]$ be the lower and upper bound of the load in the bidding contract. $\hat{L}_t$ should be constrained by $[D_{min}^b,\ D_{max}^b]$. If the consumer's load is less than or equal to the threshold amount stipulated in the contract, users pay bidding price for the electricity. However, if the electricity consumption exceeds the threshold, the user pays a higher price for the portion of the electricity used beyond the scope of the bid. Let P_t' represent the real-time price in time slot t. P_t' is defined as

$$P_t' = \begin{cases} P_t^1 & \text{for the part of } dl_t \text{ within } L_t' \\ P_t^2 & \text{for the part of } dl_t \text{ in excess of } L_t' \end{cases} \tag{6}$$

where P_t^1 and P_t^2 are two different unit prices, and L_t' is the threshold of the consumption load. If $L_t > L_t'$, customers are charged the excess part L_t-L_t' with P_t^2. The electricity payment cost with DAB pricing Pay^D can be given by

$$Pay_t^D = \sum_{t \in T} \max \left\{ P_t^1 L_t,\ P_t^2 L_t + (P_t^1 - P_t^2) L_t' \right\} \tag{7}$$

After the contracts take effect between the supplier and consumer, in the actual consumption process, the consumption load L_t may deviate from the uploaded consumption load. In this case, the consumer should undertake an additional payment for their part that deviated from the uploaded amount. The additional payment is defined as

$$Pay_t^{add} = \hat{L}_t P_t' + \left(L_t - \hat{L}_t \right) \eta_t \tag{8}$$

where η_t denotes the penalty/refund parameter and is defined [21] as

$$\eta_t = \begin{cases} 1.5 & \text{if } \frac{L_t}{\hat{L}_t} \geq 1.05 \\ \frac{L_t}{\hat{L}_t} & \textit{if } 0.95 < \frac{L_t}{\hat{L}_t} < 1.05 \\ 0.5 & \textit{if } \frac{L_t}{\hat{L}_t} \leq 0.95 \end{cases} \tag{9}$$

Thus, the total electricity payment, namely, the total electricity payment cost for all the appliances A in a day is defined as

$$Pay = \sum_{t \in T} \max\left\{P_t^1 L_t,\ P_t^2 L_t + (P_t^1 - P_t^2) L_t'\right\} + \sum_{t \in T} Pay_t^{add} \tag{10}$$

B. DISCOMFORT COST

Given the above analysis, consumers may schedule their electrical appliances to respond to the price signal or be motivated to get the rewards offered by electricity providers. As such, the discomfort cost can be produced in the process of electricity consumption. In [33], an optimal power scheduling strategy proposed that the discomfort cost was modelled from the operation time and power of the appliances. In this way, the discomfort caused by some operations out of the consumer's willingness was effectively quantitated. In this study, we introduce the definition of the discomfort cost for smart house power scheduling. Let $\left[tr_a^b, tr_a^c\right]$ be the scheduling horizon of the time for appliance a ($a \in A_1$) with constant power r_a. Let $\left[pr_a^b, pr_a^c\right]$ be the scheduling horizon of the power for appliance a ($a \in A_1$). Let t_a^s be the time that appliance a starts to work. Thus, the formulation of the discomfort [33] derived from delaying the operation is given by

$$DC_a(t_a^s) = \delta_a (t_a^s - tr_a^b)^k \quad s.t.\ \ t_a^s \in T,\quad t_a^s \in [tr_a^b, tr_a^c]\ and\ a \in A_1 \tag{11}$$

where $k \geq 1$ is real numbers, when the appliance a is delayed, the users must undertake some countermeasure called ϕ' constrained by the operational characteristics φ_a of appliance a, and $0 < \varphi_a < 1$ whose setting as reference [33], $\delta_a = \phi' \varphi_a$.

The formulation of the discomfort [34] caused by the power deviation from normal electricity consumption is given by

$$DC_a^t = \rho_a^t (x_a^t - \hat{x}_a^t)^2 \quad s.t.\ \ t \in T,\quad t_a^s \in [tr_a^b, tr_a^c]\ and\ a \in A_2 \tag{12}$$

where $\hat{x}_a^t$ represents the normal electricity consumption of appliance a that varies with different time slots. when $x_a^t = \hat{x}_a^t$, $(x_a^t - \hat{x}_a^t)^2$ is minimum. If $\Delta = x_a^t - \hat{x}_a^t$, $\hat{x}_a^t + \Delta$ or $\hat{x}_a^t - \Delta$, all result in customer discomfort. When the electricity consumption is $\hat{x}_a^t \pm \Delta$, the users must undertake some countermeasure called ϕ. ρ_a^t is a parameter that can be obtained by ϕ / Δ^2.

The formulation of the total discomfort caused by the above two kinds of discomfort can then be defined as

$$DC = \sum_{a \in A_1} \delta_a (t_a^s - tr_a^a)^k + \sum_{t \in T} \sum_{a \in A_2} \rho_a^t (x_a^t - \hat{x}_a^t)^2 \quad s.t.\ \ t_a^s \in [tr_a^a, tr_a^b] \tag{13}$$

C. UTILITY FUNCTION

Let TL_n^a denote the length of time that appliance a fulfils the nth task to expend and T^a is the number of tasks for appliance a in a day. Then, appliance a works continuously to fulfil the nth task to produce the total demand defined as follows:

$$d_n^a = \sum_{t \in TL_n^a, n \in T^a} x_a^t \tag{14}$$

Users operate the appliance a to fulfil the nth task to produce the utility of appliance a. Thus, the user's electricity consumption utility is based on the task cycle of each electrical appliance. The utility value [21] for appliance a in the nth task cycle can be calculated as

$$U_{a,n}(d_n^a) \triangleq U(d_n^a, \beta^a) \tag{15}$$

where β^a is a parameter that reflects the consumer satisfaction level of appliance a. Here, we solve the problem of Eq. (13) by the quadratic utility functions [35] as

$$U_{a,n}(d_n^a) = \begin{cases} \beta^a d_n^a - \dfrac{\theta^a}{2}(d_n^a)^2 & if\ 0 \leq d_n^a < \dfrac{\beta^a}{\theta^a} \\ \dfrac{(\beta^a)^2}{2\theta^a} & if\ d_n^a \geq \dfrac{\beta^a}{\theta^a} \end{cases} \tag{16}$$

where θ^a is a predetermined parameter.

In view of the above analysis, the utility of the operation of an appliance is based on its load consumption. Additionally, the settings of parameters β and θ determine the capability of an appliance to create utility. Each appliance should be set a unique value for β and θ that depends on consumer preference [29]. For example, the consumer operates the oven to fulfil a task for 0.5 h to produce the best utility of 8/3. Thus, the operation of the oven consumes 1 kWh electricity to work 0.5 h and creates a utility value of 8/3. According to Eq. (14), we have $\beta/\theta = 0.5$ and $(\beta)^2/2\theta = 8/3$. To meet the two equations, the value of β and θ are 16/3 and 32/3, respectively.

D. CONSUMPTION BEHAVIOUR BASED ON COST EFFICIENCY

On the basis of the previous description, the consumption cost includes the electricity payment and the discomfort cost. Due to consumers having different preferences for electricity payments and discomfort costs, the cost efficiency varies as preference weights of electricity payments and discomfort costs change. From Eq. (3), it is easy to trade-off the electricity payment and consumers' discomfort, but the reduction in electricity consumption comes at the expense of a loss of user comfort. An optimal residential power scheduling algorithm needs to consider consumer consumption efficiency. In this section, we model consumption behaviour based on cost efficiency. In the process of which, we propose to reduce consumers' electricity consumption and improve their satisfaction through maximizing cost efficiency based on their consumption preferences. The proposed approach can be presented as Eq. (17), as shown at the bottom of the next page.

Eq. (17) shows that if the users are committed to reducing their electricity payment by tolerating discomfort, their preference weight for the discomfort cost decreases as their tolerating capacity increases. When the consumers do not consider completely the discomfort and only care about the reduction of their electricity bill. That is to say, the consumers have maximal tolerability for the discomfort with a complete preference for the electricity payment, and μ_1=1, μ_2=0. Mathematically, Eq. (17) can be converted into the following optimization problem:

$$\underset{\hat{\mathbf{X}}\in\mathbf{X}}{\text{maximize}} \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a,\omega^a)}{\sum_{t\in T}\max\left\{P_t^1 L_t,\ P_t^2 L_t+(P_t^1-P_t^2)L_t'\right\}+\sum_{t\in T} Pay_t^{add}} \tag{18}$$

In contrast, if users enjoy the process of electricity consumption, their preference weight for the electricity payment decreases as their discomfort preference weight increases. In this case, the consumers select a comfortable power for each appliance to operate it in a satisfactory time slot t, in order to minimize their discomfort and maximize their consumption utility. Thus, consumers have a complete preference for discomfort, and μ_1=0, μ_2=1. Mathematically, Eq. (17) can be converted into the following optimization problem:

$$\underset{\hat{\mathbf{X}}\in\mathbf{X}}{\text{maximize}} \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a,\omega^a)}{\sum_{a\in A_1}\delta_a(t_a^s-tr_a^b)^k+\sum_{t\in T}\sum_{a\in A_2}\rho_a^t(x_a^t-\hat{x}_a^t)^2} \tag{19}$$

where $\hat{\mathbf{X}}$ denotes the feasible consumption set after optimizing its electricity consumption demand.

IV. LOAD SCHEDULING BASED ON COST EFFICIENCY

In the proposed method, the trade-off of the electricity payment cost and the discomfort cost reflects the consumer's satisfaction; consumers consider not only the electricity payment but also comfort in electricity consumption. According to the characteristics of the scheduled and non-scheduled appliances in an in-home environment, users can schedule their electrical appliances or curtail a specific part of their electric load to reduce their consumption of electricity. Thus, except for electricity payment, some discomfort costs need to be involved in calculating cost efficiency. In view of the aforementioned analysis, a complementary relationship exists between the electricity payment and the discomfort cost. In this paper, we use a pair of parameters, μ_1 and μ_2, to map out the relationship and model consumption behaviour for a smart house based on the distribution of the parameter values. Detailed information for the consumption models is provided below.

A. SMART HOUSE CONSUMPTION MODEL I

In actual electricity consumption, some users consume electricity and manage their load demand through TOU pricing. In this case, the best cost efficiency can be defined as follows:

$$CE^I=\frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a,\omega^a)}{\sum_{a\in A}\sum_{t\in T} P_t^1 x_a^t} \tag{20}$$

The consumption load allocation based on CE^I can be obtained by solving the following optimization problem:

$$\hat{\mathbf{X}}_1=\arg\max_{\hat{\mathbf{X}}_1\in\mathbf{X}} \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a,\omega^a)}{\sum_{a\in A}\sum_{t\in T} P_t^1 x_a^t} \tag{21}$$

where $\hat{\mathbf{X}}_1$ denotes the feasible consumption set after optimizing its electricity consumption demand for smart house consumption model I.

$$\begin{aligned}
C.E. &= \frac{U_{a,n}(d_n^a)}{\mu_1 Pay+\mu_2 DC}\\
&= \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a,\omega^a)}{\mu_1\left(\sum_{t\in T}\max\left\{P_t^1L_t,\ P_t^2L_t+(P_t^1-P_t^2)L_t'\right\}+\sum_{t\in T}Pay_t^{add}\right)+\mu_2\left(\sum_{a\in A_1}\delta_a(t_a^s-tr_a^b)^k+\sum_{t\in T}\sum_{a\in A_2}\rho_a^t(x_a^t-\hat{x}_a^t)^2\right)}\\
s.t.\quad & C1:\ L_t=\sum_{t\in T,a\in A} x_a^t,\ Pay_t^{add}=P_t'(dl_t)\left(L_t-\hat{L}_t\right)\eta_t\\
& C2: x_a^t=r_a,\ \forall t\in\{t_a^s,\ldots,t_a^s+TL_n^a-1\}\subset[tr_a^b,tr_a^c],\ \forall a\in A_1\\
& C3: x_a^t=0,\ \forall t\in T\backslash\{t_a^s,\ldots,t_a^s+TL_n^a-1\},\ \forall a\in A_1\\
& C4: pr_a^b\le x_a^t\le pr_a^c,\ \forall t\in[tr_a^b,tr_a^c],\ \forall a\in A_2\\
& C5: x_a^t=0,\ \forall t\in T\backslash[tr_a^b,tr_a^c],\ \forall a\in A_2\\
&\text{Variables}:\\
&\quad t_a^s(a\in A_1)\\
&\quad x_a^t(a\in A_2,\ t\in T)
\end{aligned} \tag{17}$$

where C1 is the definition of L_t and Pay_t^{add} as Eq. (4) and Eq. (8). C2 is the consumption requirements for the appliance $a(a\in A_1)$. C3 denotes the non-operating state of the appliance $a(a\in A_1)$. C4 is the consumption boundaries for the appliance $a(a\in A_2)$. C5 denotes the non-operating state of the appliance $a(a\in A_2)$. Variables are the constrain for t_a^s and x_a^t besides C1, C2, C3, C4 and C5.

B. SMART HOUSE CONSUMPTION MODEL II

In DR programmes based on DAB pricing, consumers upload the load demand $\hat{L}=(\hat{L}_1, \hat{L}_2, \ldots, \hat{L}_{24})$ to bid for their electrical energy. In this case, to meet the bid requirements, consumers predetermine their load starting time and work power. If users operate their electrical appliances according to the upload demand without scheduling, the best cost efficiency can be defined as follows:

$$CE^{II} = \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a, \omega^a)}{\sum_{t\in T} \max\left\{P_t^1 L_t,\ P_t^2 L_t + (P_t^1 - P_t^2)L_t'\right\}} \tag{22}$$

The consumption load allocation based on CE^{II} can be obtained by solving the following optimization problem:

$$\hat{\mathbf{X}}_2 = \arg\max_{\hat{\mathbf{X}}_2\in\mathbf{X}} \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a, \omega^a)}{\sum_{t\in T} \max\left\{P_t^1 L_t,\ P_t^2 L_t + (P_t^1 - P_t^2)L_t'\right\}}$$
$$s.t.\ C1:\ L_t = \sum_{t\in T, a\in A} x_a^t \tag{23}$$

where $\hat{\mathbf{X}}_2$ denotes the feasible consumption set after optimizing its electricity consumption demand for smart house consumption model II.

C. SMART HOUSE CONSUMPTION MODEL III

In actuality, consumers tend to choose lower prices for the operation of their electrical appliances. In this case, consumers shift their load into times with lower prices rather than a predetermined operation time or by decreasing the work power of some appliances. As a result, the discomfort cost is produced, and the best cost efficiency can be defined as follows:

$$CE^{III} = \frac{\sum_{a\in A}\sum_{n\in T^a} U(d_n^a, \omega^a)}{\mu_1\left(\sum_{t\in T} \max\left\{P_t^1 L_t, P_t^2 L_t + (P_t^1 - P_t^2)L_t'\right\}\right) + \mu_2\left(\sum_{a\in A_1} \delta_a(t_a^s - tr_a^a)^k + \sum_{t\in T}\sum_{a\in A_2} \rho_a^t(x_a^t - \hat{x}_a^t)^2\right)} \tag{24}$$

The consumption load allocation based on CE^{III} can be obtained by solving the optimization problem as Eq. (25) and (26), as shown at the bottom of the next page.

D. SMART HOUSE CONSUMPTION MODEL IV

For real-time consumption, consumers can slightly change their load demand, resulting in a real-time load above or below the original load demand. As a result, the portion in excess of the original load should be punished while the portion that is inferior to the original load should be rewarded. In this case, the best cost efficiency under the proposed power manager method can be defined as follows:

The consumption load allocation based on CE^{IV} can be obtained by solving the optimization problem as Eq. (27), as shown at the bottom of the next page.

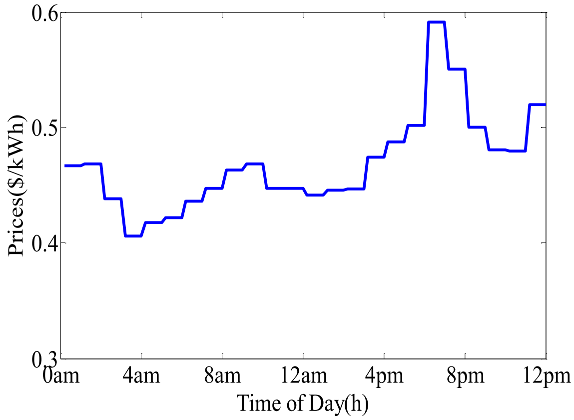

FIGURE 2. Day-ahead electricity prices.

V. SIMULATION RESULTS AND DISCUSSION

A. THE DESCRIPTION OF THE CASE

In this section, we calculate the cost efficiency of the different consumption preferences, analyse the consumers' consumption efficiency for maximal cost efficiency, and test the performance of the proposed power scheduling algorithm.

The used DAB, derived from the electricity price offered to the public in Australia in 2013.9.1 [36], is introduced. The retail electricity prices announced by the utility one day ahead are presented in Figure 2. We set $P_t^2 = 1.5P_t^1$ as a reference [21]. The two types of residential electrical appliances with scheduling horizons mentioned above are managed. The refrigerator is operated at a constant power of 0.15 kWh all day. The oven works at a power of 1 kWh to fulfil a task for 1.5 h during its scheduling horizon (e.g., 6 am-8 am, 11 am-1 pm and 6 pm-8 pm). The CW is operated at a power of 0.5 kWh to fulfil a task for 1 hour during its scheduling horizon (e.g., 6 pm-8 am). The TV is operated at the power of 0.15 kWh within an interruptible time range (e.g., 7 am-9 am, 11 am-2 pm and 7 pm-11 pm). The 3 appliances mentioned above belong to the first group of appliances. However, lighting works by the power in [0.3, 0.8] within an interruptible time range (e.g., 6 am-12 pm). The AC is operated with the power in [0.8, 2] all day. The 2 appliances belong to the second group of appliances.

More than one task may be fulfilled by one appliance in a day. Different appliances have different utility parameters on the basis of their task fulfilment and power, and the utility produced by the fulfilment of every single task composes its total utility. For instance, if the CW is operated continuously two times in a day, its task number is 2. Similar to those of the CW, the utility and power $\mu_1\mu_2\mu_1\mu_2$ parameters of all typical appliances selected in this paper are presented in Table 1 as [21], [33]. In addition, the time horizon, the predetermined starting time, the task number, the predetermined demand and demand constraints for consumers are all set in Table 1 as [21], [33]. The parameters (μ_1 and μ_2) set for the different models are discussed in the following simulation experiments shown in Table 2.

B. COST EFFICIENCY ANALYSIS

In this section, we conduct a simulation experiment based on model I to calculate the cost efficiencies of each appliance at starting time slot t. In the experiment, the 6 kinds of appliances mentioned above are used, and their settings are shown in Table 1. Two types of cost efficiencies are analysed. The first is a case in which the appliances work with a constant power, as in Table 1; especially in the case of lighting and AC power, which are set to 0.4 kWh and 1 kWh, respectively, with demands of 3.2 kW and 24 kW, respectively. The number of tasks for all appliances is one, and additional electricity payments are not considered. The experiment aims to find the best consumption case by analyzing the cost efficiency of each appliance to fulfil one task at starting time slot t. The simulation results of cost efficiencies are shown in Figure 3.

From Figure 3, under the price mechanism shown in Figure 2, the best cost efficiency for an oven is obtained at 6 am, and the CW has the best cost efficiency at 4 am.

$$\begin{aligned}
\hat{\mathbf{X}}_3 = \arg \max_{\hat{\mathbf{X}}_3 \in \mathbf{X}} & \frac{\sum\limits_{a\in A}\sum\limits_{n\in T^a} U(d_n^a,\omega^a)}{\mu_1\left(\sum\limits_{t\in T}\max\left\{P_t^1 L_t, P_t^2 L_t + (P_t^1 - P_t^2)L_t'\right\}\right) + \mu_2\left(\sum\limits_{a\in A_1}\delta_a(t_a^s - tr_a^a)^k + \sum\limits_{t\in T}\sum\limits_{a\in A_2}\rho_a^t(x_a^t - \hat{x}_a^t)^2\right)} \\
s.t.\quad & C1: L_t = \sum_{t\in T, a\in A} x_a^t \\
& C2: x_a^t = r_a,\ \forall t\in\{t_a^s,\ldots,t_a^s + TL_n^a - 1\}\subset[tr_a^b, tr_a^c],\ \forall a\in A_1 \\
& C3: x_a^t = 0,\ \forall t\in T\backslash\{t_a^s,\ldots,t_a^s + TL_n^a - 1\},\ \forall a\in A_1 \\
& C4: pr_a^b \le x_a^t \le pr_a^c,\ \forall t\in[tr_a^b, tr_a^c],\ \forall a\in A_2 \\
& C5: x_a^t = 0,\ \forall t\in T\backslash[tr_a^b, tr_a^c],\ \forall a\in A_2 \\
\text{Variables}: & \\
& t_a^s(a\in A_1) \\
& x_a^t(a\in A_2,\ t\in T)
\end{aligned} \tag{25}$$

where $\hat{\mathbf{X}}_3$ denotes the feasible consumption set after optimizing its electricity consumption demand for smart house consumption model III.

$$CE^{IV} = \frac{\sum\limits_{a\in A}\sum\limits_{n\in T^a} U(d_n^a,\omega^a)}{\begin{array}{l}\mu_1\left(\sum\limits_{t\in T}\max\left\{P_t^1 L_t,\ P_t^2 L_t + (P_t^1 - P_t^2)L_t'\right\}\right) \\ \quad + \sum\limits_{t\in T} Pay_t^{add} + \mu_2\left(\sum\limits_{a\in A_1}\delta_a(t_a^s - tr_a^a)^k + \sum\limits_{t\in T}\sum\limits_{a\in A_2}\rho_a^t(x_a^t - \hat{x}_a^t)^2\right)\end{array}} \tag{26}$$

$$\begin{aligned}
\hat{\mathbf{X}}_4 = \arg\max_{\hat{\mathbf{x}}_4\in\mathbf{X}} & \frac{\sum\limits_{a\in A}\sum\limits_{n\in T^a} U\left(d_n^a,\omega^a\right)}{\mu_1\left(\sum\limits_{t\in T}\max\left\{P_t^1 L_t, P_t^2 L_t + \left(P_t^1 - P_t^2\right)L_t'\right\}\right) + \sum\limits_{t\in T} Pay_t^{add} + \mu_2\left(\sum\limits_{a\in A_1}\delta_a\left(t_a^s - tr_a^a\right)^k + \sum\limits_{t\in T}\sum\limits_{a\in A_2}\rho_a^t\left(x_a^t - \hat{x}_a^t\right)^2\right)} \\
s.t.\quad & C1: L_t = \sum_{t\in T, a\in A} x_a^t,\ P\,ay_t^{add} = P_t'\left(dl_t\right)\left(L_t - \hat{L}_t\right)\eta_t \\
& C2: x_a^t = r_a, \forall t\in\left\{t_a^s,\ldots,t_a^s + TL_n^a - 1\right\}\subset\left[tr_a^b, tr_a^c\right], \forall a\in A_1 \\
& C3: x_a^t = 0, \forall t\in T\backslash\left\{t_a^s,\ldots,t_a^s + TL_n^a - 1\right\}, \forall a\in A_1 \\
& C4: pr_a^b \le x_a^t \le pr_a^c, \forall t\in\left[tr_a^b, tr_a^c\right], \forall a\in A_2 \\
& C5: x_a^t = 0, \forall t\in T\backslash\left[tr_a^b, tr_a^c\right], \forall a\in A_2 \\
\text{Variables:} & \\
& t_a^s\left(a\in A_1\right) \\
& x_a^t\left(a\in A_2, t\in T\right)
\end{aligned} \tag{27}$$

where $\hat{\mathbf{X}}_4$ denotes the feasible consumption set after optimizing its electricity consumption demand for smart house consumption model IV.

TABLE 1. Smart house appliance settings and constraints.

Appliance	Power (kW)	Utility Per kWh	Demand Per Task(kWh)	β^a	θ^a	The time horizon	Predetermined starting time and task	Origin demand	D^b_{min}	D^b_{max}
Oven	1	8/3	0.5	16/3	32/3	6am-8am 11am-1pm 6pm-8pm	7am (1 task) 12am (1 task) 7pm (1 task)	1.5	1.5	1.5
Fridge	0.15	10/9	3.6	20/9	50/81	8am-8am	8am-8am (1 task)	3.60	3.60	3.60
TV	0.15	20/3	1.8	40/3	200/27	6am-9am 11am-2pm 6pm-12pm	7am (0.3 task) 11:30am (0.3 task) 7pm (0.6 task)	1.4	1.27	1.27
Lighting	[0.3,0.8]	25/18	[2.4,6.4]	25/9	125/288	6am-11pm	6:30am (1 task)	2.13	2.4	3.2
CW	0.5	3	0.5	12	24	6pm-8am	10pm (1 task)	0.5	0.5	0.5
AC	[0.8,2]	1.25	[19.2,48]	2.5	5/96	8am-8am	8am-8am (1 task)	26.2	19.2	24

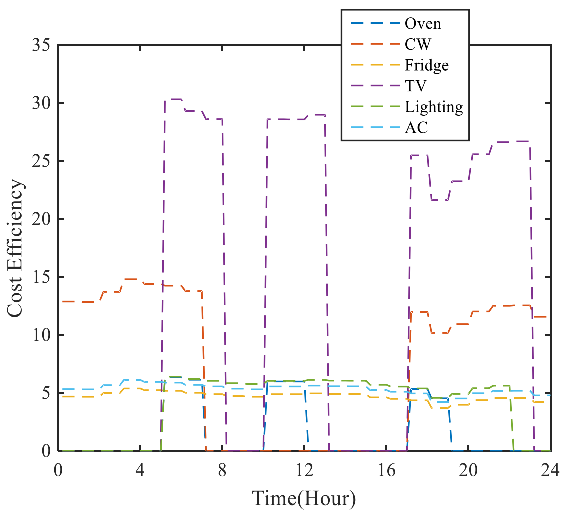

FIGURE 3. The cost efficiencies of each appliance at starting time slot t.

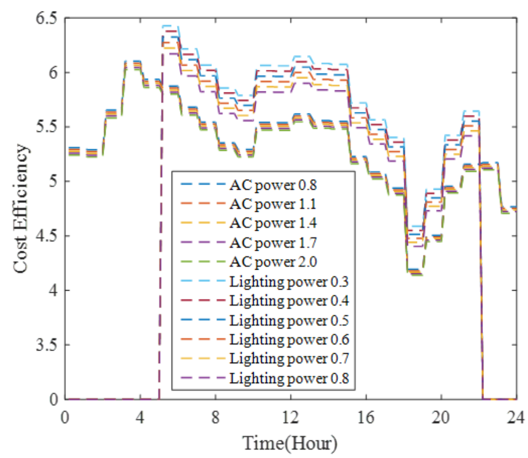

FIGURE 4. The cost efficiencies of AC and Lighting at with different work power at starting time slot t.

If the oven fulfils a task in the morning, at noon and at night, respectively, it has higher cost efficiency when ending its work at 7 am, 12 am and 7 pm, respectively. Similarly, if the CW fulfils two tasks during its operational time range, it can obtain a higher cost efficiency working between 4 am and 6 am. The TV, lighting and AC are interruptible appliances, and their time length in the fulfilment of one task is flexible. The refrigerator is a non-schedulable appliance. In view of its characteristics, the power management of the refrigerator can be enforced by the appliance itself. However, the consumer can select the starting time for the TV, lighting and AC based on their preferences and the distribution of the corresponding cost efficiencies. In addition, of the four kinds of appliances compared, the TV has the highest cost efficiency, the AC has the second highest cost efficiency, the refrigerator has the third highest cost efficiency, and the lighting has the smallest cost efficiency. Based on the results, to reduce electricity consumption, consumers can selectively shift or curtail the electricity consumption derived from the TV, lighting and AC.

In another case, appliances work on a flexible power schedule. For example, lighting and the AC are operated by steps 0.1 and 0.3 in their power intervals, respectively. The simulation results of the cost efficiencies for lighting and the AC at different powers at starting time slot t are shown in Figure 4. From Figure 4, under different power usages, lighting and the AC achieve different cost efficiencies, and they have higher cost efficiencies at higher power usages. Thus, lighting and the AC can be scheduled by changing their work power based on consumer preference.

C. IMPACT OF DISCOMFORT COST AND ADDITIONAL PAYMENT

Based on the analysis of the six household electrical appliances, to reduce electricity consumption, we consider not

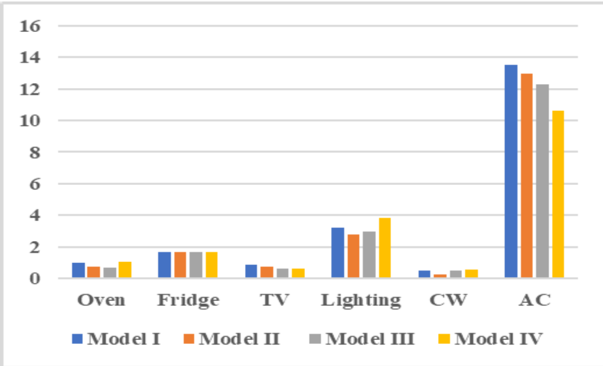

FIGURE 5. Electricity payment cost in Model I-IV, respectively.

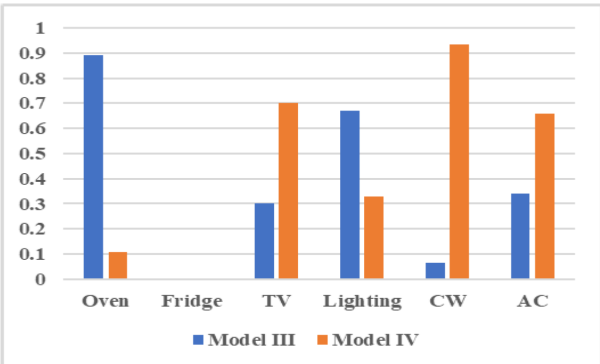

FIGURE 6. Normalization discomfort cost in Model III-IV.

only the consumer's electricity payment but also the consumer's comfort in changing the predetermined status for each appliance. For instance, we can shift the oven from 7 am to 6 am and change the work power of the AC from 1.5 kWh to 1 kWh. However, this will produce discomfort costs. In this section, a simulation experiment is conducted to test the impact of the discomfort cost. In the experiment, parameters (μ_1 and μ_2) setting are set as shown in Table 2, and the appliance setting is as presented in Table 1. For each appliance, the electricity payment cost before and after scheduling and the discomfort cost after scheduling are shown in Figure 5 and Figure 6, respectively. From Figure 5, due to the starting time and operation power (except for the load demand in different models being different, the electricity payment costs in models I-IV are different.

From Figure 6, the discomfort cost of the refrigerator is zero because it is a non-schedulable appliance. In addition, since model I and model II have no time delay and power change, a discomfort cost is not produced. Due to the oven operation having a longer time delay and the operational power of the lighting being lower in model III than in model IV, the discomfort costs of the oven and lighting in model III are higher than those in model IV. However, since consumers respond to the price signal by shifting TV, CW and AC use to the times with lower electricity prices and because the operational power of the TV is lower than in model III, the discomfort cost of the TV, CW and AC in model IV is higher than in model III.

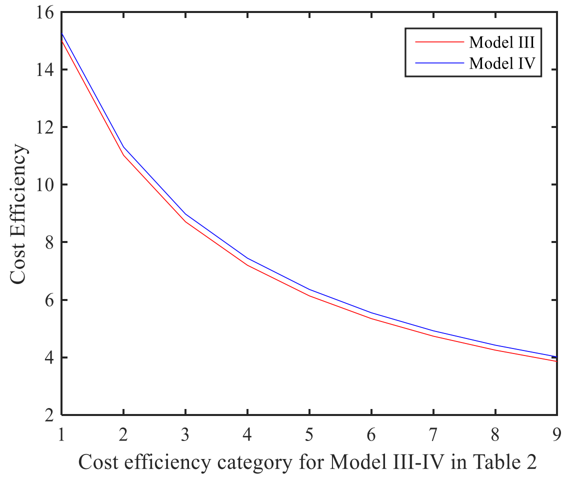

FIGURE 7. Interval cost efficiency of the Model III-IV.

The distribution of the cost efficiencies after scheduling is shown in Figure 7. From Figure 7, the different electricity consumption preferences for consumers achieve different cost efficiencies. Cost efficiency is the lower when users have a greater preference for the discomfort cost. Cost efficiency is the higher when users have a greater preference for the electricity payment. In real-time consumption, the two extreme cases are not advisable because the former produces maximal discomfort, whereas the latter leads to expensive electricity bills. We also find that the cost efficiency gradually decreases as the consumer comfort preference goes down. Additionally, we calculate the cost efficiency before scheduling and find that its value is 3.6169. Compared with the values in Figure 7, the smallest cost efficiency in the interval is larger than the cost efficiency of 3.6169. Therefore, electricity consumption satisfaction depends on the electricity payment and consumer discomfort preference; when taking these preferences into account, the discomfort cost helps to boost the cost efficiency. Consumers can choose a kind of cost efficiency that is preferentially suitable for managing their load by assessing their load demands and income and then constraining their electrical consumption behaviour in concert with this.

For the additional payment, in model IV, consumers' real-time consumption deviates from bid demands and results in lower or higher electricity payments or discomfort costs. From Figure 7, cost efficiency in model IV is higher than in model III, which shows that the additional payment can increase the value of cost efficiency because of the policy in which people are rewarded for falling below the threshold and punished for exceeding it. In addition, the simulation result presented in Figure 7 shows that it is easy to produce higher electricity payments or lower discomfort costs because of consumers' increasing comfort preferences. Whether the additional payments increase or decrease the total electricity cost, the variation trends of cost efficiency and the additional payment in the corresponding interval are consistent. Furthermore, as shown in Figure 8, the consumption shape curves of models I and II have a wide range of oscillation. However, in contrast to the curves of model I and II, the consumption

TABLE 2. Parameters (μ_1 and μ_2) setting for the different smart house consumption models.

Variable	Interval	Model I	Model II	Model III and IV								
				1	2	3	4	5	6	7	8	9
μ_1	[0,1]	0	1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
μ_2	[0,1]	1	0	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1

TABLE 3. Values of indicators for the consumption model I-IV.

Pattern	Total electricity consumption	Utility	Payment ($)	μ_1	μ_2	C.E.	Electricity reduction	Electricity reduction ration (%)
Model I	41.2	78.37	20.7	\	\	3.77	0	0
Model II	35.33	72.3	19.05	\	\	3.79	5.87	14.25
Model III	32.37	67.3	19.08	0.5	0.5	6.1358	8.83	21.43
Model IV	32.37	67.3	18.31	0.5	0.5	6.3591	8.83	21.43

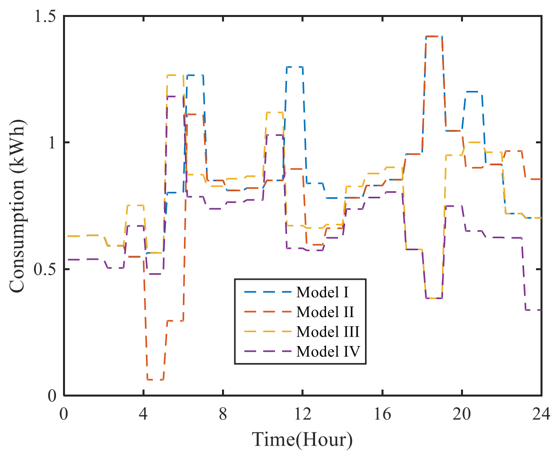

FIGURE 8. Load shapes of the Model I-IV, respectively.

shape curves of models III and IV are smoother. Notably, the consumption shape curve of model IV is smoother than the other curves. The results show that the discomfort and the additional payment can effectively smooth the user consumption shape curve.

D. EFFECT OF COST EFFICIENCY SCHEDULING BASED ON CONSUMER PREFERENCE

In this section, the total electricity consumption, consumer's electricity payment and the electricity consumption reduction ratio, *et al.*, of the different models are compared to test the performance of the proposed power scheduling algorithm. In the experiment, we assume the consumer's preference weight for the electricity payment and the discomfort cost are 0.5 and 0.5, respectively (namely, $\mu_1 = 0.5$ and $\mu_2 = 0.5$). The simulation results are shown in Table 3.

As presented in Table 3, the total electricity consumption of model IV is the lowest among all consumption models, whereas that of model I is the highest. Compared with model I, model III and IV can achieve reduced electricity consumption of 8.83 kW, and rate reductions of 21.43%, respectively, whereas model II achieves a reduction in electricity consumption by 5.87 kW with a rate reduction of 14.25%. Additionally, although model III and IV have the same reduction rate in electricity consumption, the cost efficiency of model IV is the highest, and its electricity payment is the lowest among all of the consumption models. At the same time, as shown in Figure 8, compared to that of the other consumption models, the consumption shape curve of model IV is the smoothest. According to the above analysis, the proposed DR algorithm can achieve better consumption efficiency than other consumption models. Additionally, the cost efficiency scheduling based on consumer's preference is effective.

VI. CONCLUSION

In this paper, a novel residential power scheduling algorithm based on cost efficiency in a smart grid is proposed. The consumption cost for this is composed of the electricity payment cost and the discomfort cost, and the trade-off of the electricity payment cost and the discomfort cost is achieved by tuning the values of parameters (μ_1 and μ_2). The consumption costs and cost efficiencies based on the consumer consumption preferences of six electric appliances (including an oven, a refrigerator, a TV, lighting, a CW and an AC) derived from a smart house were discussed. Four smart house consumption models (model I, model II, model III and model IV) were constructed: model I is a DR programme with TOU pricing mechanism, model II is based on the DAB pricing mechanism without load scheduling, model III is based on the DAB pricing mechanism with load scheduling, and model IV is the proposed algorithm based on real-time consumption with RT pricing. Through the discussion of the four consumption models, consumption that satisfies consumers for the six electric appliances is analysed, the impact of the discomfort and additional payment is discussed, and the effect of the proposed method is validated. The following detailed conclusion can be drawn from this research.

1) The electricity payment and consumer discomfort caused by scheduling of electrical appliances are considered together to model cost efficiency. A series of simulation experiments are conducted to analyse the cost efficiency of each appliance using different starting times or flexible work power. The simulation results show that users can find the optimal work time and power for their electrical appliances, not blindly, but felicitously, scheduling their load through the application of the proposed method.

2) Consumer preferences regarding electricity payments and discomfort costs are mapped into the distribution of the parameters (μ_1 and μ_2). The corresponding parameter values in the distribution by step 0.1 are set to analyse consumer satisfaction with the cost efficiency. The simulation results show that the electricity payment and consumer discomfort preference affect electricity consumption satisfaction, and taking this into account, we find the discomfort cost helps to boost cost efficiency. This information helps users effectively trade-off their consumption preferences to obtain the best economic efficiency by setting reasonable weights for electricity payments and discomfort costs.

3) TOU, DAB and RT pricing mechanisms are used in the proposed method. Some cases are studied to test the performance of the proposed power scheduling algorithm, and the impact of the discomfort and additional payment are discussed. The simulation results show that the discomfort and the additional payment can effectively smooth users' consumption shape curves. The proposed method based on DAB and RT pricing mechanisms can effectively reduce users' electricity consumption. Notably, the RT pricing mechanism is adopted in the proposed method to help consumers obtain the best consumption efficiency.

4) The electricity payments and discomfort costs of six residential electrical appliances are analysed in models I-IV. In view of the analysis, the effect of cost efficiency scheduling based on consumer consumption preferences is demonstrated by discussing the load shapes of models I-IV and assessing the reduction of electricity consumption. The simulation results show that the proposed method with RT pricing can curtail 8.83 kW of electricity use and that the reduction ratio is 21.34%. In contrast, the proposed method with RT pricing obtains the smoothest load shape curve and provides the best consumption efficiency among all consumption models.

This work describes a power scheduling algorithm based on cost efficiency and consumer consumption preferences for effectively scheduling the electrical appliances in a smart house. Consumer consumption efficiency, satisfactory and consumption behavior are discussed. Some hidden information has been explored that can help the electricity industry successfully execute DR schemes in the face of future challenges. Even so, a further investigation should be required to consider the renewable energy resources such as photovoltaic system and wind turbine in smart house. Future studies should explore the distributed generation and storage model.

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