User Comfort-Oriented Home Energy Management System Under Demand Response

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***Abstract*—Home Energy Management Systems (HEMS) are a key technology that enables residential customers to actively participate in Demand Response (DR) programs by controlling their energy usage and reducing or shifting their consumption outside periods of grid stress in response to financial rewards such as tax breaks or rebates. However, DR trials across the world have shown that most of the customers remain reluctant to enroll into these programs due to undesirable power interruptions and strict guidance from the utilities which cause inconvenience to the users. This paper presents a human comfort-based control approach for home energy management to stimulate the active participation of residential customers in DR. The proposed algorithm seeks to minimize peak load demands by scheduling the operation of electric appliances and shifting controllable loads during periods when electricity prices are high, to off-peak periods, when electricity prices are lower without compromising the customer's preferences. The results demonstrate the effectiveness of the proposed DR strategy in managing the daily household energy consumption and improving the occupants' comfort.**

Keywords— demand response, smart home, home energy management system, human comfort factors.

I. Introduction

The rising levels of greenhouse gases into the atmosphere is posing a global concern due to its significant impact on climate change and environmental degradation. In the meantime, the world is the midst of an unprecedented global energy crisis due to the growing and emerging economies and industrial revolution. New investments are needed to reinforce and expand the existing grid infrastructures and promote the widespread adoption of renewable energy sources, which may lead to a gradual increase in energy prices. Demand Response (DR) can be considered as a type of demand-side management programs, where utilities incentivise consumers to monitor and control their electricity consumption [1]. End-users who participate in DR programs can lower their energy usage during peak demand periods, resulting in potential savings on their energy bills [2]. DR involves a modification in the energy consumption patterns of consumers, whereby they adjust their energy usage levels in response to signals or incentives provided by the power utility [2], [3]. However, many residents are reluctant to invest time in calculating and analysing their energy usage and scheduling their household appliances to minimize their electricity bills. Home Energy Management System (HEMS) is a DR tool that optimizes electricity consumption and seeks to reduce electricity bills by adjusting and curtailing energy demand during peak periods in response to electricity price signals and user preferences [1], [4]. Current research is focusing on the development of reliable and efficient HEMS, which can be divided into real-time management and predictive energy management. In recent literature [5], [6], forecasting techniques are utilised along with HEMS to predict energy usage and supply availability to a chieve a balance between demand and supply and contribute to grid stability enhancement. However, existing prediction algorithms are often very complex and inaccurate [7] and the design of forecasting algorithms with higher accuracy and lower computational cost remains an ongoing research challenge. Other studies have worked on developing real-time algorithms [8], that manage thermal devices or control the operation time of controllable appliances. The main goal of these algorithms is to reduce peak demands and electricity costs. Other researchers, on the other hand, utilised these real-time techniques to find the optimal energy usage patterns with different consumer satisfaction levels [9]. In this paper, the proposed control strategy utilises a DR algorithm which aims to achieve a smooth power consumption profile, while ensuring that consumers comfort and preferences are not compromised.

II. Smart Home Energy Management Systems

HEMS is considered as a key enabling technology for the intelligent power grid and plays an essential role in the implementation of DR at residential premises, with the objective of reducing energy costs and optimising energy efficiency. HEMS provides economic incentives to users, enabling them to control their energy consumption by adjusting the operating time of home appliances in response to energy price signal during peak demand.. Fig. 1 illustrates a typical smart HEMS architecture.

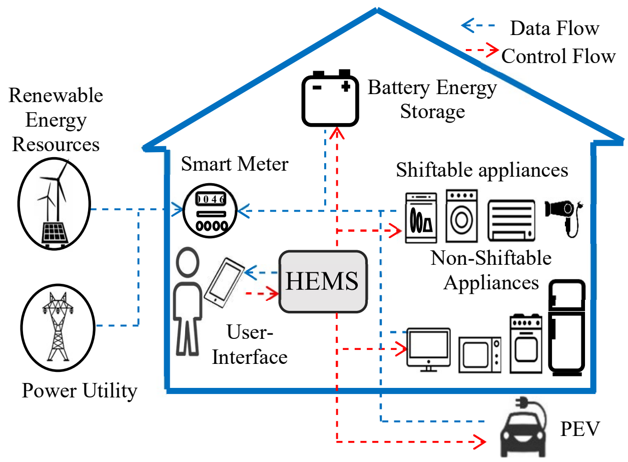

Fig. 1. Smart HEMS architecture.

TABLE 1 RATED POWER FOR SHIFATBLE APPLIANCES.

Index Number	Appliance	Rated Power (W)
1	Washing machine (WM)	800
2	Dish washer (DW)	1100
3	Hair dryer (HD)	450
4	Clothes dryer (CD)	400
5	Hair straightener (HS)	20

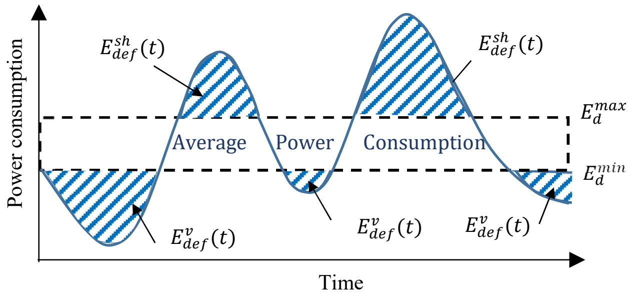

Fig. 3. Household power consumption and average power region.

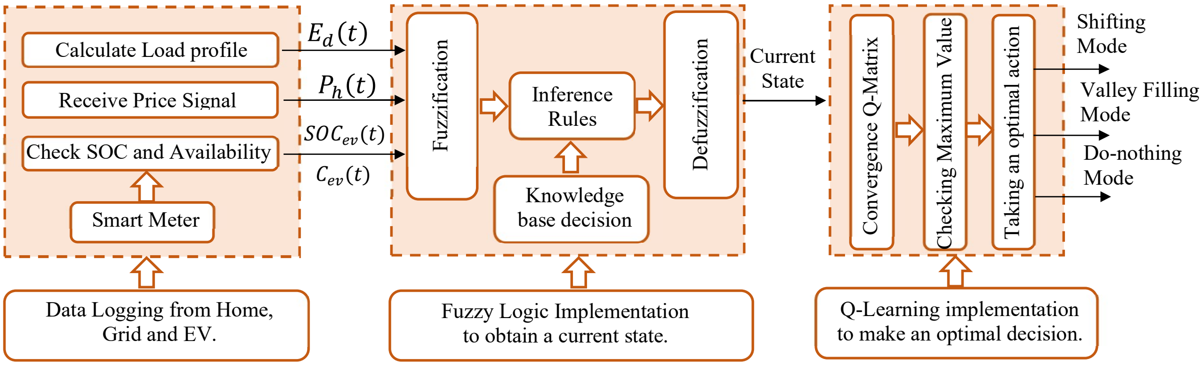

Fig. 2 Proposed demand response strategy.

In this paper, a DR strategy is proposed to enhance the efficiency of the HEMS and enable end-users to actively engage in the DR program without compromising their preferences. A typical daily energy consumption profile is depicted in Fig. 2. It reveals two critical peak demand periods which occur during the morning and evening hours when energy prices are high. Conversely, during off-peak demand periods, corresponding to lower energy prices, there is a decrease in user activities such as washing, cleaning, cooking, and watching TV. The proposed algorithm aims to avoid electricity consumption during these peak periods while ensuring, as much as possible, that energy usage remains within an reasonable limits. This objective is achieved by shifting the operational times of controllable appliances from peak demand periods to off-peak periods without sacrificing the user's comfort. Consequently, domestic appliances are categorized into two types: shiftable appliances that can adjust their operating time based on load priority and user preferences, such as washing machine, dish washer, and electric vehicle, and non-shiftable appliances that require continuous power supply during operating hours regardless of the energy price. Table 1 provides the rated power of shiftable appliances.

III. PROPOSED DEMAND RESPONSE STRATEGY

In our previous work [10], Reinforcement Learning (RL) and Fuzzy Reasoning (FR) were used to provide an effective energy management in residential premises in an attempt to reduce the power consumption and electricity bills by scheduling household appliances, in response to energy price signals. In this paper, however, the DR strategy is developed to improve the satisfaction of end-users while participating in DR. In [10], ~~the~~ household appliances are categorised into shiftable and non-shiftable, and the total power demand of shiftable $E_d^{shift}(t)$ and non-shiftable $E_d^{non}(t)$) appliances are calculated as follows:

$$E_d^{shift}(t) = \sum_{n=1}^{N} e_t^{n,shft} . J_t^n \tag{1}$$

$$E_d^{non}(t) = \sum_{m=1}^{M} e_t^{m,non} . J_t^m \tag{2}$$

$$E_d(t) = E_d^{shift}(t) + E_d^{non}(t) \tag{3}$$

Subject to:

$$E_d^{max} > E_d(t) > E_d^{min} \tag{4}$$

Where $e_t^{n,shft}$ and $e_t^{n,non}$ refer to the rated power of each shiftable appliance and non-shiftable appliance, respectively. J_t^n denotes the status of the appliance and takes values 0 (off) or 1 (on). $t \in \{1, 2, 3, \ldots, 24\}$ represents the hour of the day, $n \in \{1,2, \ldots, N\}$ is the appliance number and N is the total number of the shiftable appliances. $m \in \{1,2, \ldots M\}$ represents the appliance number and M is the total number of the non-shiftable appliances.

Using the proposed DR strategy in [10] as shown in Fig. 3, customers are provided with electricity price signals on hour-ahead or day-ahead. Smart meters receive these price signals from a utility and record the energy usage data of all household appliances during their operation times, and then transmit this data to the HEMS to be analysed, and then take the appropriate action whether *Shifting*, *Valley filling* or *Do-nothing*:

A. Mode 1: Shifiting

As shown in Fig. 3, the *Shifting* mode occurs when $P_h(t)$ is higher than P_{avg}, $E_d(t)$ is greater than E_d^{max} and $E_d^{shift}(t)$ is greater than zero. In this case, the power deficiency to meet the average power demand as shown in Fig. 2 by shifting the deferable appliances to off-peak period is calculated as:

$$E_{def}^{sh}(t) = |E_d(t) - E_d^{max}| \quad (5)$$

$E_{def}^{sh}(t)$ is the deficiency power of *Shifting* mode. E_d^{max} denotes the upper limit of the average power. To shift the appliances, there are two possible scenarios, firstly, when the deficiency power is higher than the total power demand of the deferable appliances that are working at that time step:

$$E_{def}^{sh}(t) - E_d^{shi}(t) \geq 0 \quad (6)$$

In this case, all deferable appliances will be shifted. However, when the deficiency power is lower than the demand of the deferable appliances, there is no need to shift all appliances to meet the average power demand.:

$$E_{def}^{sh}(t) - E_d^{shift}(t) < 0 \quad (7)$$

In this case, the system selects the appliances based on user-comfort factors to achieve the user's satisfaction as much as possible namely, priority of the appliance to be shifted, the power rate of the appliances, the operating time interval and the waiting time which are defined below:

- The priority of each appliance that is set by the user and this means how much the user can manage without this appliance at this time step:

$$\delta_s = [\delta_s^1, \delta_s^2, \ldots, \delta_s^N] \quad (8)$$

  δ_n indicates the priority value of n appliances, hence each appliance takes a value between 0 and 1 to evaluate the priorities, where 1 means the appliance is not essential to be working.

- When $E_{def}^{sh}(t)$ is lower than $E_n^{shift}(t)$, the power rate e_t^n of each appliance is considered for selecting which appliance is to be shifted compared to $E_n^{shift}(t)$. Consequently, the shifting probability based on power rate (ω_s^n) of each appliance is calculated as:

$$\omega_s^n = 1 - \left|\frac{e_t^n - E_{def}^{sh}(t)}{e_t^n + E_{def}^{sh}(t)}\right| \quad (9)$$

  Where the appliance that has the power rate close to the power deficiency will have the highest probability.

- The operating time interval (T_n) of each appliance is considered. The appliance that has shorter operating time interval to finish its task will have the higher probability to be shifted to off peak period.

$$\beta_s^n = \begin{cases} 0 & \text{when } T_{n,o} = t \\ \dfrac{t}{T_{n,o}} & \text{when } T_{n,o} \neq t \end{cases} \quad (10)$$

- The system considers the shifted appliances (appliances that have been shifted before). The shifting time T_n of each appliance is calculated and compared to the time step τ.

$$\varphi_s^n = \begin{cases} 0 & \text{when } T_{n,s} = t \\ \dfrac{t}{T_{n,s}} & \text{when } T_{n,s} \neq t \end{cases} \quad (11)$$

The total shifting probability γ_n for each appliance will be calculated by adding up the four previous calculated probabilities, hence, the highest γ_s^n will be shifted first:

$$\gamma_s^n = \frac{\delta_s^n + \omega_s^n + \beta_s^n + \varphi_s^n}{4} \quad (12)$$

B. Mode 2: Valley Filling

This mode occurs when $P(t) < P_{avg}$ and $E_d(t) < E_d^{min}$ as shown in Fig. 3. This mode aims to turn on the appliances that have been shifted during the peak period. Therefore, the total power demand of the shifted appliances to be operating again is calculated as:

$$E_n^{shifted} = \sum_{n=1}^{N} \rho_n \times e_t^n \quad (13)$$

ρ_n represents the shifting signal of each appliance and takes the value 1 if the appliance has been shifted during shifting mode and 0 otherwise. The power deficiency required to meet the lower limit of average power is:

$$E_{def}^{v}(t) = \left|E_d(t) - E_d^{min}\right| \quad (14)$$

To select which appliance needs to be turned on, $E_{def}(t)$ is compared to the E_n^{shift}. Therefore, there are also two scenarios. First, when the power deficiency is higher than the total rated power of the appliances which have been shifted:

$$E_{def}^{v}(t) - E_d^{shift}(t) \geq 0 \quad (15)$$

In this case, all shifted appliances will be switched on as the demand will not exceed the lower limit of the average power, However, when the power deficiency is lower than the rated power of the shifted appliances, it is not desirable to run all shifted appliances. Therefore, the selection of the appliance depends on user comfort-factors, the priority of the appliances to be filled (δ_v), and the power rating of the appliances (ω_v^n). The operating time interval (φ_v^n) and the waiting-time of the appliance (ε_v^n): CHECK THIS AND INTRODUCE BULLET POINTS

$$E_{def}^{v}(t) - E_d^{shifted}(t) < 0 \quad (16)$$

- For how long the user needs to operate each specific shifted appliance. This value is denoted by:

$$\delta_v = [\delta_v^1, \delta_v^2, \ldots, \delta_v^N] \quad (17)$$

  δ_v^n is the valley filling priority for appliance n. The appliance with the highest priority will be most likely switched on.

- When $E_{def}^{v}(t) < E_d^{shifted}(t)$, it is better to distribute the shifted appliances on the valley filling time period rather that switching on all shifted appliances at the same time to keep $E_d(t)$ in the average demand region. Therefore, the rated power of the shifted appliance is considered and the probability to be switch on is calculated as:

$$\omega_v^n = 1 - \left|\frac{e_t^n - E_{def}^{v}(t)}{e_t^n + E_{def}^{v}(t)}\right| \quad (18)$$

When ω_v^n is 1 (highest value), this means the appliance's power rating equals the power deficiency ($e_t^n = E_{def}(t)$) and has the highest probability to be turned and meet the average power demand.

- In *Valley filling* mode, the waiting time of an appliance that has been shifted is considered. The

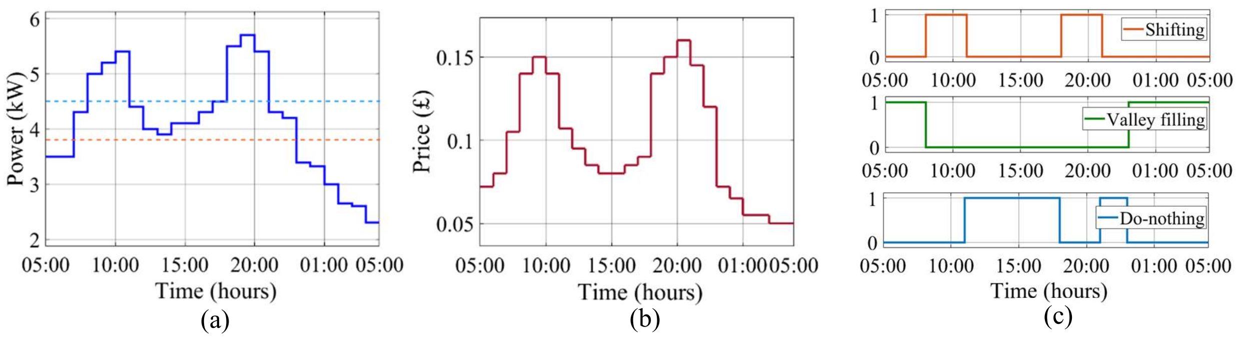

Fig. 4 (a) power demand of household appliances, (b) real time price and (c) output of DR strategy consisting of three modes.

appliance that has longest waiting time has the highest priority to operate. The probability of switching on the appliance is defined as follows:

$$\varepsilon_v^n = \begin{cases} 0 & \text{when } T_{n,w} = t \\ 1 - \dfrac{t}{T_{n,w}} & \text{when } T_{n,w} \neq t \end{cases} \tag{19}$$

$T_{n,w}$ is the waiting time of appliance n and ε_v^n is the probability of switching on of the appliance.

- The probability of time interval required by the appliances to finish its task is given by:

$$\varphi_v^n = \begin{cases} 0 & \text{when } T_{n,s} = \tau \\ 1 - \dfrac{\tau}{T_{n,s}} & \text{when } T_{n,s} \neq \tau \end{cases} \tag{20}$$

At each time step τ, the system reads the profile of each appliance (a_n) and determines the *Shifting* and *Valley filling* probabilities denoted by R_s and R_v respectively:

$$a_n = [J_t^n, e_t^n, T_{n,o}, T_{n,s}, T_{n,w}] \tag{21}$$

$$R_s = \left[\begin{array}{cccc|c} \delta_s^1 & \omega_s^1 & \beta_s^1 & \varphi_s^1 & \gamma_s^1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \delta_s^N & \omega_s^N & \beta_s^N & \varphi_s^N & \gamma_s^N \end{array}\right] \tag{22}$$

$$R_v = \left[\begin{array}{cccc|c} \delta_v^1 & \omega_v^1 & \varepsilon_v^1 & \varphi_v^1 & \gamma_v^1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \delta_v^N & \omega_v^N & \varepsilon_v^N & \varphi_v^N & \gamma_v^N \end{array}\right] \tag{23}$$

The pseudo-code listed in Table 2 (Algorithm 1) illustrates the procedure for selecting the appliances to be shifted or turned on based on the user comfort-factors.

IV. Results and Discussion

This paper is an extension of the work done in [10] and Fig. 4 (a) shows the total household power demand that HEMS received from the smart meter. Fig. 4 (b) presents the electricity price signal received from the utility grid. Based on the proposed approach as shown in Fig. 3, HEMS detects the *Shifting*, *Valley filling* and *Do-nothing* modes as shown in Fig. 4 (c). For example, at 8:00 am, the energy price (£0.14) is higher than the average price and the power demand is higher than the upper limit of the average power demand, therefore the *Shifting* mode is detected.

At 3:00 pm the electricity price is low (£0.08), and the power consumption is ~~located~~ between the upper and lower limits of the average demand. Thus, the *Do-nothing* mode is active. During night-time, for example at 1:00 am, the *Valley-filling* mode is detected because both the electricity price and power consumption are low.

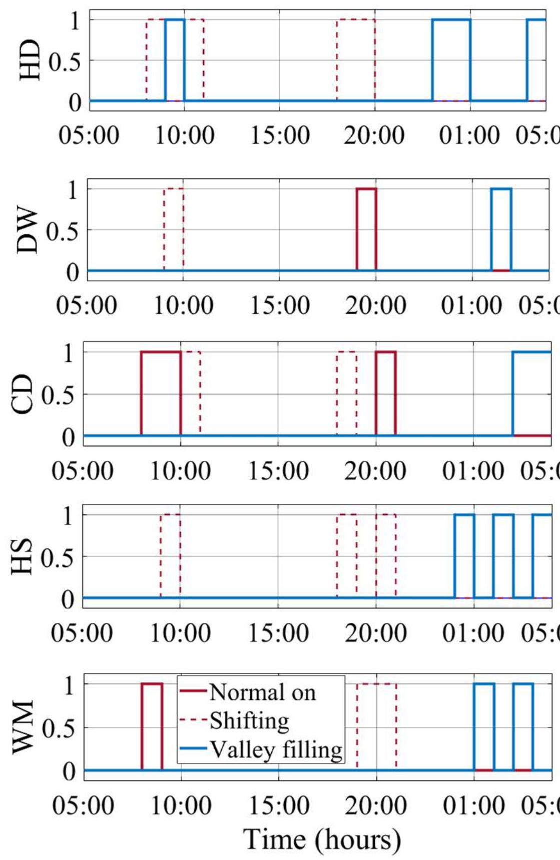

Fig. 5 Status of the shiftable appliances after implementing the proposed strategy; WM: Washing Machine, DW: Dish Washer, CD: Clothes Dryer, HD: Hair Dryer and HS: Hair Straightener.

During *Shifting* and *Valley filling* modes, Algorithm 1 is implemented to select which appliance needs to be shifted or turned on. The selecting process of sample hours is shown in Appendix 1. For example, at 8:00 am, HD, CD and WM are supposed to be operating, because the *Shifting* mode is active during this hour and the deficiency power to meet the average demand is less than the total power consumption of these three appliances, only the HD is shifted. In the next hour (9:00 am), DW, CD and HS could be operated but the DW and HS are shifted because they have the highest shifting priority to meet the average demand. After shifting these two appliances, the power consumption becomes lower than the upper limit of the average demand. Therefore, HD can be turned on as it has been shifted during the previous hour. The final operation status of the deferable appliances is presented in Fig. 5. The total power consumption of the household appliances throughout a day is shown in Fig. 6.

TABLE 2 SELECTION PROCEDUTE OF DEFERABE APPLIANCES

Algorithm 1
- Set δ_s and δ_v for all shiftable appliances, E_d^{min} , E_d^{max}, and P_{avg}.
- Initialise R_s and R_v.
For each time step τ do
- Read $E_d(t)$ and $P_h(t)$.
- detects the active mode.
While Shifting mode is active and $E_d^{shift}(t) > 0$
- Determine $E_{def}^{sh}(t)$ using Equation 6 and $a_n = [J_t^n, e_t^n, T_{n,o}, T_{n,s}, T_{n,w}]$.
If $E_{def}^{sh}(t) - E_d^{shift}(t) \geq 0$
- Shift all deferable appliances.
Elseif $E_{def}^{sh}(t) - E_d^{shift}(t) < 0$
- Calculate γ_s^n for each appliance using Equations (9-13).
- Identify R_s, select and shift the appliance that has highest probability value γ_s^n.
- Update a_n and R_s.
End if
End while
While Valley filling mode is active and $E_d^{shift}(t) > 0$
- Determine $E_{def}^{v}(t)$ using Equation 15 and $a_n = [J_t^n, e_t^n, T_{n,o}, T_{n,s}, T_{n,w}]$.
If $E_{def}^{v}(t) - E_d^{shift}(t) \geq 0$
- Shift all operating appliances.
Elseif $E_{def}^{v}(t) - E_d^{shifted}(t) < 0$
- Detect the shiftable appliances that are working and read $a_n = [J_t^n, e_t^n, T_{n,o}, T_{n,s}, T_{n,w}]$.
- Calculate γ_v^n for each appliance using Equations (18- 21).
- Identify R_v, select and run the appliance that has highest probability value γ_v^n.
- Update a_n and R_s.
End if
End while
End for

The cost of energy usage is calculated as:

$$C_t = \min\left\{0, \sum E_d(t) \times P_h(t)\right\} \tag{24}$$

$P_h(t)$ is the electricity price received from the utility grid and C_t is the total cost of energy consumption. The proposed HEMS works based on RTP, which is considered as a dynamic pricing. Fig.7 shows the comparison of the cost reduction using both algorithms.

To evaluate how much the proposed strategy can increase the user's comfort, the dissatisfaction index is calculated as:

$$\pi_t = (1 - \tfrac{1}{S}\textstyle\sum_{n=1}^{S}\gamma_s^n)^2 - \left(\tfrac{1}{V}\textstyle\sum_{n=1}^{V}\gamma_v^n\right) \tag{25}$$

Where the first term indicates the user's dissatisfaction rate achieved by shifting S appliances during *Shifting* mode, which depends on the user-comfort factors. While the dissatisfaction index can be reduced by switching on V appliances during *Valley-filling* mode as described by the second term. Fig. 8 shows the variations of the dissatisfaction index throughout the day.

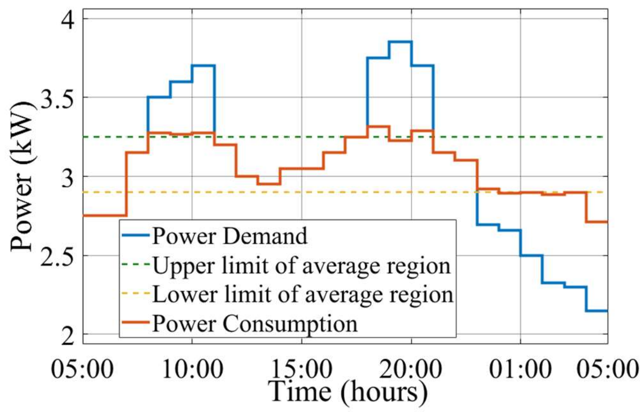

Fig. 6 Power demand and power consumption after implementing DR strategy.

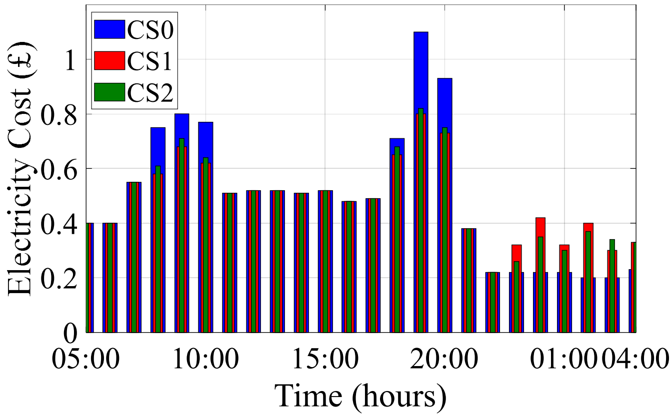

Fig. 7 Electricity cost; CS0: cost without HEMS, CS1: cost using ref [11], CS2: cost under proposed strategy.

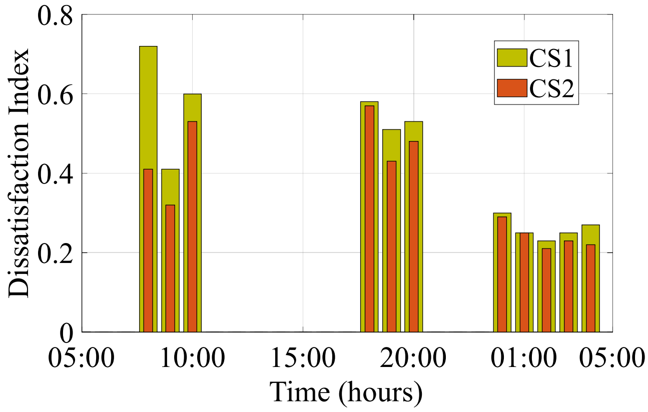

Fig. 8 Dissatisfaction index during Shifting and valley filling modes.

V. CONCLUSION

This paper proposed a human comfort-based control approach for home energy management to encourage residential customers to participate in the DR programs. The proposed algorithm strives to minimise peak load demands by scheduling the operation of electric appliances and shifting controllable loads from high-priced peak periods to lower-priced off-peak periods, while ensuring that customer preferences are satisfied. Simulation results have shown that the proposed DR approach results in a smooth power consumption profile and a reduction in the overall electricity costs by 16.4% and 17.5% during morning and evening peak periods, respectively. In addition, the proposed approach has reduced the dissatisfaction index by 18.2%.

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APPENDIX 1

Time	Mode	Appliance detail	R matrices	Actions
8:00	Shifting	$a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 1 & 800 & 1 & 0 & 0 \\ 2 & 0 & 1100 & 0 & 0 & 0 \\ 3 & 1 & 450 & 2 & 0 & 0 \\ 4 & 1 & 400 & 3 & 0 & 0 \\ 5 & 0 & 20 & 0 & 0 & 0 \end{bmatrix}$	$R_s=\left[\begin{array}{ccccc\|c} Inx & \delta_s^n & \omega_s^n & \beta_s^n & \varphi_s^n & \gamma_s^n \\ 1 & 0.1 & 0.7692 & 0.25 & 1 & 0.5298 \\ 3 & 0.3 & 0.9474 & 0.25 & 1 & 0.6243 \\ 4 & 0.4 & 0.8888 & 0.1667 & 1 & 0.6139 \end{array}\right]$	Shift No.3
9:00		$a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 0 & 0 \\ 2 & 1 & 1100 & 1 & 0 & 0 \\ 3 & 0 & 450 & 2 & 1 & 1 \\ 4 & 1 & 400 & 2 & 0 & 0 \\ 5 & 1 & 20 & 1 & 0 & 0 \end{bmatrix}$ $a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 0 & 0 \\ 2 & 0 & 1100 & 1 & 1 & 0 \\ 3 & 1 & 450 & 1 & 0 & 0 \\ 4 & 1 & 400 & 2 & 0 & 0 \\ 5 & 1 & 20 & 1 & 0 & 0 \end{bmatrix}$	$R_s=\left[\begin{array}{ccccc\|c} Inx & \delta_s^n & \omega_s^n & \beta_s^n & \varphi_s^n & \gamma_s^n \\ 2 & 0.2 & 0.7778 & 0.5 & 1 & 0.6195 \\ 4 & 0.4 & 0.7272 & 0.25 & 1 & 0.5940 \\ 5 & 0.5 & 0.0556 & 0.5 & 1 & 0.5139 \end{array}\right]$ $R_s=\left[\begin{array}{ccccc\|c} Inx & \delta_s^n & \omega_s^n & \beta_s^n & \varphi_s^n & \gamma_s^n \\ 4 & 0.4 & 0.2222 & 0.25 & 1 & 0.4675 \\ 5 & 0.5 & 0.5714 & 0.5 & 1 & 0.6435 \end{array}\right]$	Shift No.2 Turn on No.3 Shift No.5
10:00		$a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 0 & 0 \\ 2 & 0 & 1100 & 1 & 1 & 0 \\ 3 & 1 & 450 & 1 & 0 & 0 \\ 4 & 1 & 400 & 1 & 0 & 0 \\ 5 & 0 & 20 & 1 & 1 & 1 \end{bmatrix}$	$E_{def}^{sh}(t)-E_d^{shift}(t)\geq 0$	Shift all
23:00	Valley filling	$a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 2 & 4 \\ 2 & 0 & 1100 & 0 & 1 & 14 \\ 3 & 0 & 450 & 0 & 3 & 13 \\ 4 & 0 & 400 & 0 & 2 & 13 \\ 5 & 0 & 20 & 0 & 3 & 14 \end{bmatrix}$	$R_s=\left[\begin{array}{ccccc\|c} Inx & \delta_v^n & \omega_v^n & \varepsilon_v^n & \varphi_v^n & \gamma_v^n \\ 1 & 0.5 & 0.6777 & 0.875 & 0.75 & 0.7007 \\ 2 & 0.4 & 0.5430 & 0.9643 & 0.5 & 0.6018 \\ 3 & 0.3 & 0.9535 & 0.9615 & 0.8333 & 0.7621 \\ 4 & 0.2 & 0.9876 & 0.9615 & 0.75 & 0.7248 \\ 5 & 0.1 & 0.0930 & 0.9643 & 0.8333 & 0.4977 \end{array}\right]$	Turn on No.3
00:00		$a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 2 & 5 \\ 2 & 0 & 1100 & 0 & 1 & 15 \\ 3 & 0 & 450 & 0 & 2 & 6 \\ 4 & 0 & 400 & 0 & 2 & 14 \\ 5 & 0 & 20 & 0 & 3 & 15 \end{bmatrix}$ $a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 2 & 5 \\ 2 & 0 & 1100 & 0 & 1 & 15 \\ 3 & 0 & 450 & 0 & 2 & 6 \\ 4 & 0 & 400 & 0 & 2 & 14 \\ 5 & 0 & 20 & 0 & 3 & 15 \end{bmatrix}$	$R_v=\left[\begin{array}{ccccc\|c} Inx & \delta_v^n & \omega_v^n & \varepsilon_v^n & \varphi_v^n & \gamma_v^n \\ 1 & 0.5 & 0.75 & 0.9 & 0.75 & 0.725 \\ 2 & 0.4 & 0.6076 & 0.9667 & 0.5 & 0.6186 \\ 3 & 0.3 & 0.9677 & 0.9177 & 0.75 & 0.7339 \\ 4 & 0.2 & 0.9090 & 0.9643 & 0.75 & 0.7058 \\ 5 & 0.1 & 0.08 & 0.9667 & 0.8333 & 0.4950 \end{array}\right]$ $R_v=\left[\begin{array}{ccccc\|c} Inx & \delta_v^n & \omega_v^n & \varepsilon_v^n & \varphi_v^n & \gamma_v^n \\ 1 & 0.5 & 0.0722 & 0.9 & 0.75 & 0.5556 \\ 2 & 0.4 & 0.0531 & 0.9667 & 0.5 & 0.4799 \\ 4 & 0.2 & 0.1395 & 0.9643 & 0.75 & 0.5134 \\ 5 & 0.1 & 0.5 & 0.9667 & 0.8333 & 0.6000 \end{array}\right]$	Turn on No.3 Turn on No.5
04:00		$a=\begin{bmatrix} Inx & J_t^n & e_t^n & T_{n,o} & T_{n,s} & T_{n,w} \\ 1 & 0 & 800 & 0 & 0 & 0 \\ 2 & 0 & 1100 & 0 & 0 & 0 \\ 3 & 0 & 450 & 0 & 1 & 9 \\ 4 & 0 & 400 & 0 & 1 & 10 \\ 5 & 0 & 20 & 0 & 1 & 8 \end{bmatrix}$	$E_{def}^{sh}(t)-E_d^{shift}(t)\geq 0$	Switch on all