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Price-based demand response for household load management with interval uncertainty

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A B S T R A C T

In a smart grid, efficient load management can help balance and reduce the burden on the national power grid and also minimize local operational electricity cost. Robust optimization is a technique that is increasingly used in home energy management systems, where it is applied in the scheduling of household loads through demand side control. In this work, interruptible loads and thermostatically controlled loads are analyzed to obtain optimal schedules in the presence of uncertainty. Firstly, the uncertain parameters are represented as different intervals, and then in order to control the degree of conservatism, these parameters are divided into various robustness levels. The conventional scheduling problem is transformed into a deterministic scheduling problem by translating the intervals and robustness levels into constraints. We then apply Harris' hawk optimization together with integer linear programming to further optimize the load scheduling. Cost and trade-off schemes are considered to analyze the financial consequences of several robustness levels. Results show that the proposed method is adaptable to user requirements and robust to the uncertainties.

1. Introduction

Smart grid (SG) is an advanced technology which comprises a variety of components and operations with digital communications technology enabling the energy system to pro-act, detect and react to changes in usage and numerous other events. It is integrated with advanced metering infrastructure (AMI), a smart meter (SM), intelligent control system and advanced communication technologies. Load management (Shehadeh et al., 2020; Talaat et al., 2020), power system stability and control (Huang et al., 2017), monitoring of transmission lines (Mahin et al., 2020; Judge et al., 2020), and secure data transmission (Guan et al., 2017; Manzoor et al., 2018; El Mrabet et al., 2018; Manzoor et al., 2019; Beg et al., 2021) are major issues concerning SG deployment and uptake. Load management has promising impact on peak load reduction, cost minimization, load balancing and peak to average ratio. The management of power is classified as either supply side management (SSM) and demand side management (DSM). The former ensures efficient generation, transmission and distribution of electricity; this is also responsible for providing reliable energy at minimum economic cost However, our work is focused on the latter and aims to address issues in planning and monitoring activities. A key component of DSM is Demand response (DR), which encourages consumers to modify their energy consumption patterns and shift their load from peak hours to off-peak hours. Cost-sensitive consumers participate in DR by adjusting their power demand in response to time-varying prices.

Domestic electrical energy usage represents a significant proportion of total electricity consumption in many nations. Across the UK, this is approximately 2/5 of the total consumption (see BEIS, 2020), with the proportion increasing in urban areas such as London. Hence, efficient residential energy consumption can reduce several grid setbacks, such as reliability matters, congestion issues, power stability problems, and power quality concerns. The idea of smart homes involves various types of energy production & storage devices, information & communication infrastructures, and control mechanism to adjust the energy consumption pattern automatically. An essential device in a smart electricity grid environment known as Home energy management system (HEMS),

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Nomenclature

Variables

$S_{WH,n}$	ON/OFF status of water heater
$S_{AC,n}$	ON/OFF status of air conditioner
$S_{DW,n}$	ON/OFF status of dish washer
$S_{WM,n}$	ON/OFF status of washing machine
$S_{DM,n}$	ON/OFF status of dryer machine
$\vartheta_{WH,n}$	Hot water temperature interval over time $[tn, tn+1]$
$\vartheta_{AC,n}$	Indoor temperature interval over time $[tn, tn+1]$
$\vartheta_{WH,cur}$	Current temperature of hot water
$\vartheta_{en,n}$	Ambient temperature Interval over time $[tn, tn+1]$
C_{WH}	Total capacity of water Heater
C_{AC}	Total capacity of air conditioner
TC_{WH},	Thermal capacitance of water heater
R_{WH},	Total resistance of water heater
TC_{AC}	Thermal capacitance of air conditioner
R_{AC},	Total resistance of air conditioner
E_{hj}	The energy demand for energy stage j in appliance h
l_{DW}	Total time steps of dish washer over scheduling horizon
l_{WM}	Total time steps of washing machine over scheduling horizon
l_{DM}	Total time steps of dryer machine over scheduling horizon

Parameters

$t_{DW,st}$, $t_{DW,f}$	The start and finish time of dish washer
$t_{WM,st}$, $t_{WM,f}$	The start and finish time of washing machine
$t_{DM,st}$, $t_{DM,f}$	The start and finish time of dryer machine
$P_{n,h}$	Appliance h that consume power in each time slot n
P_h	Appliance h that consume power
p_n	Electricity price over time $[t_n, t_{n+1}]$
D_n	Demand of hot water for daily use drawn over time $[t_n, t_{n+1}]$
M	Total mass of water in tank
t_n	Time at n step
T_{hj}	The number of time intervals for energy stage j in appliance h
Γ_D, Γ_ϑ	The robust levels indicating daily hot water need and ambient temperature
a_D , a_ϑ	Auxiliary parameters
$g_{n,hj}$	The total number of time slots n used in middle of the energy stages j in an appliance h
$PEAK_n$	Peak signal at time slot n
$TP_{n,h}$	Time preference slot
n	Time slot index
en	Environment
h	Appliance index
j	Energy stages

which allows the users to participate in the load shifting plan where they can shift their load in an off-peak hour (Sattarpour et al., 2018). Having new developments and highly demand of pricing schemes and smart-loads, residential users find it hard to schedule these loads manually. Hence, HEMS is becoming more significant in residential sector for cost-saving, and comfortable living (Ha et al., 2012).

Smart home appliances can be scheduled through the use of HEMS, optimizing the time slots of operation according to a variety of pricing schemes. Nowadays, incentives based on monetary profits are the key motives for household users to take part in home load management. Utility companies provide flexible pricing schemes like the day ahead (DA) and real-time pricing (RTP) to stimulate end-users, so that they can participate in demand-side management (Corsi et al., 2020). In DA pricing scheme, the selling and buying price of electricity is known just one day before and participants can shift the loads according to the energy prices. However, the RTP pricing scheme is regarded as a reliable for power system operation because the production and consumption of electricity can be adjusted in real-time (Shahidehpour et al., 2002). Responding to the different pricing schemes, HEMS effectively decreases home electricity bills and improves household load's energy consumption profiles under considering the comfort requirements (Hosseini et al., 2018; Javadi et al., 2020). In addition, water heater (WH) and air conditioner (AC) are regarded as well befitted for load management, because of their large nominal power ratings (Kepplinger et al., 2015). Hence, the scheduling strategies of WH and AC are important in HEMS to assist the end-users, so that they can automatically receive optimal scheduling pattern. With such knowledge, numerous worthy works have been done on WH and AC load scheduling.

In Goh and Apt (2004), authors studied three customer strategies for WH scheduling under a dynamic pricing scheme, including timely interruption of power, double period setback timer, and price-sensitive thermostat. Further, they analyzed a group of situations with various set points of water temperature to investigate the relevance of electricity price with the setpoints. One of the most crucial parts of HEMS is the scheduling of household loads (Gonçalves et al., 2019; Lu et al., 2020). Most of the research community focuses on deterministic optimization techniques for household load management. In Pipattanasomporn et al. (2012), the authors proposed an algorithm for HEMS to optimal schedule the home appliances by considering customer's preference. Meanwhile, they addressed the consequences of various energy demand limit levels on demand response potential. Home scheduling frameworks based on energy consumption pattern proposed in Mohsenian-Rad and Leon-Garcia (2010). Further, they presented a trade-off between energy price and waiting time. In that work, an Inclined block rate combined with real-time price is employed as a pricing scheme. To forecast the electricity price in real-time, the authors developed a prediction filter by allowing various coefficients to electricity costs on past days. Consumers firstly set five different values to desired energy services in Pedrasa et al. (2010) so that their performance can differentiate. Later, a particle swarm optimization was proposed to obtain an effective operation schedule for distributed energy resources (DERs).

Many types of uncertainties like model uncertainties, communication uncertainties, measurement and forecast uncertainties, should be considered in a real condition; therefore, research on domestic load scheduling has become crucial. Pedrasa et al. proposed a modern framework for resource management for smart house including non-controllable and controllable loads and domestically available renewable energy resources (Rad and Barforoushi, 2020). That paper also considered the uncertainties of renewable energy resources, market rate, and non-controllable loads. A Markov chain and multi-layer perceptron are applied to forecast renewable energy generation. Results illustrate that the proposed method reduces both user costs and peak to average ratio. The authors in Wang et al. (2020b) and Han et al. (2019) proposed a stochastic linear programming model for scheduling electric vehicle charging rules for several electric grid demands in real-time utilizing a rolling window approach. The proposed model examines the uncertainties in the availability of electric vehicle and electricity requirements upon arrival. Monte Carlo simulation reveals that varying input parameters may change the results.

A late-night charging of electric vehicles in distribution networks is proposed in Sun et al. (2020) for robust, cost-efficient, and day-ahead scheduling in a stochastic environment. The stochastic environment takes many uncertainties such as stochastic everyday trip distances, arrival and exit times. The simulation results tell the impact of uncertainty and the effectiveness of discussing features of risk through optimization. In this Wang et al. (2020a), authors discuss the optimal decision problem of a DERs aggregator who handles wind turbine resources, solar photovoltaics (PV) units, and energy storage systems while implementing a real-time pricing scheme. A robust optimization scheduling model is proposed for DERs by combinedly consider both uncertainties of renewable energy generations and user's responsiveness. Case studies illustrate that the proposed model can decrease the bidding and scheduling expenses to achieve a higher profit. A hybrid robust-stochastic optimization is proposed to handle the uncertain optimization of smart HEMS (Akbari-Dibavar et al., 2020). Authors investigated the uncertainties associated with energy costs and PV generation by controlling parameters of robust-stochastic optimization. In Wang et al. (2019), parallel stochastic programming is introduced to control the uncertain nature of renewable energy sources and the buffering impact of energy storage systems. Another traditional method called fuzzy programming is proposed in Hong et al. (2012), Wu et al. (2015) to manage the uncertain optimization of smart HEMS. Where uncertain parameters such as electricity expenses and outdoor temperature, were represented by fuzzy parameters.

In the literature, extra information is needed to include in domestic load scheduling to convert uncertain load optimization into certain load optimization like the probability distribution and fuzzy membership function in stochastic programming and fuzzy programming. However, the extra information will make the optimization more difficult to some degree. Besides, both fuzzy membership and the probability distribution function depends on historical information. In such condition, it is difficult to collect new house data.

A robust optimization performs well in a problem where some level of uncertainties exists. Its assessment and analysis are compact enough and does not require any further auxiliary variables. Random parameters in a robust optimization are represented as a set of uncertainty, unlike stochastic programming employing the probability distribution. Generally, in robust optimization, the optimization problem is formulated in such a way that gives the optimum solution for a worst-case scenario so that any random parameters can take from an established set of uncertainty. Furthermore, robust optimization assumes a "hard" constraint. For instance, any violation of constraint is not permitted for any data realization in the set of uncertainties. It works remarkably due to its computational tractability for various forms of sets of uncertainty and types of problems.

In contrast with conventional approaches for uncertain problems, interval analysis needs bounds of the uncertainties' magnitude and do not require the particular probabilistic distribution densities. While limited uncertain data is required, an interval

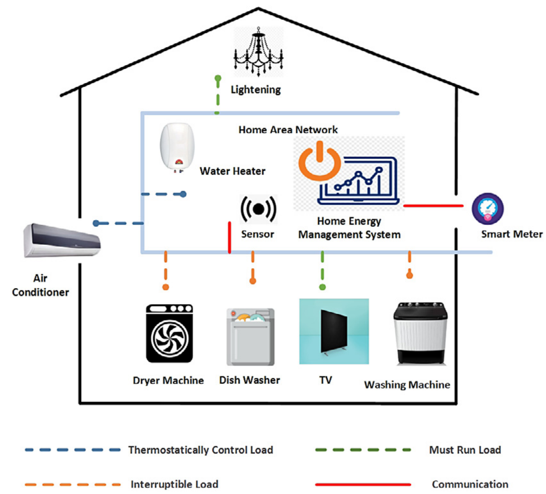


Fig. 1. System model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

number is appropriate for explaining the uncertain parameters of WH and AC loads scheduling with insufficient uncertainty information.

In this work, we have considered two type of loads namely, time-shiftable and thermostatically controlled loads. Time-shiftable loads can delay their operation to some other time slot in response to the varying pricing signal. These loads include dish washer (DW), washing machine (WM) and dryer machine (DM). Operational priorities of these loads are also taken into consideration as shown in Tables 1–3. Thermostatically controlled loads are those that perform temperature control operation to adjust heat energy and get the desired output temperature. Parameters of thermostatically controlled loads are provided in Table 4. Thermostatically controlled loads include WH and AC which are modeled under uncertain conditions. The uncertain parameters of WH and AC are represented as an interval numbers. Further, these parameters associate uncertainties into various robust levels. The WH and AC load scheduling problems are re-modeled under several robust-levels, and their constraints are transformed into an equivalent form for solving. The experimental results validate the robustness of proposed optimization technique for getting a feasible scheme that could meet the user's comfort zone despite uncertainties. Having diverse consumers' needs, and the balance between comfort and costs of the schemes with several robust levels are explained to give more options to users. Main contributions of this paper are:

- Robust optimization is proposed to handle uncertainties associated with thermal loads such as heating and air conditioning.
- The uncertain parameters are converted into different intervals, and these parameters are divided into various robust levels to control the degree of conservatism.
- Harris' Hawk optimization together with integer linear programming is used to solve the uncertainty problem.
- Cost and trade-off schemes are analyzed for the user satisfaction and financial benefits of several robust levels.
- Additionally, three time-shiftable appliances with operational constraints are considered for optimal scheduling.

Rest of the paper is organized as follows. Section 2 discusses the proposed system method followed by problem formulation in Section 3. Section 4 contains results and discussions of the proposed work. Finally Section 5 concludes the work.

Table 1
Dish washer specifications (Rugo, 2011).

Energy stage	Energy (Wh)	Min power (W)	Max power (W)	Nominal op time (min)
Pre-wash	16	6.47	140	14.9
Wash	751.2	140.26	2117.8	32.1
1st rinse	17.3	10.28	132.4	10.1
Drain	1.6	2.26	136.2	4.3
2nd rinse	572.3	187.3	2143	18.3
drain & dry	1.7	0.2	2.3	52.4

Table 2
Washing machine specifications (Rugo, 2011).

Energy stage	Energy (Wh)	Min power (W)	Max power (W)	Nominal op time (min)
Movement	118	27.231	2100	26
Pre-heating	5.5	5	300	6.6
Heating	2054.9	206.523	2200	59.7
Maintenance	36.6	11.035	200	19.9
Cooling	18	10.8	500	10
1st rinse	18	10.385	700	10.4
2nd rinse	17	9.903	700	10.3
3rd rinse	78	23.636	1170	19.8

Table 3
Dryer machine specifications (Rugo, 2011).

Energy stage	Energy (Wh)	Min power (W)	Max power (W)	Nominal op time (min)
Drying	2426.3	120.51	1454	120.8

Table 4
Water heater and air conditioner specifications.

Task	Power	Capacity	Resistance	Thermal capacitance	Gallon	Upper temp. limit	Lower temp. limit
Water heater	3.6	120	0.7623	431.7012	40	56	68
Air conditioner	1.8	1.8	18	0.525	–	23	26

2. System model

A generic smart home's structure considers in this work as in Fig. 1, where HEMS control the loads in a smart home. Under the premises of a smart home, appliances/loads are categorized as controllable loads, and uncontrollable loads (Wang et al., 2015a). The WH and AC are thermostatically controlled loads (TCL). Time shiftable appliances include WM, DW, and DM are another type of controllable load. While lighting and TV consider as uncontrollable loads which remain in must run states throughout the day. All appliances are categorized in different colors in Fig. 1. Smart meter gets outside signals and forwards it to HEMS. Home area network gets the information of appliance's scheduling pattern and then communicated with HEMS. Then HEMS schedules the appliances at optimal time slots by taking the directions from inside installed algorithm (Wang et al., 2015b). In this paper, uncertainties associated with hot water demand for daily use and ambient temperature are taken into account. Because of high power consumption of TCL, these loads are well suited for home energy management.

It is estimated that both these appliances share a large proportion of domestic load, which could reach 40% to 50% (Iwafune and Yagita, 2016). The scheduling of TCL is intended to maintain thermal satisfaction inside the home; therefore, it is highly important to consider TCL for optimal scheduling.

A common appliance in all domestic users' houses is WH. Generally, electrical energy and natural gas are the two main ingredients for domestic water. For example, in Canada, 51.4% uses natural gas for resident water heating; 44.1% employ electrical energy as heating, and the remaining 4.5% utilize other sources (Council et al., 2010). This section primarily focuses on the WH and its working. When the water temperature falls to the lower limit its switches turn on to heat the cold water, on the other side when the temperature rises to the upper threshold limit it turns off. In the case of WH total heat loss causes from two perspectives: when cold water inflows in the tank while using hot water, secondly when the heat exchanges with the surroundings.

3. Problem formulation

3.1. Thermostatically controlled loads

The operation of WH can be expressed by the thermal dynamic model (Du and Lu, 2011). When hot water use is not considered, the thermal dynamics of an WH is calculated by

$$\vartheta_{WH.n+1} = \vartheta_{en,n} + S_{WH,n}C_{WH}R_{WH} - (\vartheta_{en,n} + S_{WH,n} C_{WH}R_{WH} - \vartheta_{WH.n})exp[-\frac{(t_{n+1} - t_n)}{R_{WH} \times TC_{WH}}] \quad (1)$$

Where $\vartheta_{WH.n}$ is the hot water temperature at time t_n while $\vartheta_{WH.n+1}$ denotes the ambient temperature at time t_n. $S_{WH,n}$ represents the switch ON/OFF state of WH at time $[t_n, t_{n+1}]$.

Further, If hot water demand for daily use considers then Eq. (1) is changed as follow,

$$\vartheta_{WH.n+1} = [\vartheta_{WH,cur}(M - D_n) + \vartheta_{en,n}D_n]/M \quad (2)$$

In above equation, $\vartheta_{WH,cur}$ is same as $\vartheta_{WH,n+1}$ in Eq. (1), D_n is the demand of water at t_n, M is the water mass. Both the above equations can jointly express the thermal model as below in Eq. (3).

$$\vartheta_{WH.n+1} = f(\vartheta_{WH.n}, t_n, C_{WH}, TC_{WH}, R_{WH}, D_n, S_{WH,n}, \vartheta_{en,n}) \quad (3)$$

The above equation straightforwardly determines the temperature of water in each time slot, and sets WH's scheduling foundation.

In addition, another load is also installed widely at homes alongside WH is AC (Pérez-Lombard et al., 2008). Its primary working principles are similar to WH despite a few specific differences like AC losses heat in the form of heat exchange outside the surroundings. Just like WH, AC thermal dynamic model can be represented as below.

$$\vartheta_{AC.n+1} = \vartheta_{en,n} + S_{AC,n}C_{AC}R_{AC} - (\vartheta_{en,n} + S_{AC,n}C_{AC}R_{AC} - \vartheta_{AC.n})exp[-\frac{(t_{n+1} - t_n)}{R_{AC} \times TC_{AC}}] \quad (4)$$

Other than TCL, some interruptible appliances like DW, WM, and DM are also considered. Their operation can interrupt at any time and again can resume in the upcoming optimal scheduling slots.

Mathematically, DW's model is expressed as,

$$\sum_{n=t_{DW,st}}^{t_{DW,f}} S_{DW,n} = l_{DW} \quad (5)$$

Eq. (6) describes the model of WM as,

$$\sum_{n=t_{WM,st}}^{t_{WM,f}} S_{WM,n} = l_{WM} \quad (6)$$

Mathematically, DM is represented as,

$$\sum_{n=t_{DM,st}}^{t_{DM,f}} S_{DM,n} = l_{DM} \quad (7)$$

The overall objective function is to reduce the total electricity cost, and mathematically it is expressed as in Eq. (8). Constraints in Eqs. (9) and (11) are the comfort constraints for the WH, while AC's comfort constraints represent in Eqs. (10) and (12).

$$min \sum_{n=1}^{N} \sum_{h}^{H} p_n S_{h,n} P_{n,h} \quad (8)$$

Subject to

$$\vartheta_{WH.n} = uf(\vartheta_{WH.n-1}, t_{n-1}, C_{WH}, TC_{WH}, R_{WH}, D_{n-1}, S_{WH,n-1}, \vartheta_{en,n-1}) \quad (9)$$

$$\vartheta_{AC.n} = f(\vartheta_{AC.n-1}, t_{n-1}, C_{AC}, TC_{AC}, R_{AC}, S_{AC,n-1}, \vartheta_{en,n-1}) \quad (10)$$

$$\vartheta_{WH}^{low} \le \vartheta_{WH,n} \le \vartheta_{WH}^{up} \quad (11)$$

$$\vartheta_{AC}^{low} \le \vartheta_{AC,n} \le \vartheta_{AC}^{up} \quad (12)$$

3.2. Energy and timing constraints for time-shiftable loads

The following constraint is inflicted to assured that the energy stages satisfy their energy requirements.

$$\sum_{n=1}^{N} P_{n,hj} = E_{hj} \quad (13)$$

E_{hj} represents energy demand for energy stage j in appliance h.

The following constraint is inflicted to show whether an energy stage is being utilized during time slot n and the upper and lower boundaries of power assignment to the stage,

$$P_{n,hj}^{low} S_{n,hj} \le P_{n,hj} \le P_{n,hj}^{up} S_{n,hj} \quad (14)$$

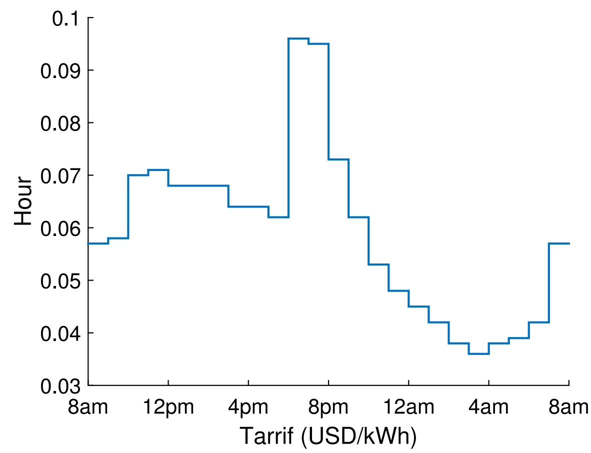


Fig. 2. Day-ahead real time pricing signal.

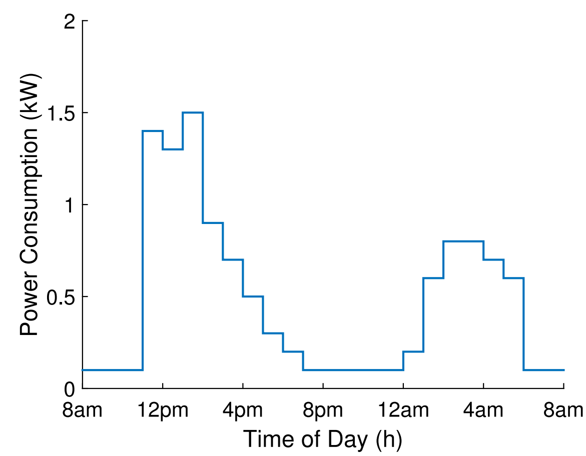


Fig. 3. Power consumption pattern of uncontrollable load.

Where $P_{n,hj}^{up}$ and $P_{n,hj}^{low}$ are appliance particular data describing the upper and lower boundaries of power assignment to the energy stages respectively.

Eq. (15) is the safety constraint. Maximum power consumption of all appliances in each time slots should not be exceeded the maximum value and can be formulated as below.

$$\sum_{h}^{H} \sum_{j}^{m_h} P_{n,hj} \le Peak_n \quad (15)$$

$PEAK_n$ is the peak signal at n time slot, and its value is determined by the grid operator through demand response signal (see Fig. 3).

The following constraint is imposed to limit the processing time of the energy stage

$$T_{hj}^{low} \le \sum_{n=1}^{N} S_{n,hj} \le T_{hj}^{up} \quad \forall h, j \quad (16)$$

where T_{hj}^{up} and T_{hj}^{low} are the upper and lower boundaries for the number of time intervals for appliance h in energy stage j.

Sequential processing of an appliance anticipates that a new energy stage is unable to start until its previous stages have completed. This situation can easily be defined by using the variables $A_{n,h(j)}$ as in Eq. (17).

$$S_{n,hj} \le A_{n,h(j-1)}, \quad \forall h, n.\forall j = 2, 3, \ldots, m_h \quad (17)$$

Likewise, consecutive operation between the appliances can be modeled, a constraint in the above equation can be formulated as:

$$S_{n,h1} \leq A_{n,\bar{h}m_{\bar{h}}}, \quad \forall n \tag{18}$$

Where $\bar{h}$ is the appliance index that must be ended before h starts. In above equation, $A_{n,\bar{h}m_{\bar{h}}}$ means appliance $\bar{h}$, energy stage $m_{\bar{h}}$ and time slot n.

Decision variable $g_{n,hj}$ represented to compute the number of time slots that is used in the middle of the energy stages in an appliance. During any time slot n, $g_{n,hj}$ will be one only when a particular appliance h has completed processing energy stage $j-1$, and it is anticipating to process the next stage j. The corresponding constraint is

$$g_{n,hj} = A_{n,h(j-1)} - (S_{n,hj} + A_{n,h(j)}), \quad \forall h, n, \forall j = 2, 3, \ldots, m_h \tag{19}$$

Note that $S_{n,hj} + A_{n,h(j)} \leq 1$ because both the processing and task completion cannot together be possible in an energy stage. Therefore, logically equality in the above Eq. (19) is correct. With $g_{n,hj}$ determined, the constraint imposing the upper and lower boundaries of the number of transition time slots can be written as,

$$O_{hj}^{low} \leq \sum_{n=1}^{N} g_{n,hj} \leq O_{hj}^{up}, \quad \forall h, \forall j = 2, 3, \ldots, m_h \tag{20}$$

In above, O_{hj}^{low} and O_{hj}^{up} are the appliance technical terms addressing the middle of the energy stage delay in several time slots.

The household customer can make the time choice constraints by defining an optimal time slot for a particular appliance that must finish its task within the allowed time. It means that appliances cannot operate outside the allowed time zone, and mathematically express as,

$$S_{n,hj} \leq TP_{n,h}, \quad \forall h, j, n \tag{21}$$

where $TP_{n,h}$ indicates the time preference slots. That is, $TP_{n,h} = 0$ only when the energy stages of appliance h run during time slot n.

3.3. Load scheduling problem of WH and AC under various robust levels

Both WH and AC aim to maximize the financial benefits while maintaining the hot water temperature and room temperature inside the comfort zones. Due to the unpredictable nature of the environment, the uncertain parameters associated with the WH and AC cannot determine accurately. Hence, these uncertain parameters may start to violate comfort zones and should explain in more aspects.

According to Wang et al. (2016), it is understandable to express the uncertainties with uncertain but bounded parameters whose boundary values always depend on the prediction. By adding two auxiliary parameters, the uncertain but bounded parameters can demonstrate as intervals. Further, a pair of robust levels are predetermined to divide the uncertainties into various categories so that the degree of the conservativeness of the uncertain parameters can be maintained. With this knowledge, the intervals having several levels of the uncertainties in hot water demand represented as:

$$D_n^U(a_D, \Gamma_D) = D_n^{min} + a_D \Gamma_D \Delta D_n \tag{22}$$

$$\Delta D_n = \frac{D_n^{max} - D_n^{min}}{N_D} \tag{23}$$

$$a_D \in [0, 1], \Gamma_D \in [0, N_D], \forall \Gamma_D, N_D \in N^+ \tag{24}$$

Correspondingly, the intervals under several levels of the uncertain ambient temperature are represented as:

$$\vartheta_{en,n}^U(a_\vartheta, \Gamma_\vartheta) = \vartheta_{en,n}^{max} + a_\vartheta \Gamma_\vartheta \Delta\vartheta_{en,n} \tag{25}$$

$$\Delta\vartheta_{en,n} = \frac{\vartheta_{en,n}^{max} - \vartheta_{en,n}^{min}}{N_\vartheta} \tag{26}$$

$$a_\vartheta \in [0, 1], \Gamma_\vartheta \in [0, N_\vartheta], \forall \Gamma_\vartheta, N_\vartheta \in N^+ \tag{27}$$

In the above equations, the auxiliary parameter for hot water demand is a_D, while a_ϑ represents the auxiliary parameter for ambient temperature. Additionally, robust levels of these uncertain parameters are represented as Γ_D and Γ_ϑ. If robust levels get 0, it indicates that users are satisfied with the prediction, and the intervals are converted into real numbers. On the other side, users are dissatisfied with the predicted values if the robust levels get equal to N_D and N_ϑ. In that instance, the range of intervals approaches to peak values. When the robust levels settle between zero and peak values, intervals having diverse uncertainties are formed.

If the uncertainties as given in Eqs. (22) and (25) are taken into account, then equations of thermal dynamic models are modified as below:

$$\begin{gathered}\vartheta_{WH,n+1}^U(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta) = \\ \left(\Pi_{i=1}^n \gamma\left[f_i^{max} - aa_D\Gamma_D\frac{\Delta D_i}{M}\right]\right)\vartheta_1 \\ + \sum_{v=1}^{n}\gamma^{n-v}\left(\Pi_{i=v}^n\left[f_i^{max} - a_D\Gamma_D\frac{\Delta D_i}{M}\right]\right)(1-\gamma)U_{heat,v} \\ + \sum_{v=1}^{n}\gamma^{n-v}\left(\Pi_{i=v+1}^n\left[f_i^{max} - a_D\Gamma_D\frac{\Delta D_i}{M}\right]\right) \\ (1-\gamma\left[f_i^{max} - a_D\Gamma_D\frac{\Delta D_i}{M}\right])\left(\vartheta_{e,v}^{max} + a_\vartheta\Gamma_\vartheta\Delta\vartheta_{en,v}\right)\end{gathered} \tag{28}$$

Eq. (28) and (29) represent the modified dynamic thermal models having the bounded uncertainties, explaining that the water temperature and room temperature will variate in a specific limits under uncertain-but-bounded hot water demand for daily use and ambient temperature respectively. Hence, Γ_D and Γ_ϑ uses to determine uncertain level.

$$\begin{gathered}\vartheta_{AC,n+1}^U(S_{AC,n}, a_\vartheta, \Gamma_\vartheta) = \gamma\vartheta_1 + (1-\gamma)U_{heat} + \\ (1-\gamma)\left(\vartheta_{en,n}^{max} + a_\vartheta\Gamma_\vartheta\Delta\vartheta_{en,n}\right)\end{gathered} \tag{29}$$

To enhance the versatility of electricity production and consumption, different time-varying pricing schemes have been introduced throughout the research body. In this article, the RTP price is taken into account as the time-varying pricing scheme. When analyzing the uncertainties, the WH and AC load scheduling problem is, same as before, to reduce the electricity charges while satisfying comfort constraints with various robust levels and can be written as,

$$min \sum_{n=1}^{N}\sum_{h}^{H} p_n S_{h,n} P_{n,h} \tag{30}$$

$$\vartheta_{WH}^{low} \leq \vartheta_{WH,n+1}^U(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta) \leq \vartheta_{WH}^{up} \tag{31}$$

$$\vartheta_{WH}^{low} \leq \vartheta_{AC,n+1}^U(S_{AC,n}, a_\vartheta, \Gamma_\vartheta) \leq \vartheta_{WH}^{up} \tag{32}$$

$$a_\vartheta \in [0, 1], a_D \in [0, 1], S_{WH,n} \in [0, 1] \tag{33}$$

$$a_\vartheta \in [0, 1], S_{AC,n} \in [0, 1] \tag{34}$$

Above optimization problem formulated from Eqs. (30) to (34) cannot be determined immediately. In order to get the bounds of uncertain hot water temperature and room temperature, it is important to discuss this uncertain optimization problem. So, there is

$$\begin{aligned}&\vartheta^{U}_{WH,n+1}(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta) = \\ &[\vartheta^{min}_{WH,n+1}(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta), \\ &\vartheta^{max}_{WH,n+1}(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta)]\end{aligned} \tag{35}$$

$$\begin{aligned}\vartheta^{U}_{AC,n+1}(S_{AC,n}, a_\vartheta, \Gamma_\vartheta) = [&\vartheta^{min}_{AC,n+1}(S_{AC,n}, a_\vartheta, \Gamma_\vartheta), \\ &\vartheta^{max}_{AC,n+1}(S_{AC,n}, a_\vartheta, \Gamma_\vartheta)]\end{aligned} \tag{36}$$

Hot water temperature for daily use and ambient temperature varies in its interval; hence, the auxiliary parameters like a_D and a_ϑ change. Limits of the interval is computed so that the constraints associated with the uncertainties can be solved,

After a long calculations, we get the below equations from (37) to (40) for WH and AC.

$$\begin{aligned}&\vartheta^{min}_{WH,n+1}(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta) = \\ &\quad \vartheta^{U}_{WH,n+1}(S_{WH,n}, 1, 1, \Gamma_D, \Gamma_\vartheta)\end{aligned} \tag{37}$$

$$\begin{aligned}&\vartheta^{max}_{WH,n+1}(S_{WH,n}, a_D, a_\vartheta, \Gamma_D, \Gamma_\vartheta) = \\ &\quad \vartheta^{U}_{WH,n+1}(S_{WH,n}, 0, 0, \Gamma_D, \Gamma_\vartheta)\end{aligned} \tag{38}$$

$$\vartheta^{min}_{AC,n+1}(S_{AC,n}, a_\vartheta, \Gamma_\vartheta) = \vartheta^{U}_{AC,n+1}(S_{AC,n}, 1, \Gamma_\vartheta) \tag{39}$$

$$\vartheta^{max}_{AC,n+1}(S_{AC,n}, a_\vartheta, \Gamma_\vartheta) = \vartheta^{U}_{AC,n+1}(S_{AC,n}, 0, \Gamma_\vartheta) \tag{40}$$

With such knowledge, the constraint (31) and (32) could be converted into

$$\begin{aligned}&\vartheta^{low}_{WH} \leq [\vartheta^{U}_{WH,n+1}(S_{WH,n}, 1, 1, \Gamma_D, \Gamma_\vartheta), \\ &\vartheta^{U}_{WH,n+1}(S_{WH,n}, 0, 0, \Gamma_D, \Gamma_\vartheta)] \leq \vartheta^{up}_{WH}\end{aligned} \tag{41}$$

$$\vartheta^{low}_{AC} \leq [\vartheta^{U}_{AC,n+1}(S_{AC,n}, 1, \Gamma_\vartheta), \vartheta^{U}_{AC,n+1}(S_{AC,n}, 0, \Gamma_\vartheta)] \leq \vartheta^{up}_{AC} \tag{42}$$

The above mentioned optimization problem formulated as an integer linear programming, and several optimization algorithms, and commercial software are widely accessible to achieve the optimal results. Several heuristics and mathematical optimization techniques have been presented in literature to solve the optimization problems. Mathematical optimization techniques provide exact solution at the cost of high computational complexity and their complexity increases with number of parameters. Heuristic optimization on other hand provide near optimal solution with low computational complexity. For instance, particle swarm optimization (Devaraj et al., 2020), genetic algorithm (Rajesh et al., 2020), teacher learning based optimization (Sharma et al., 2020), Jaya optimization (Manzoor et al., 2020), multi-layer ant colony optimization (Imtiaz et al., 2021), Harris-hawk optimization (HHO) (Heidari et al., 2019), genetic programming (Tahir et al., 2019) and wind driven optimization (RM et al., 2020) have been applied to solve various engineering problems. However, in this work, we used the HHO for the scheduling of TCL while time shiftable appliances are scheduled by the integer linear programming. The proposed technique works well in exploration and exploitation mode. It is mainly works in three stages such as non-hunting stage, searching stage, and lastly global attack stage. The non-hunting stage gives exploration, while the searching stage and the global attack stage carry out the exploitation of promising regions.

4. Result and discussion

The simulation section is divided into various subparts: At first, a sensitivity analysis is carried out to handle the uncertainties associated with hot water demand for daily use and ambient temperature. Additionally, the effects of their changes examine on simulation results. Secondly, a scheduling problem having uncertain data information is optimized by using Harris Hawks Optimization combined with integer linear programming. Further, the energy cost and appliance power consumption pattern under different schemes with different robust levels are also analyzed so that a comparison can make between user comfort and electricity cost.

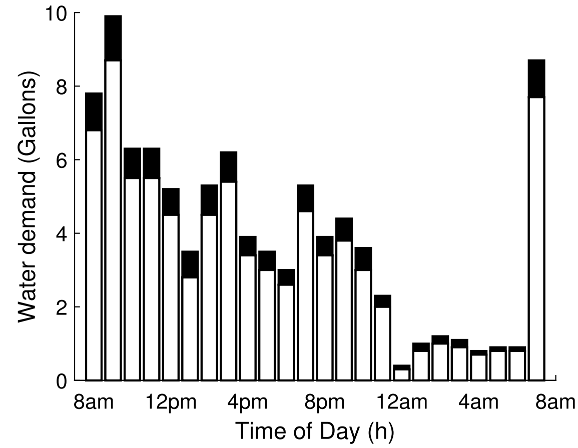


Fig. 4. Hot water demand.

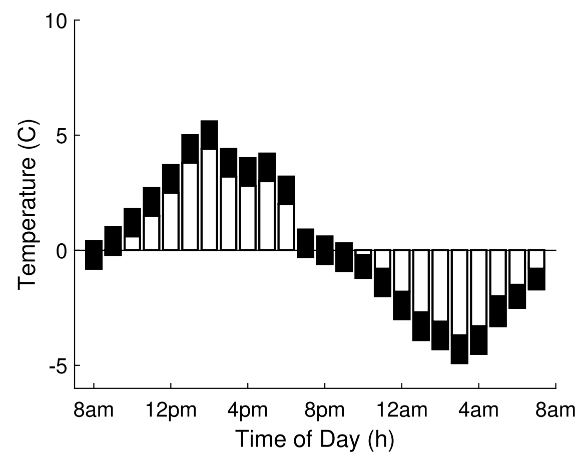
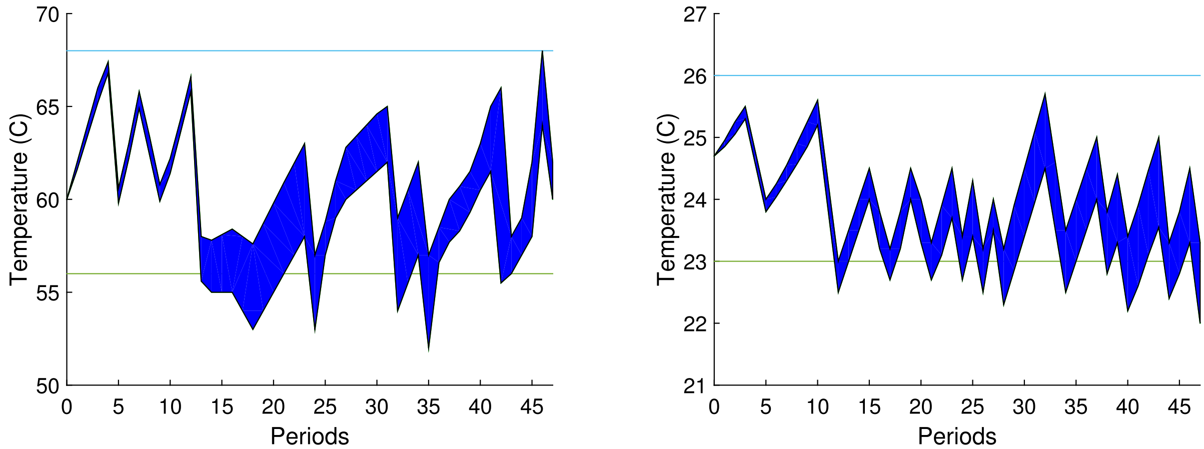


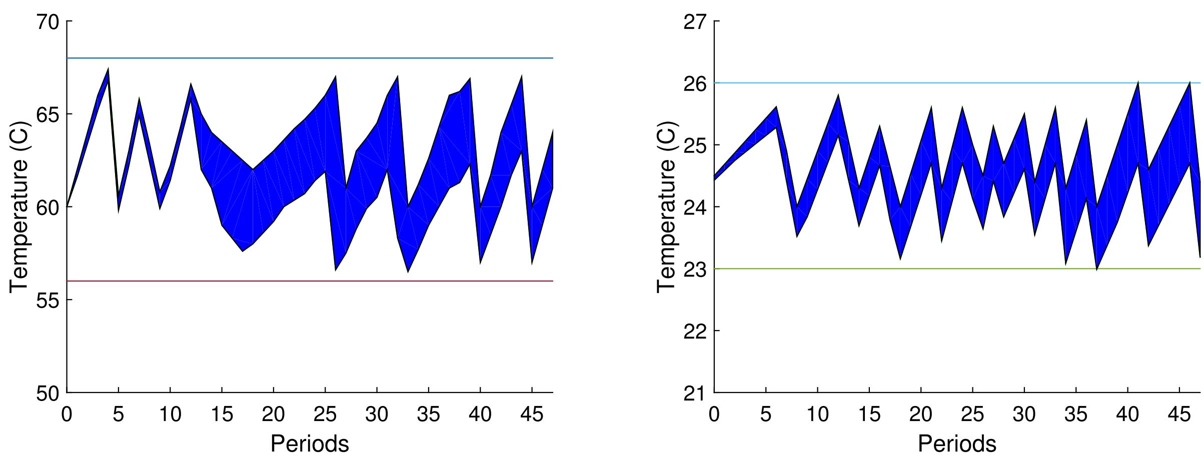
Fig. 5. Ambient temperature interval.

The scheduling time interval begins from 8 a.m to 8 a.m (next day). The length is 30 min of each time step, and demand power, P_{demand}, is 5 kW. Appliances included in this work are WH, AC, DW, WM, and Dryer, and their parameters are given in Tables 1–4. Particularly, parameters of WH and AC are taken from the american society of heating, refrigerating, and air-conditioning engineers (ASHRAE, 2012). Day-ahead real-time electricity price is assumed to be understood and refers to, as shown in Fig. 2 (Sou et al., 2011). Except the controllable loads (appliances), few uncontrollable appliances such as TV and lighting operate throughout the day in a must-run condition. The interval number uses to explain the uncertainties associated with hot water demand for daily use and ambient temperature, and by setting robust levels Γ_ϑ and Γ_D users can quantify the degree of uncertainties. Intervals for hot water throughout the day and ambient temperature are given in Figs. 4 and 5. The maximum values of robust levels, N_ϑ and N_D, are set to six which means uncertainties divides into 6 various levels, meanwhile, both or



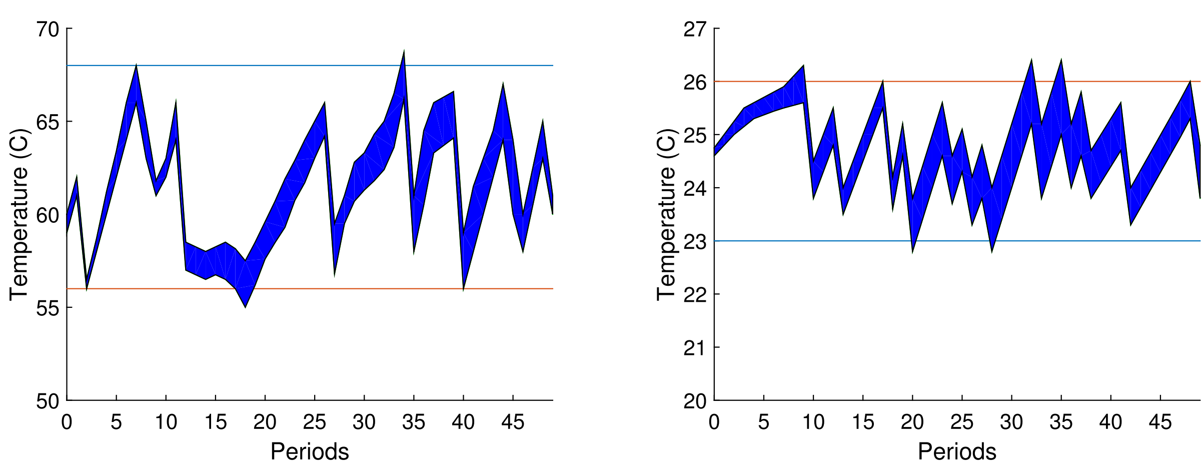
(a) Hot water temperature in tank (b) Room temperature

Fig. 6. Actual temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Hot water temperature (b) Room temperature

Fig. 7. Cost scheme. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Hot water temperature (b) Room temperature

Fig. 8. Trade-off scheme.

one of the robust levels are also taken into account, and set to zero. However, the total number of robust pairs is 7 times 7 into 49.

4.1. Sensitivity analysis

When users consider that the forecasted values are highly reliable, so the robust level values will be (0,0). In this case, there will be no uncertainties exist in both the hot water demand and also in the ambient temperature. Hence, an optimal schedule solves the problem of having no uncertainties, and it is known as a deterministic schedule. But, in practice, the uncertain behavior of hot water need for daily use and the ambient temperature provides large fluctuations of the water temperature. These fluctuations may cause water temperature away from the threshold value.

Hence, it is essential to perform a sensitivity analysis in order to understand the impact of those uncertainties. The robust parameters show the different uncertainty levels; consequently, they apply here to create multiple scenarios that are employed to check the deterministic schedule. Unfortunately, due to certain errors prediction, actual values of water demand and ambient temperature fluctuate as given in Figs. 4 and 5. As variations occur in forecasted and actual values, frequently violations seem in comfort as given in Figs. 6(a) and 6(b).

In Figs. 6(a) and 6(b), the upper surface of the actual water temperature and room temperature curves represent the zero level of uncertainties. While, blue shaded areas express different lower values in which robust pairs adjust in middle of (0,0) to (6,6). The lower surface of water temperature curve represents the maximum uncertainties in which robust level pairs are (6,6). As given in Fig. 6(a), most blue lines are below the threshold line in the time interval 12 p.m. to 9 p.m, which indicates that the users' thermal comfort constraints are violated; hence, the deterministic schedule cannot meet the users' thermal comfort demand. From the threshold value, the water temperature falls down to 52.5 °C, and the variations from the threshold approaches 3.5 °C. Such a large temperature variation is unacceptable for the consumer. Hence, it is vital to determine the uncertainty in load scheduling with robust levels to get a robust solution for uncertainties.

Due to certain errors in forecasting values, actual values of water demand and ambient temperature fluctuate as shown in Figs. 4 and 5. As variations occur between forecasted and actual values, frequent violations observe in the consumer's comfort demand shown in Fig. 6a and Fig. 6b, which is unacceptable. So, robust optimization is adopted to handle the uncertainty in load scheduling with robust levels. Cost and trade-off schemes are proposed with corresponding robust levels to prove the feasibility of the proposed methodology.

4.2. Analysis of cost scheme

When the end-users have strict comfort demands, any violations are not acceptable. This means robust levels of both uncertainties for constraint violation are adjusted as $\Gamma_{\vartheta} = \Gamma_D = 0$. The schedule that shows a conservative attitude for violation of comfort constraint is called a cost scheme. Fig. 7(a) represents the hot water temperature's interval curve, while the interval curve of room temperature depicts in Fig. 7(b). Practically, large uncertainties exist in the requirement of hot water for daily use and for ambient temperature, as shown in Fig. 4 and Fig. 5 respectively. This results in a larger interval of water temperature and room temperature and shaded in blue color in Fig. 7(a) and Fig. 7(b) respectively. Despite this reason, both the room temperature and water temperature are still inside the comfort zone. It shows the robustness of the proposed optimization technique of getting an optimal scheduling scheme, and sill can perform well under a certain level of uncertainties. The experimental results illustrate that the proposed approach efficiently solves the uncertainties related problem while satisfying the consumer's requirements.

4.3. Analysis of trade-off scheme

Due to the high electricity cost under the cost scheme, most of the users do not want to participate in the cost scheme program, while some of them prefer the trade-off scheme. In this scheme, not each value of uncertainties require to be adjusted to 0; however, different values are allotted according to the actual state. Under the trade-off scheme, $\Gamma_{\vartheta} = \Gamma_D = 3$ is considered as a representative, and graphs of requirement of hot water for daily use and ambient temperature are presented in Fig. 8(a) and Fig. 8(b), respectively. As shown in Figs. 8(a) and 8(b), comfort settings for water temperature and room temperature are infringed to specific amount; however, the amount of constraint violation is in control. The interval of the actual hot water temperature lies in between [55,68.50], while the actual room temperature interval is [22.80,25.40]. Additionally, in this scheme, the scheduler can modify the degree of uncertainties for constraint violating according to customer-specific demands.

As the robust level varies, the interval curves become wider and may violate the consumer's comfort need. However, it is observed that all the proposed schemes rigorously satisfying the consumer's comfort demands under corresponding uncertain levels. It describes the great robustness of the proposed schemes while handling various uncertainties levels.

4.4. Time shiftable appliance with operational constraints

The (planned) execution time is from 8 am to 8 am (next day). We consider three time shiftable appliances involving WM, DW, and DM. Domestic customer enforces time preference as discussed in Section 3 under energy and timing constraints. The DW is operated between the start of 8 pm and the end of the day. The WM and DR can be operated anytime between the start of 11 am and 11 pm. But, the WM time stages must be completed before the start of the dryer. The above defines the constraints in Eqs. (18) and (21). Lastly, the peak signal in Eq. (15) is expected to be fixed, and it will be equal to 5500 Wh. Fig. 9 exhibits the power profiles of three controllable smart appliances obtaining the minimum cost. All the optimal scheduling pattern of time shiftable appliances is shown in Fig. 10.

5. Conclusion

This paper introduced a robust optimization method to handle uncertainties associated with the operation of WH and AC, such as daily hot water demand and the ambient temperature. Translating both the intervals and robustness levels into constraints, the reshaped optimization problem was able to analyze the parameter uncertainties and resulted in an efficient scheduling. The proposed approach is analyzed under cost and trade-off schemes and performed well in both the schemes while considering user comfort and electricity cost. The proposed robust optimization proved its robustness in simulation results to handle the uncertainties related to hot water requirement for daily use and ambient temperature.

The robust optimization, with uncertain-but-bounded parameters, can manage the house load scheduling that was overlooked by early optimization techniques. The proposed method did not consider RESs integration, such as wind energy and solar energy.

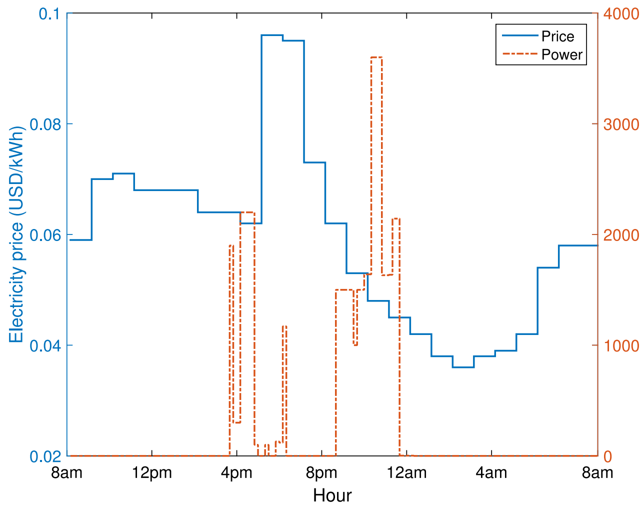


Fig. 9. Total assigned energy and the electricity price.

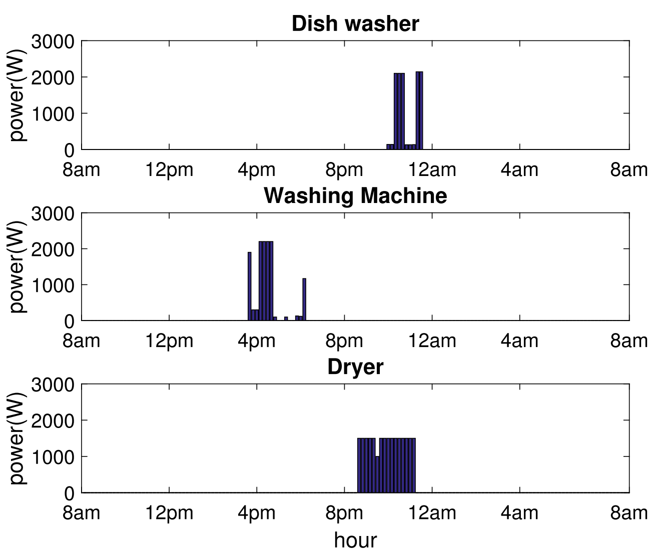


Fig. 10. Schedule of time shiftable appliances.

At present, it is only appropriate for DA load scheduling problems. However, model predictive control uses it to undertake the real-time scheduling problem.

In the future, we plan to investigate the integration of renewable energy sources with load forecasting and weather uncertainties.

CRediT authorship contribution statement

Malik Ali Judge: Methodology, Investigation, Software, Formal Verification, Writing - original draft. **Awais Manzoor:** Conceptualization, Methodology, Software, Formal Verification, Writing - review & editing. **Carsten Maple:** Visualization, Investigation, Resources, Funding acquisition, Writing - Review & Editing. **Joel J.P.C. Rodrigues:** Validation, Data Curation, Resources, Funding acquisition, Writing - review & editing. **Saif ul Islam:** Validation, Formal Verification, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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