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RESEARCH ARTICLE

Demand Response for Optimal Power Usage Scheduling Considering Time and Power Flexibility of Load in Smart Grid

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ABSTRACT Demand response (DR) shaves peak energy consumption and drives energy conservation to ensure reliable operation of power grid. With the emergence of the smart power grid (SPG), DR has become increasingly popular and highly contributes to energy optimization. On this note, in this work, DR is adopted for scheduling home appliances to reduce utility bill payment, peak to average demand ratio (PADR), and discomfort. First, home appliances are classified into two categories according to time and power flexibility: time-flexible and power-flexible. Secondly, the demand-side users power usage scheduling problem is modelled as per the user priority and modes of operation considering demand and supply. Finally, the energy consumption scheduler (ECS) is developed to adjust the time and power of both types of appliances under different operation modes to acquire desired tradeoff between utility bills payment and discomfort, and PADR and discomfort. Simulation results depict that employing the proposed ECS benefits demand-side users by minimizing their utility bills payment, PADR, and achieving the desired tradeoff between utility bill payment and discomfort, and PADR and discomfort. Results illustrate that developed model reduced utility bill payment and alleviated PADR without compromising comfort by 28% and 21%, respectively, compared to without scheduling case.

INDEX TERMS Demand response, appliances scheduling, pricing signals, optimization, smart grid.

I. INTRODUCTION

Energy demand grows around the globe due to growing population and technological advancement [1]. Also, fossil fuels are limited and environment foe, on the record, cause 27% pollution emission, which is dangerous for the environment and, in the worst case, can cause global warming [2], [3], [4]. To meet this growing energy demand and minimize dependence on the fossil fuel, load prediction and optimal energy management is needed [5]. With smart power grid (SPG) technology, users can perform energy management using demand response (DR) and renewable energy sources (RESs) [6], [7]. DR is a SPG program that encourages energy consumption monitoring and control [8], [9], [10], [11] in response to varying pricing signal or payment incentives. On the one hand, consumers control and shift their power usage pattern to low-price hours to minimize energy bills. On the other hand, the utility decline peak-to-average

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demand ratio (PADR) directly impacts the power generation, transmission, and distribution of SPG. Thus, DR is a win-win program, where the distribution networks [12], [13], [14], [15] manage demand according to supply to avoid the need for peak power plant and reduce electricity bill for consumers [16].

To solve the energy management problem, in literature, various DR models are implemented for optimal residential load scheduling considering peak energy consumption, load profiles, energy costs, environmental concerns, and consumer comfort. Different technologies like on chip-filters [17], measurement sensors [18], current sensors [19], etc are developed. However, DR implementations are ignored. Thus, a detailed review of DR models for solving energy management problems is presented in [20] and [21]. Several studies of DR models with decision maker focus on different objectives like cost minimization, which is most commonly used objective, mostly focused due to well-defined structure, ease in measurement, and implementation [22], [23]. Some authors discussed in [24], [25], [26], [27], [28], and [29] fault detection and diagnosis aspects in power grid. Few studies focused on PADR alleviation via load profile optimization [30], [31], [32]. Likewise, some authors presented research works [33], [34], [35] covering user comfort or well-being maximization. Similarly, authors discussed carbon emission reduction in [36] by optimal energy management. The above-discussed literature works achieved single objective energy optimization: energy cost or pollution emission or PADR or user comfort, via power usage scheduling and smoothing load demand profile. However, these objectives are conflicting and interdependent, so the authors ignored their simultaneous optimization. Considering this research gap, several researchers attempted to simultaneously achieve some of these conflicting objectives. For instance, authors in [37] performed optimal energy management catering cost and discomfort minimization in SPG. Authors developed deep learning models in [38], [39], and [40] for online pricing of DR smart home energy management, and commercial buildings optimization, respectively. Similarly, several studies simultaneously catered energy cost and PADR by optimal power scheduling in SPG [30], [41], [42]. Likewise, few studies addressed operational cost and pollution emission minimization by energy optimization in SPG [43], [44], [45]. However, the above-discussed works focused on two objectives simultaneous optimization like, cost and discomfort, energy cost and PADR, and operational cost and pollution emission via single energy optimization approach, which is insufficient. On this note, multi-objective optimization approches are developed in [46], [47], [48], and [49]. The work in [42] developed DA-GmEDE based model for bill payment, PADR, and tradeoff achievement between bill payment and discomfort. However, bill payment, PADR, discomfort simultaneous minimization, and a tradeoff between PADR and discomfort are not addressed. Considering some aspects and ignoring other aspects is not enough. Thus, a model is needed which solves energy management via power usage scheduling optimally.

Optimal energy management in SPG has primary objectives: utility bill payment, PADR, and user discomfort minimization. The above literature studies have investigated energy management areas from different perspectives and built an in-depth understanding of the theme. For example, on the one hand, several studies catered single objectives like utility bill payment minimization while others focused on user discomfort minimization or PADR minimization. On the other hand, few studies catered two objectives: utility bill payment and discomfort or utility bill payment and PADR or operational cost and pollution emission minimization. However, considering only one or two aspects (utility bill payment, user discomfort, PADR) is not enough. Every aspect (utility bill payment, user discomfort, PADR) are indispensable and can be catered simultaneously. Besides, above studies covered optimal energy management via a single energy optimization mechanism. Thus there is a need to develop ECS for optimal power usage scheduling in SPG. In this work, which is continuation of the previous work [42] power usage pattern is scheduled under DR by ECS to benefits demand-side users by minimizing their utility bills payment, PADR, and achieving the desired tradeoff between utility bill payment and discomfort, and PADR and discomfort.

The remaining work is arranged as follows. Section II discusses the proposed optimal energy management framework and and its mathematical modeling. Overall problem formulation is presented in Section III. The simulation results covering all objectives are discussed in Section IV. Finally this work is concluded in Section V.

II. SYSTEM MODEL FOR OPTIMAL ENERGY MANAGEMENT

The proposed system model aims to curtail utility bills, mitigate PADR, and achieve the desired tradeoff between utility bills and average waiting time via power usage scheduling of loads. The developed model has two sides: electric utility company (supply side) and residential consumers (demand-side). The demand-side considers residential homes. The homes have ECS, smart appliances, AMI, monitoring and controlling display (MCD), and smart meters similar as in [56]. The proposed system model for optimal energy management is presented in Figure 1.

The ECS is installed at the home gateway and programmed based on algorithm to schedule power usage pattern under the DR signal and available generation. Two kinds of smart appliances are considered flexible and inflexible appliances. Furthermore, flexible appliances have two types: Time flexible, and power flexible. Time flexible are those appliances with flexible operation time, like dishwashers, cloth dryers, washing machines, and water pumps. On the other hand, power flexible are those appliances with flexible operating power like air conditioners, fridges, and water dispensers.

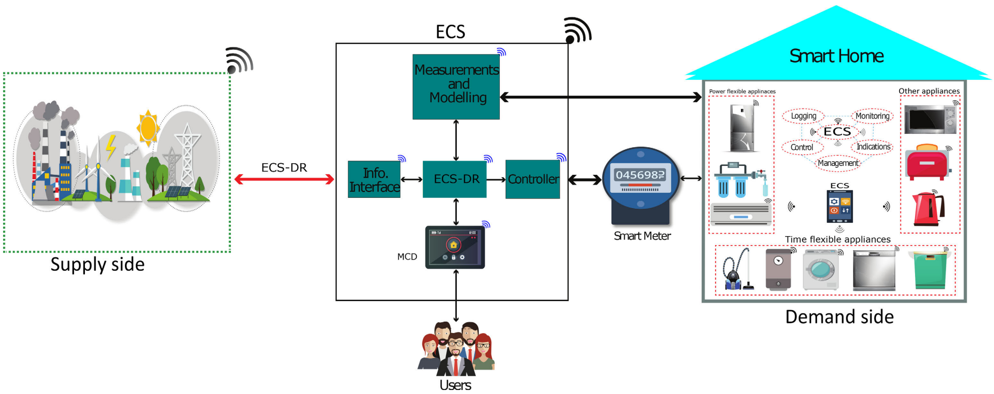

FIGURE 1. Proposed system model schematic diagram.

Inflexible appliances are those appliances, whose operating power and time both can not tolerate shifting. They are also known as critical appliances like micro-ovens, electric kettles, and electric irons. Moreover, these appliances are assumed to be smart, having transceiver (TX/RX) and data-processor to transmit/receives, process, and evaluate operation parameters. The AMI establishes bi-directional communication between the supply side (electric utility company (EUC)) and demand-side via smart meter. The AMI collects and exchanges energy consumption data from demand-side and delivers it to EUC. The EUC generates utility bill for consumed energy and delivers it to the demand-side through smart meter (SM) [56]. The SM is responsible for measuring and monitoring energy and load. Also, SM exchanges energy consumption records from demand-side to EUC and DR signal from EUC to ECS on demand-side for power usage scheduling. The SM is installed outdoor at homes between ECS and AMI. The ECS receives DR signal and appliances operation pattern for power usage scheduling of consumers. The communication between SMs, smart appliances, and ECS can prevail via communication infrastructures like ZWave, WiFi, and ZigBee [57], [58], which is schematically illustrated in Figure 2. The appliances can not consult with each other, and can only consult with ECS as depicted in Figures 1 and 2. The ECS schedules appliances in aspects of both power and time flexibility via DR signal and operation profile subjected to constraints: EUC available power supply, demand-side priority, operation modes, etc. The ECS broadcast created operation schedule for all appliances, which is received by the transceiver (TX/RX) of appliances, and processed by data processor to operate appliances as per the schedule. The ECS created schedule and set out parameters like operation power level, operation starting time, appliance class, etc., to monitor and control the overall energy management process using MCD/mobile installed at home. The proposed system model modeling is presented in the subsequent section.

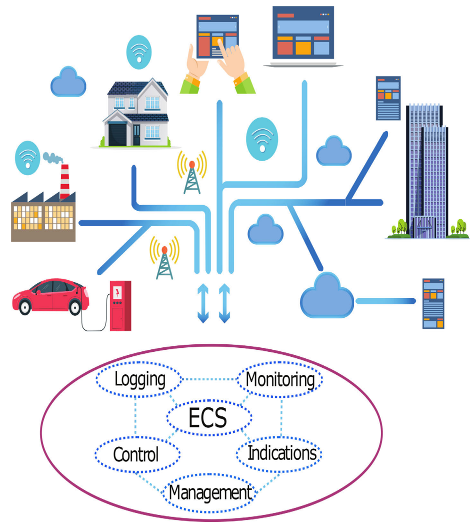

FIGURE 2. The ECS created schedule broadcasting via communication links like ZWave, WiFi, and ZegBee.

A. PROPOSED SYSTEM MODEL MATHEMATICAL MODELING

This section presents the mathematical modeling of the proposed system model. The EUC sends DR signal ρ_t for day-ahead time span $H = \{1, 2, 3, 4, \ldots\ldots, T\}$. The entire time span is 24 hours, where 1 shows the first hour, and T denotes the last 24^{th} hour. The demand-side has two types of appliances $A = \left\{A_f^{OT} \cup A_f^{OP} \cup A_f^{I}\right\}$. A_f^{OT}, A_f^{OP}, and A_f^{I} represent time flexible, power flexible, and inflexible appliances, respectively. An appliance a starting time is α_a and operation finishing time β_a. Appliances on/off status are indicated by X_a^t, remaining operation hours r_a^t, and waiting hours w_a^t. Furthermore, E_a^t is energy consumption. We assume it is zero for $t < \alpha_a$ & $t > \beta_a$ because outside the operation time period energy consumption is zero. Smart appliances modeling is presented below.

1) TIME FLEXIBLE APPLIANCES MODELING

These appliances have flexible operation time, tolerate operation delay/advance during the scheduling period, and work with predefined power rating p_a^r for defined operation hours T_a^l. Consequently, operation time can be scheduled to any hour in the entire period (shifted, delayed, advanced, and shutdown) to achieve desired objectives. Time flexible appliances current status is defined below.

$$\chi_a^t = \left(T_a^l, \alpha_a - \beta_a - T_a^l + 1\right), \tag{1}$$

$$\chi_a^{t+1} = \begin{cases} \left(r_a^t, w_a^t - 1\right) & \text{if } X_a^t = 0,\ w_a^t \geqslant 1 \\ \left(r_a^t - 1, w_a^t\right) & \text{if } X_a^t = 1,\ \ r_a^t \geqslant 1, \end{cases} \tag{2}$$

where Eqs. (1) and (2) represent the current and next status of time-flexible appliances, respectively, similar as in [42]. Time flexible appliances energy consumption and utility bill are computed below [42].

$$E_a^A = \sum_{a \in A_f^{OT}} \sum_{t=1}^{T} (p_a^r \times X_a^t), \tag{3}$$

$$C_a^A = \sum_{a \in A_f^{OT}} \sum_{t=1}^{T} \left(p_a^r \times X_a^t \times \rho_t^f\right), \tag{4}$$

Eqs. (3) and (4) denote net energy consumption E_a^A and utility bill C_a^A, respectively.

2) POWER FLEXIBLE APPLIANCES MODELING

Power flexible appliances have flexible operating power between $p_a^{r\min}$ and $p_a^{r\max}$ minimum and maximum power ratings, respectively. For instance, in fridges, air conditioners, etc., operation power regulates between $p_a^{r\min}$ and $p_a^{r\max}$ during the scheduling period to achieve desired objectives. Power flexible appliances current and next status are determined below using Eqs. (5) and (6), respectively, [42].

$$\chi_a^t = \left(T_a^l, \alpha_a - \beta_a - T_a^l + 1\right), \tag{5}$$

$$\chi_a^{t+1} = \begin{cases} \left(r_a^t - 1, 0\right) & \text{if } X_a^t = 1,\ r_a^t \geqslant 1 \\ p_a^{r\min} \leqslant p_a^r \leqslant p_a^{r\max} & \text{if } X_a^t = 1,\ \ r_a^t \geqslant 1, \end{cases} \tag{6}$$

Power flexible appliances net energy consumption and utility bill is computed below using Eqs. (7) E_a^A and (8) C_a^A, respectively, [42].

$$E_a^A = \sum_{a \in A_f^{OP}} \sum_{t=1}^{T} (p_a^r \times X_a^t), \tag{7}$$

$$C_a^A = \sum_{a \in A_f^{OP}} \sum_{t=1}^{T} \left(p_a^r \times X_a^t \times \rho_t^f\right), \tag{8}$$

3) INFLEXIBLE APPLIANCES

Inflexible appliances cannot be shed/shutdown during operation because they have critical nature and are also known as critical appliances. Inflexible appliances current and next status are calculated below from Eqs. (9) and (10), respectively, [42].

$$\chi_a^t = \left(T_a^l, \alpha_a - \beta_a - T_a^l + 1\right), \tag{9}$$

$$\chi_a^{t+1} = \begin{cases} \left(r_a^t, w_a^t - 1\right) & \text{if } X_a^t = 0,\ w_a^t \geqslant 1 \\ \left(r_a^t - 1, 0\right) & \text{if } X_a^t = 1,\ \ r_a^t \geqslant 1, \end{cases} \tag{10}$$

Inflexible appliances net energy consumption and utility bill are calculated from Eqs. (11) E_a^A and (12) C_a^A, respectively, [42].

$$E_a^A = \sum_{a \in A_f^{I}} \sum_{t=1}^{T} (p_a^r \times X_a^t), \tag{11}$$

$$C_a^A = \sum_{a \in A_f^{I}} \sum_{t=1}^{T} \left(p_a^r \times X_a^t \times \rho_t^f\right), \tag{12}$$

Smart appliances optimal operation scheduling set κ is defined below [42].

$$\begin{aligned} \kappa = \{E/E_a^t &= p_a^r,\ \forall t \in \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\} \\ &\subset [\alpha_a, \beta_a],\ \forall a \in A_f^{OT}, \\ E_a^t &= 0,\ \forall t \in H \backslash \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\}, \forall a \in A_f^{OT}, \\ p_a^{r\min} &\leqslant E_a^t \leqslant p_a^{r\max},\ \forall t \in [\alpha_a, \beta_a],\ \forall a \in A_f^{OP}, \\ E_a^t &= 0,\ \forall t \in H \backslash [\alpha_a, \beta_a],\ \forall a \in A_f^{OP}, \\ E/E_a^t &= p_a^r,\ \forall t \in T_a^l \subset [\alpha_a, \beta_a],\ \forall a \in A_f^I, \\ E_a^t &= 0,\ \forall t \in T_a^l \backslash [\alpha_a, \beta_a],\ \forall a \in A_f^I\}. \end{aligned} \tag{13}$$

Scheduling set κ depends on control parameters like α_a, β_a, T_a^l, p_a^r, $p_a^{r\max}$, $p_a^{r\min}$, and DR signal.

III. PROBLEM FORMULATION

The ECS receives DR signal and demand-side power pattern to schedule appliances operation hours in such a way as to achieve desired objectives like utility bill minimization, PADR alleviation, and tradeoff between utility bills and discomfort achievement. However, obtaining all objectives simultaneously is challenging due tradeoff and conflicting parameters. For instance, in the case of time-flexible appliances, the washing machine has assigned the task of laundry to finish before the afternoon with specifications like $\alpha_a = 10am$ and $\beta_a = 1pm$. The ECS postpones the washing machine task to $\alpha_a = 5pm$ and $\beta_a = 9pm$ as per user priority to minimize utility bills. However, the demand-side user confront discomfort due to the delayed operation of washing machine. For power flexible appliances, the ECS regulates power between $p_a^{r\min}$ and $p_a^{r\max}$ to curtail utility bill. Consequently, curtailed utility bills cause user discomfort. The ECS regulates appliances such that desired tradeoff between utility bills and discomfort is achieved. Hence, objective function is formulated as minimization problem to minimize utility bills, PADR, user discomfort, etc. First, desired objectives like utility bills, PADR, and user discomfort are modeled separately. Then, the complete scheduling problem as minimization problem is modeled [42]. The utility bill of smart appliances during the scheduling period is computed below.

$$C_a^A = \sum_{a \in A} \sum_{t=1}^{T} \left(p_a^r \times X_a^t \times \rho_t^f\right). \tag{14}$$

User discomfort arising due to time-flexible appliance scheduling is calculated below.

$$d_t^{A_f^{OT}}(F_a^t) = \lambda_a \left(F_a^t - \alpha_a\right)^n, \tag{15}$$

where $0 < \lambda_a < 1$ and $n \geqslant 1$ represent time shiftable appliances operation characteristics.

Power flexible appliances cause discomfort due to power regulation, defined below.

$$d_p^{A_f^{OP}}(E_a^t) = \omega_a^t \left(E_a^t - \hat{E}_a^t\right)^2, \tag{16}$$

where ω_a^t is the time varying parameter and normal energy consumption is $\hat{E}_a^t$. Moreover, $d_p^{A_f^{OP}} = 0$ at $E_a^t = \hat{E}_a^t$ for $t \in H \setminus [\alpha_a, \beta_a]$. The quadratic function is minimum at $E_a^t = \hat{E}_a^t$ and increases as the deviation of E_a^t increases from $\hat{E}_a^t$. An appliance malfunction occurs at two extremes of deviation $\hat{E}_a^t \pm \Delta$. Hence, countermeasures are necessary to overcome such malfunction. At extreme $\hat{E}_a^t + \Delta$ or $\hat{E}_a^t - \Delta$ counter measure for malfunction is ς. Inflexible appliances are operated as per user priority and thus can not tent discomfort. The time and power-flexible appliances posed discomfort cost is defined below.

$$d_a^A = \sum_{a \in A_f^{OT}} \lambda_a \left(F_a^t - \alpha_a\right)^n + \sum_t \sum_{a \in A_f^{OP}} d_p^{A_f^{OP}}(E_a^t). \tag{17}$$

The PADR created during the scheduling period is defined below in Eq. (18) denoted by R_A^P. Minimization of PADR is one of our objectives, described below.

$$R_A^P = \frac{\max(E_a^t)}{\frac{1}{T}\sum_{t=1}^{T}\sum_{i=}^{A}(E_a^t)}, \tag{18}$$

The complete power usage scheduling problem is modeled as minimization problem, which is formulated below in Eq. (19).

$$
\begin{aligned}
&\min \ \left(\gamma_1 C_a^A + \gamma_2 R_A^P + \gamma_3 d_a^A\right) \\
&E/E_a^t = p_a^r, \ \forall t \in \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\} \\
&\ \subset [\alpha_a, \beta_a], \ \forall a \in A_f^{OT}, \\
&E_a^t = 0, \ \forall t \in H \setminus \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\}, \forall a \in A_f^{OT}, \\
&p_a^{r\min} \leqslant E_a^t \leqslant p_a^{r\max}, \ \forall t \in [\alpha_a, \beta_a], \ \forall a \in A_f^{OP}, \\
&E_a^t = 0, \ \forall t \in H \setminus [\alpha_a, \beta_a], \ \forall a \in A_f^{OP}, \\
&E/E_a^t = p_a^r, \ \forall t \in T_a^l \subset [\alpha_a, \beta_a], \ \forall a \in A_f^I, \\
&E_a^t = 0, \ \forall t \in T_a^l \setminus [\alpha_a, \beta_a], \ \forall a \in A_f^I\}, \\
&\text{var iables } F_a^t \ (a \in A_f^{OT}, \ t \in H), \\
&\qquad E_a^t \ (a \in A_f^{OP}, \ t \in H), \\
&\qquad p_a^r \ (a \in A_f^I),
\end{aligned} \tag{19}
$$

where C_a^A, R_A^P, and d_a^A denote objective functions of the utility bill, PADR, and discomfort, which are defined in Eqs. (14), (18), and (17), respectively. γ_1, γ_2, and γ_3 are weights that are tuned to achieve the desired tradeoff between conflicting objectives.

Demand-side users operate based on priority, and desired objectives are classified into four modes, formulated in the subsequent section.

1) DEMAND-SIDE USERS MODE 1

Demand-side users mode 1 aims to curtail their utility bill even at the expense of high discomfort. The ECS tune weights ($\gamma_1 = 1, \gamma_2 = 0, \gamma_3 = 0$) of the objective function to ensure utility bill minimization. Hence, the optimization problem is modified in Eq. (20) to ensure operation for mode 1.

$$
\begin{aligned}
&\min \sum_{a \in A} \sum_{t=1}^{T} \left(p_a^r \times X_a^t \times \rho_t^f\right) \\
&\text{sub. to: } E/E_a^t = p_a^r, \ \forall t \in \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\} \\
&\qquad \subset [\alpha_a, \beta_a], \ \forall a \in A_f^{OT}, \\
&\qquad E_a^t = 0, \ \forall t \in H \setminus \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\}, \forall a \in A_f^{OT}, \\
&\qquad p_a^{r\min} \leqslant E_a^t \leqslant p_a^{r\max}, \ \forall t \in [\alpha_a, \beta_a], \ \forall a \in A_f^{OP}, \\
&\qquad E_a^t = 0, \ \forall t \in H \setminus [\alpha_a, \beta_a], \ \forall a \in A_f^{OP}, \\
&\qquad E/E_a^t = p_a^r, \ \forall t \in T_a^l \subset [\alpha_a, \beta_a], \ \forall a \in A_f^I, \\
&\qquad E_a^t = 0, \ \forall t \in T_a^l \setminus [\alpha_a, \beta_a], \ \forall a \in A_f^I\}, \\
&\qquad \text{variables } F_a^t \ (a \in A_f^{OT}, \ t \in H), \\
&\qquad\qquad E_a^t \ (a \in A_f^{OP}, \ t \in H), \\
&\qquad\qquad p_a^r \ (a \in A_f^I).
\end{aligned} \tag{20}
$$

2) DEMAND-SIDE USERS MODE 2

In mode 2, the users desire to operate their appliances to smoothly run their activities even during high-price hours because mode 2 is user comfort centric. In this mode of operation, users do not tolerate delay and are willing to pay more to enhance their comfort. The ECS tunes the ($\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = 1$) weights of the optimization problem to ensure smooth operation of the activities as per the priority of users irrespective of utility bills. The modified optimization problem as per the demand-side users mode 2 is modeled below.

$$
\begin{aligned}
&\min \sum_{a \in A_f^{OT}} \lambda_a \left(F_a^t - \alpha_a\right)^n + \sum_t \sum_{a \in A_f^{OP}} d_p^{A_f^{OP}}(E_a^t) \\
&\text{sub. to: } E/E_a^t = p_a^r, \ \forall t \in \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\} \\
&\qquad \subset [\alpha_a, \beta_a], \ \forall a \in A_f^{OT}, \\
&\qquad E_a^t = 0, \ \forall t \in H \setminus \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\}, \forall a \in A_f^{OT}, \\
&\qquad p_a^{r\min} \leqslant E_a^t \leqslant p_a^{r\max}, \ \forall t \in [\alpha_a, \beta_a], \ \forall a \in A_f^{OP}, \\
&\qquad E_a^t = 0, \ \forall t \in H \setminus [\alpha_a, \beta_a], \ \forall a \in A_f^{OP}, \\
&\qquad E/E_a^t = p_a^r, \ \forall t \in T_a^l \subset [\alpha_a, \beta_a], \ \forall a \in A_f^I, \\
&\qquad E_a^t = 0, \ \forall t \in T_a^l \setminus [\alpha_a, \beta_a], \ \forall a \in A_f^I\},
\end{aligned}
$$

$$\begin{aligned} \text{variables } & F_a^t \ (a \in A_f^{OT},\ t \in H), \\ & E_a^t \ (a \in A_f^{OP},\ t \in H), \\ & p_a^r \ (a \in A_f^I). \end{aligned} \tag{21}$$

3) DEMAND-SIDE USERS MODE 3

Mode 3 is favorable for end-users and utility both because it reduces PADR. Consequently, reduces the burden on utility by decreasing the need for peak power plants and curtails the burden on end-users by lowering utility bills. The ECS tune($\gamma_1 = 0, \gamma_2 = 1, and \gamma_3 = 0$) weights to ensure mode 3 operation and achieve desired objectives. The optimization problem is adapted for mode 3 and formulated below.

$$\begin{aligned} & p_a^r \ (a \in A_f^I) \\ \min \ & \frac{\max(E_a^t)}{\frac{1}{T}\sum_{t=1}^{T}\sum_{i=}^{A}(E_a^t)} \\ \text{sub. to: } & E/E_a^t = p_a^r,\ \forall t \in \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\} \\ & \subset [\alpha_a, \beta_a],\ \forall a \in A_f^{OT}, \\ & E_a^t = 0,\ \forall t \in H \backslash \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\}, \forall a \in A_f^{OT}, \\ & p_a^{r\min} \leqslant E_a^t \leqslant p_a^{r\max},\ \forall t \in [\alpha_a, \beta_a],\ \forall a \in A_f^{OP}, \\ & E_a^t = 0,\ \forall t \in H \backslash [\alpha_a, \beta_a],\ \forall a \in A_f^{OP}, \\ & E/E_a^t = p_a^r,\ \forall t \in T_a^l \subset [\alpha_a, \beta_a],\ \forall a \in A_f^I, \\ & E_a^t = 0,\ \forall t \in T_a^l \backslash [\alpha_a, \beta_a],\ \forall a \in A_f^I\}, \\ & \text{variables } F_a^t \ (a \in A_f^{OT},\ t \in H), \\ & \qquad E_a^t \ (a \in A_f^{OP},\ t \in H), \\ & \qquad p_a^r \ (a \in A_f^I). \end{aligned} \tag{22}$$

4) DEMAND-SIDE USER MODE 4

Mode 4 focuses on balancing operations to achieve all objectives simultaneously, i.e., utility bill and PADR reduction and desired tradeoff between the utility bills and discomfort achievement. The ECS set weights ($\gamma_1 = 1/3, \gamma_2 = 1/3, and \gamma_3 = 1/3$) ensure mode 4 operation and achieve desired objectives. The mode 4 adopted optimization problem is formulated below.

$$\begin{aligned} \min \ & \left(\frac{1}{3}C_a^A + \frac{1}{3}R_A^P + \frac{1}{3}d_a^A\right) \\ \text{sub. to: } & E/E_a^t = p_a^r,\ \forall t \in \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\} \\ & \subset [\alpha_a, \beta_a],\ \forall a \in A_f^{OT}, \\ & E_a^t = 0,\ \forall t \in H \backslash \left\{F_a^t, \ldots, F_a^t + T_a^l - 1\right\}, \forall a \in A_f^{OT}, \\ & p_a^{r\min} \leqslant E_a^t \leqslant p_a^{r\max},\ \forall t \in [\alpha_a, \beta_a],\ \forall a \in A_f^{OP}, \\ & E_a^t = 0,\ \forall t \in H \backslash [\alpha_a, \beta_a],\ \forall a \in A_f^{OP}, \\ & E/E_a^t = p_a^r,\ \forall t \in T_a^l \subset [\alpha_a, \beta_a],\ \forall a \in A_f^I, \\ & E_a^t = 0,\ \forall t \in T_a^l \backslash [\alpha_a, \beta_a],\ \forall a \in A_f^I\}, \\ & \text{variables } F_a^t \ (a \in A_f^{OT},\ t \in H), \\ & \qquad E_a^t \ (a \in A_f^{OP},\ t \in H), \\ & \qquad p_a^r \ (a \in A_f^I). \end{aligned} \tag{23}$$

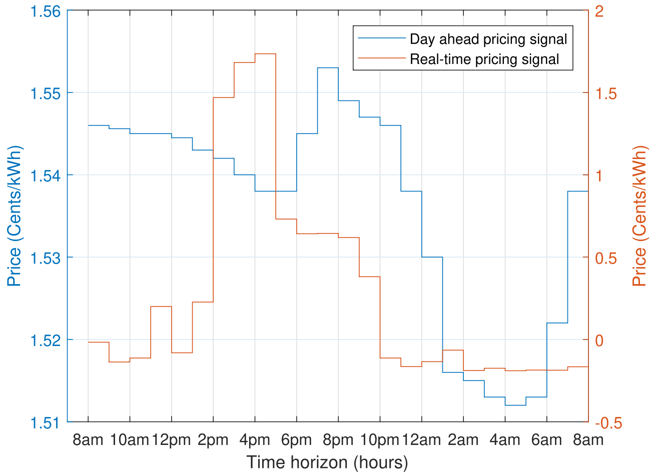

FIGURE 3. Real-time and day-ahead pricing signals adopted from FERC MISO.

IV. SIMULATION RESULTS AND DISCUSSION

This section presents simulation results of the developed power usage scheduling strategy under DR signals like day-ahead and real-time pricing for performance validation. Two classes of appliances: power and time flexible, are considered under four modes of operation. Parameters and descriptions of appliances are listed in Table 1, which is taken from [42]. The time horizon considered for scheduling is twenty four hours, i.e., from 8am to 8am. DR signals like day-ahead and real-time pricing are taken from FERC MISO [58], which is depicted in Figure 3. The energy consumption scheduler (ECS) schedules the operation of appliances under the pricing signal for four modes to acquire desired objectives and meet demand-side users requirements. The detailed description is as follows.

Demand-side users appliances power consumption pattern for four modes of operation are shown in Figures 4, 5, 6, and 7. Appliances power consumption under mode 1 is depicted in Figure 4. In mode 1 the ECS operate only essential power flexible appliances at minimum power level. In contrast, all-time flexible appliances are scheduled by ECS to low price hours because the focus of demand-side users in mode 1 is on utility bill payment reduction. Precisely, time-flexible appliances like washing machines, dishwashers, and clothdryers operation are shifted from high to low price hours by ECS, and power-flexible appliances like Air conditioners, refrigerators, dispensers, etc. are operated with lower power ratings to ensure utility bill payment minimization. The ECS minimizes utility bill payments without taking care of user comfort. In mode 2, the ECS schedules time-flexible and power-flexible appliances such that to improve the comfort of demand-side users, this behavior is depicted in Figure 5. It is clear from Figure 5 that power-flexible appliances:

TABLE 1. **Parameters of demand-side users appliances.**

Types	Appliances	Power rating (kW)	Operation time horizon (hours)
Power flexible	Air conditioner	[0.5 1.8]	24
	Water dispenser	[0 0.1]	24
	Refrigerator	[0.1 0.2]	24
Time flexible	Washing machine	0.5	4
	Clothdryer	1	4
	Dishwasher	1.5	3

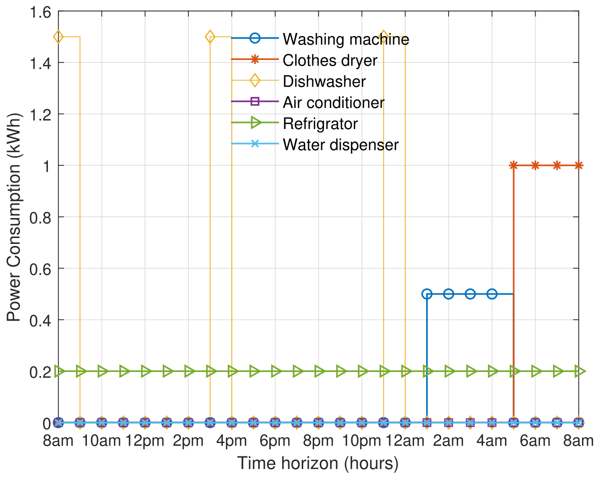

FIGURE 4. **Demand-side users power consumption of power and time-flexible appliances for mode 1.**

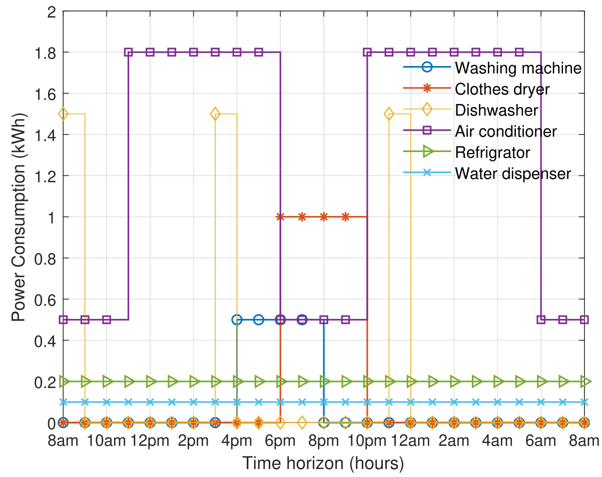

FIGURE 5. **Demand-side users power consumption of power and time-flexible appliances for mode 2.**

air conditioners, refrigerators, dispensers, etc., are mostly operated at their maximum rated power, and time-flexible appliances: washing machines, dishwashers, and clothdryers are scheduled by ECS as per the users priority without taking care bill payment maximization. Thus, the ECS ensured user comfort as per their priority under operation mode 2 without considering bill payment minimization. The power consumption of appliances under operation mode 3 is illustrated in Figure 6. In mode 3, the ECS focus is on PADR minimization to satisfy both utility and demand-side users at the same time. The ECS ensures PADR minimization such that sometimes flexible appliances are postponed during peak hours and shifted to operate during low-price hours. On the other hand, some power-flexible appliances are operated with lower power ratings to ensure PADR minimization. This behavior is clearly depicted in Figure 6. Likewise, appliance power consumption under mode 4 is illustrated in Figure 7. In this mode of operation, the ECS schedule operation of both type of appliances such that to achieve the desired tradeoff between utility bills payment and discomfort, and PADR and discomfort.

The average energy consumption of both types of appliances for modes 1, 2, 3, and 4 is depicted in Figure 8. It is obvious from the results presented in Figure 8 that the energy consumption of operation mode 2 is highest compared to mode 1, 3, and 4, respectively, because under mode 2 the ECS ensures demand-side users comfort even at expense of

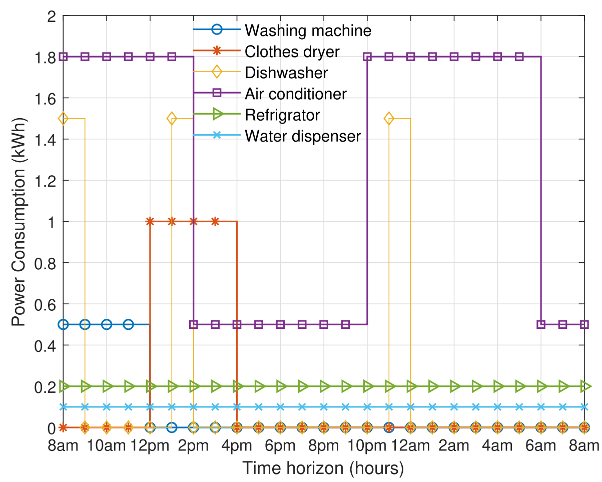

FIGURE 6. **Demand-side users power consumption of power and time-flexible appliances for mode 3.**

increased utility bill payment. In contrast, the energy consumption under mode 1 is lowest compared to mode 2, 3, and 4, respectively, because under operation mode 1 the ECS ensures utility bill payment minimization at the cost of high discomfort as per the users priority. The energy consumption under operation mode 3 is lower than mode 2 and higher than modes 1 and 4 because under mode 3 the ECS ensures PADR minimization. Likewise, the mode 4 energy consumption is moderate compared to modes 1, 2, and 3 because the ECS in

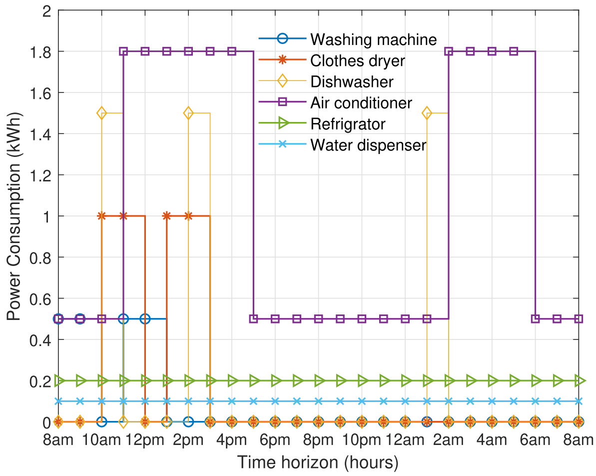

FIGURE 7. Demand-side users power consumption of power and time-flexible appliances for mode 4.

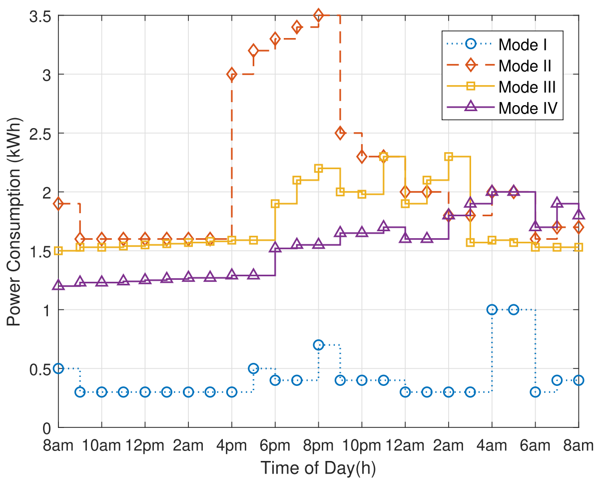

FIGURE 8. Demand-side users average power consumption for modes 1, 2, 3, and 4.

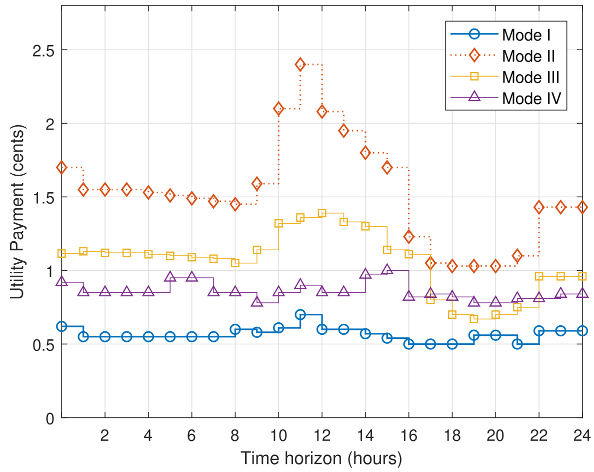

FIGURE 9. Demand-side users utility bill payment against consumed energy for modes 1, 2, 3, and 4.

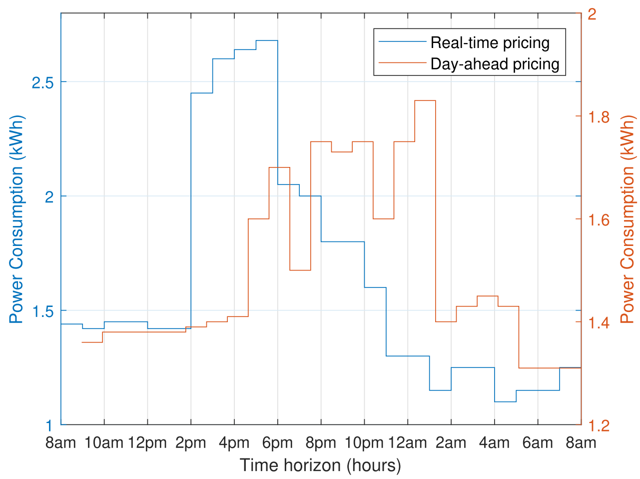

FIGURE 10. Demand-side users power consumption under real-time and day-ahead pricing signals.

mode 4 achieves desired tradeoff between utility bill payment and discomfort, and PADR and discomfort.

The utility bill payment against the consumed energy for modes 1, 2, 3, and 4 is illustrated in Figure 9. It is clear from the results presented in Figure 9 that demand-side users in operation mode 2 pay high utility bills compared to modes 1, 3, and 4 because, in mode 2, demand-side users want to enhance their comfort, leading high utility bill payment. On the other hand, demand-side users in mode 1 want to minimize bill payment that causes high discomfort. Likewise, in mode 3 the ECS minimizes PADR to satisfy both demand-side users and utility, and thus, energy consumption under 3 is higher than mode 1 and mode 4. The ECS schedules appliances for mode 4 such that to achieve the desired tradeoff between user discomfort and bill payment and PADR and discomfort. Thus, energy consumption under mode 4 is moderate compared to modes 1, 2, and 3, and it achieves desired tradeoff between objectives.

The power usage scheduling based on real-time and day-ahead pricing signals is compared to ensure which pricing is suitable in returning to the optimal schedule, where desired objectives are achieved. Comparative results are shown in Figures 10 and 11. The comparison reveals that in a day-ahead pricing signal, demand-side users are charged against a day-ahead broadcasted signal which is a stable signal for that day and does not have any flexibility for demand-side users. Consequently, leading to high peak energy consumption and utility bill payment as depicted in Figures 10 and 11. In contrast, real-time pricing signal changes in real-time so demand-side users can easily adapt their load, and thus ECS can easily achieve the desired objectives. Besides, the peak energy consumption under day-ahead pricing scheme is higher than the real-time pricing signal, as clearly seen in Figure 10. The ECS via real-time pricing signal uniformly distributes energy consumption than the day-ahead pricing signal. Thus, real-time pricing signal is more effective and suitable for reducing peak energy consumption, PADR, and

TABLE 2. Comparison between different pricing signals in aspects of PADR and utility bill payment.

Pricing signals	Utility bill payment (cents)	Peak demand (kW)	Average demand (kW)	PADR
Day-ahead	19.7	2.4	1.5	1.6
Real-time	14.6	2.98	1.95	1.52

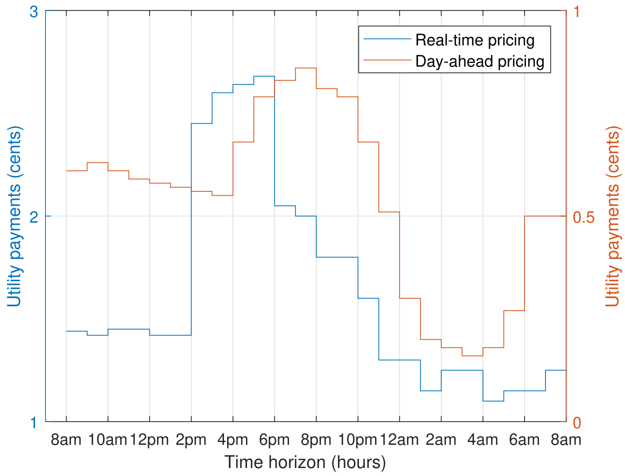

FIGURE 11. Demand-side users utility bill payment under real-time and day-ahead pricing signals.

utility bill payment. Utility bills payment under real-time and day-ahead pricing signals are shown in Figure 11, and results are presented in Table 2. Findings reveal that ECS using real-time pricing signal effectively reduced peak energy consumption, PADR, and utility bill payment compared to day-ahead pricing signal.

V. CONCLUSION

In this work, ECS is developed for power usage scheduling of time and power-flexible appliances under a real-time pricing scheme for four modes of operation as per the demand-side users priority and utility constraints. The developed ECS aims to minimize utility bill payment, PADR, and achieve the desired tradeoff between utility bills payment and discomfort, and PADR and discomfort. For this purpose, the power usage scheduling problem is formulated as an optimization problem implementing DR in aspects of a real-time pricing scheme for four modes of operation. Simulations are conducted for the developed model's validity and applicability in aspects of performance metrics. Findings reveal that the developed model under a real-time pricing scheme achieves desired objectives and tradeoff between utility bill payment and discomfort, and PADR and discomfort.

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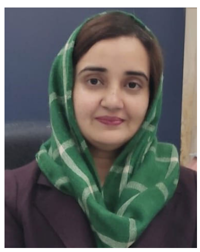

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