# Real-Time Price Based Home Energy Management Scheduler

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***Abstract*—With the recent development of advanced metering infrastructure, real-time pricing (RTP) scheme is anticipated to be introduced in future retail electricity market. This paper proposes an algorithm for a home energy management scheduler (HEMS) to reduce the cost of energy consumption using RTP. The proposed algorithm works in three subsequent phases namely real-time monitoring (RTM), stochastic scheduling (STS) and real-time control (RTC). In RTM phase, characteristics of available controllable appliances are monitored in real-time and stored in HEMS. In STS phase, HEMS computes an optimal policy using stochastic dynamic programming (SDP) to select a set of appliances to be controlled with an objective of the total cost of energy consumption in a house. Finally, in RTC phase, HEMS initiates the control of the selected appliances. The proposed HEMS is unique as it intrinsically considers uncertainties in RTP and power consumption pattern of various appliances. In RTM phase, appliances are categorized according to their characteristics to ease the control process, thereby minimizing the number of control commands issued by HEMS. Simulation results validate the proposed method for HEMS.**

***Index Terms*—Energy demand, home energy management, Markov decision process, real-time electricity price.**

## NOMENCLATURE

| | |
|---|---|
| HEM | Home energy management. |
| HEMS | Home energy management scheduler. |
| RTP | Real-time pricing. |
| RTM | Real-time monitoring. |
| STS | Stochastic scheduling. |
| RTC | Real-time control. |
| CoEC | Cost of energy consumption. |
| SDP | Stochastic dynamic programming. |
| MDP | Markov decision process. |
| $INTRP_{Dj}$ | Interrupt signal from customer for $j$th appliance. |
| $W_{Dj}^{max}$ | Maximum waiting time of $j$th appliance. |
| $W_{Dj}^{initial}$ | Initial waiting time of $j$th appliance. |
| $t_{Dj}^{connect}$ | Plug in time of $j$th appliance. |
| $\pi_n$ | RTP of electricity at $n$th time instant. |
| $M_{Dj}^{n}$ | Operating statuses of $j$th appliance $n$th time such as *WAIT*, *OPERATION*, *SKIP*, and *ADJUST*. |
| $P_{Dj}^{n}$ | Power consumption of $j$th appliance at $n$th time. |
| $P_{Dj}^{rating}$ | Rated power of $j$th appliance at $n$th time step. |
| $P_{n}^{total}$ | Total power consumption of a house at $n$th time. |
| $C_{n}^{total}$ | Total CoEC of a house at $n$th time instant. |
| $C_{n}^{Aq}$ | Total CoEC at $n$th time instant and $q$th action. |
| $N_{ij}^{Aq}$ | Number of days for a specific state change from $i$ to $j$ at $q$th action. |
| $\lambda_n$ | Policy mapped from value function at $n$th time. |
| $V_\lambda$ | Value function as a mapping of states in MDP. |
| $\zeta_{max}^{intrp}$ | Appliance's maximum number of interruptions. |
| $\beta_{n}^{Dj}$ | Constants representing operating status of $j$th appliance at $n$th time instant. |
| $Tr$ | Transitional probability. |
| $\alpha$ | Coefficient related to reward function. |

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## I. INTRODUCTION

ENERGY retailers in most electricity markets, provide a fixed electricity tariff scheme for customers, independent of the cost of electricity generation during the time of consumption. However, the true opportunity cost of electricity consumption varies with the marginal cost of electricity production. This causes inelastic behavior in customer electricity demand within short time frames which may ultimately lead to losses for both retailers and customers during adverse conditions such as price spikes/falls [1].

Introducing a time varying electricity retail price, known as real-time pricing (RTP) is one of the solution. The concept of RTP was introduced long back, but it has been only recently possible for practical implementation due to vast technological improvements in advance metering infrastructure [2], [3]. RTP provides benefit to retailers by reflecting marginal cost of production and encourages customers to control their electricity consumption [4]. Smart meters and in-home display units aim to help customers in reducing their cost of energy consumption (CoEC) and control their appliances on a regular basis [5]. However, due to uncertainty in price variation and electricity demand, appropriate control of appliances is cumbersome.

A home energy management (HEM) system helps residential customers to respond to RTP by reducing CoEC [6]. Authors in [7]–[9] have proposed a real-time HEM system with a complex scheduler, using "particle swarm optimization", "genetic algorithm" and "linear optimization techniques". However, the uncertainties in RTP of electricity or the power consumption of appliances are not considered during their appliance scheduling processes. Authors in [10], whereas, propose a decision support tool using linear programming optimization and a price predictor to get hour ahead price information and plan the upcoming energy consumption. However, the predicted price is not included in the optimal scheduling of appliances. This problem is mitigated by [11] and [12], where a predictive tool along with real-time optimization is proposed. Nevertheless, the real-time optimization and control along with predictive techniques is a difficult task and may lead to less accurate results

In another study, stochastic optimization with an objective of minimizing expected electricity payment using Monte Carlo simulations [13] and Markov decision process (MDP) [14], [15] is proposed. The uncertainty in RTP is incorporated via expected downside risk [13] and price prediction noise [14]. MDP is used at individual appliance level in [14] with an objective of reducing the appliance's energy consumption cost. The optimal time slots that can be used for appliance operation are found. Similarly in [15], appliances are scheduled individually using MDP to find the optimal appliance switching statuses. However, uncoordinated MDP at appliance level may lead to sudden increase in the cost of energy consumption at house level (i.e., sudden operation of several appliances may lead to an increased cost of consumption). Authors in [16] developed a hardware design for HEM system to reflect the RTP variations. They use machine learning algorithm with hidden Markov chain to incorporate uncertainties in both RTP and customer behavior. However, the stochastic appliance scheduling process needs to be defined well.

*Contributions:* The objective of this paper, therefore, is to find the optimal way of scheduling the appliances to minimize the CoEC and hence proposes home energy management scheduler (HEMS). This paper is unique from [7]–[14], as it considers the uncertainties in both RTP and residential appliance power consumption pattern during appliance scheduling. Unlike [14] and [15], a top down approach from house to appliance level is taken, i.e., a set of appliances are selected optimally for control based on their stochastic behavior, with an overall objective of reducing the total cost of energy consumption in a house. The proposed HEMS works in three subsequent phases, i.e., real-time monitoring (RTM), stochastic scheduling (STC), and real-time control (RTC).

*Synopsis:* In Section II, the proposed HEMS is described. The operation of HEMS with these three subsequent phases is summarized in Section III. A test system description and simulation results are presented in Section IV followed by conclusions in Section V.

## II. Proposed HEMS Using SDP

This section introduced a new HEMS using SDP and can be deployed in houses. Retailers bid in the wholesale electricity market on a day-ahead/real-time basis to cater their load demand. The customers/end-users, whereas, have a choice to either take fixed price or RTP based tariff from demand aggregator or retailer. In some cases, the demand aggregator uses RTP signal from retailers and provide demand-response/load-reduction by adjusting customers' load and provide coupons/incentives in return. Although promising, this method may not be attractive to the customers who want to have the flexibility to modulate their loads themselves and be rewarded accordingly.

This paper, therefore, proposes RTP signals (from either demand aggregators or retailers) to be send directly to customers/end-users to adjust the loads themselves, giving them flexibility to choose the level of load adjustments and achieve the reduced cost of energy consumption. The optimal decision to control the appliance is taken by HEMS in order to reduce the cost of energy consumption. Appliance control process is performed by HEMS at house level where every HEMS in a network are remotely connected to the utility to obtain RTP information. Therefore, network size is not an issue for practical implementation due to the independent operation of HEMS. It has better performance than a centrally controlled algorithm for residential appliances in a large network which may raise scalability issue.

The functionality of HEMS and retailer/utility and demand aggregator interference can be summarized using Fig. 1. In this paper, seven controllable appliances including water heater (WH), air conditioner (AC), electric vehicle (EV), dish washer (DW), cloth washer (WA), cloth dryer (DR), and swimming pool pump (PP) are connected through HEMS and the uncontrollable appliances are directly connected to utility. The proposed HEMS works in three subsequent phases, i.e., RTM, STS and RTC and can be summarized in Fig. 2. In RTM phase, HEMS monitors appliance characteristics and data is processed to make it ready for the STS phase, where SDP is used for scheduling appropriate appliances. In RTC phase, HEMS takes appropriate actions on the selected loads. The dispatch of RTP signal can be done every 5/15/30 min depending on the local distribution network and market arrangement. This paper assumes that RTP signal is available every 5 min and hence the proposed process is repeated every 5 min. The three phases are described below in detail.

Flow chart of the overall control process is summarized in Fig. 3. At each time step, real-time price and the total energy consumption of a house is observed to compute the cost of energy consumption. If the CoEC exceeds a predetermined limit, RTM, STS, and RTC phases are triggered subsequently. (The limit of CoEC is predetermined as the average of maximum CoEC of a house.) This is necessary to reduce the number of control commands, which in turn will affect the longevity of various appliances.

The current state of CoEC is mapped with the policy values to obtain optimal action or schedule of curtailment. Transition

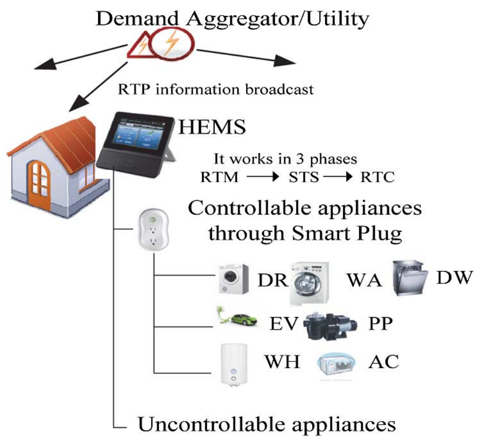


Fig. 1. Descriptive diagram of HEMS and utility interference.

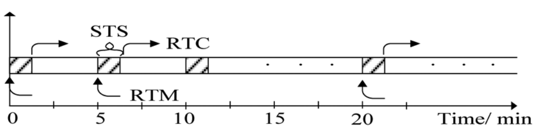


Fig. 2. Timing diagram of control process.

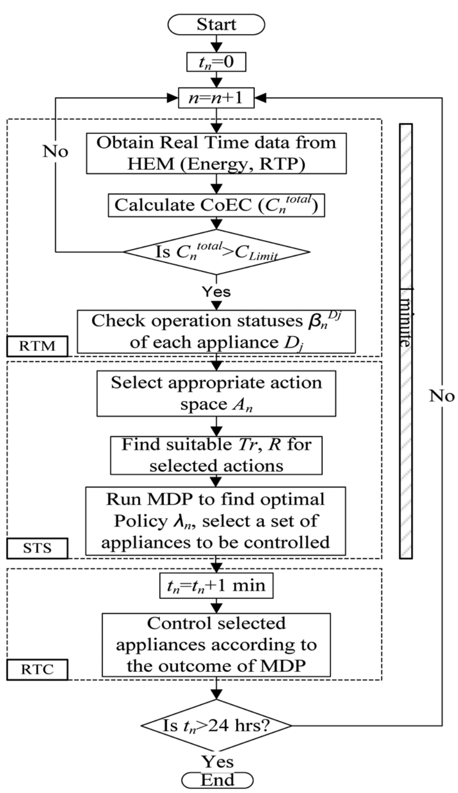


Fig. 3. Operation of HEM Scheduler with RTM, STC, and RTC phases.

and reward blocks help to run MDP for the above computation. After 1 min, the selected appliances are controlled or switched off. This process is repeated every 5 min (same as RTP update) to have an optimal control of appliances to reduce the cost of consumption. The terms Transition probability $(Tr)$, Reward $(R)$, Action $(A)$, Policy $(\lambda)$ at $n$th time step are elaborated in detail later in this paper.

## A. Real-Time Monitoring (RTM) Phase

In RTM phase, the RTP and Appliance data is collected, which can be used in STS phase. RTM phase is vital as it provides the currents statuses of the appliances which is used to predict the optimal set of appliances for control in the next time step. Based on appliances characteristics, they can be classified into three categories namely *Cat1*, *Cat2*, and *Cat3*:

- *Cat1*: Appliances that can be delayed for a certain time such as DW, WA, DR, and PP.
- *Cat2*: Appliances whose operation schedule depends on its charging characteristics such as EV.
- *Cat3*: Appliances that can be adjusted with the change in the temperature set point such as WH and AC.

Customers have flexibility to specify whether an appliance can be interrupted or not, i.e., Appliance $D_j$ with signal $INTRP_{Dj}$ = '$True$' or "*False*". Furthermore, maximum number of interruptions $(\zeta_{max}^{intrp})$ of a particular appliance is maintained below 'two' to prevent adverse effect on life span of the appliance. Depending on the appliance category (*Cat1/Cat2/Cat3*), the operating status of appliances (*WAIT/OPERATION/SKIP/ADJUST*) is determined. Descriptions of various statuses are as below:

- Appliances which are connected to HEMS but not in operation are in status "*WAIT*"
- Appliances which are already in operation are in status "*OPERATION*"
- Appliances which should not be controlled at a particular time due to constraints are in status "*SKIP*"
- Appliance which can be adjusted with its set point is in status "*ADJUST*"

The algorithm provides less possibility of interruption to the appliances which are in "*OPERATION*" and "*ADJUST*" status during STS whereas appliances in "*WAIT*" status have higher possibility to be controlled. Appliances' lifespan is reduced and customers' comfort is affected when operating appliance are interrupted. Therefore, the rationale is to avoid interrupting those appliances which are in operation. Appliances that are waiting to be connected, whereas, can be delayed up to maximum allowable time and hence are suitable for control. The three categories (*Cat1/Cat2/Cat3*) of appliances and the decision for corresponding operating status (*WAIT/OPERATION/SKIP/ADJUST*) are discussed further.

*Cat1 and Cat2 Appliances:* Maximum allowable waiting time or delay $(W_{Dj}^{max})$ of a corresponding appliance $D_j$ under *Cat1* is specified by the customer. Customer also specifies departing time $(t_{dept})$ and charging status of electric vehicle (*Cat2*) which helps to calculate maximum possible delay of electric vehicle. Slow $(CH_1)$ and normal charging $(CH_2)$ are the two possible charging statuses. The maximum allowable delay for electric vehicle can be calculated using (1)–(3) as follows:

$$\Gamma_{total}^{CH_k} = \frac{E_{no\min al}}{P_{ch\arg ing}^{CH_k}} \tag{1}$$

$$\tau_{remaining}^{CH_k} = (1 - SOC_{initial}).\Gamma_{total}^{CH_k} \tag{2}$$

$$W_{D_j}^{\max} = t_{dept} + \left(24 - t_{D_j}^{connect}\right) - \tau_{remaining}^{CH_k}. \tag{3}$$

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Charging cycle duration ($\Gamma_{total}^{CHk}$) of a battery can be obtained by dividing the nominal capacity ($E_{nominal}$) of the battery by charging power ($P_{charging}^{CHk}$) for the $k$th charging status as in (1). Remaining charging time ($\tau_{remaining}^{CHk}$) can be calculated as in (2). Here, $SOC_{initial}$ is the initial state of charge (SOC) of the battery when electric vehicle is plugged in to HEMS. Here, evolution of SOC of the battery is considered to have linear relationship with time while charging [17]. Maximum allowable waiting time of electric vehicle is calculated as in (3). Here, $t_{Dj}^{connect}$ is the time when electric vehicle is plugged in to HEMS. Status of appliances in *Cat1* and *Cat2* are determined using Algorithm 1.

When appliance, $D_j$, is plugged in to HEMS at time $t_{Dj}^{connect}$ ($t_{n-1} < t_{Dj}^{connect} < t_n$), it should wait until the next time step $t_n$. The initial waiting time before connecting the appliance is denoted as $W_{Dj}^{initial}$. If an appliance is still waiting to be connected at time $t_n$, it should be assigned "*WAIT*" status. This is valid irrespective of customer input, $INTRP_{Dj}$. If plug in time, $t_{Dj}^{connect}$, of an uninterruptible appliance is before $t_{n-1}$, it means that the appliance is already in operation which should not be interrupted and hence is assigned "*SKIP*" status. Whereas, if $t_{Dj}^{connect}$ is less than earlier time step $t_{n-1}$ and if total waiting time ($W_{Dj}$) and number of interruptions ($\zeta_{Dj}^{intrp}$) are within limits, then appliance $D_j$ can remain in the previous status (i.e., it can be delayed further until limits are not exceeded). When limits for $W_{Dj}$ and $\zeta_{Dj}^{intrp}$ are exceeded, appliance is considered in "*SKIP*" status.

**Algorithm 1** (Cat1 and 2)—Determine status $M_{D_j}^n$ of appliance $D_j$ at time $t_n$

**input** $W_{Dj}^{\max}, INTRP_{D_j}, t_{D_j}^{connect}$

**if** $INTRP_{D_j} = False$

if $t_{n-1} < t_{D_j}^{connect} < t_n$

$M_{D_j}^n = WAIT, W_{D_j}^{initial} = t_2 - t_{D_j}^{connect}$

elseif $t_{D_j}^{connect} < t_{n-1}$

$M_{D_j}^n = SKIP$

**elseif** $INTRP_{D_j} = True$

if $t_{n-1} < t_{D_j}^{connect} < t_n$

$M_{D_j}^n = WAIT, W_{initial} = t_2 - t_{D_j}^{connect}$

elseif $t_{D_j}^{connect} < t_{n-1}$ and $0 \leq W_{Dj} < W_{A_j}^{\max}$ and $\zeta_{D_j}^{\text{intrp}} \leq \zeta_{\max}^{\text{intrp}}$

if $M_{D_j}^{n-1} = WAIT$ then $M_{D_j}^n = WAIT$

if $M_{D_j}^{n-1} = OPERATION$ then $M_{D_j}^n = OPERATION$

elseif $t_{D_j}^{connect} < t_{n-1}$ and ($W_{Dj} > W_{D_j}^{\max}$ or $\zeta_{D_j}^{\text{intrp}} > \zeta_{\max}^{\text{intrp}}$)

$M_{D_j}^n = SKIP$

end

**Algorithm 2** (Cat3)—Determine status $M_{D_j}^n$ of appliance $D_j$ at time $t_n$

**if** $P_{D_j}^n > 0$ and $INTRP_{D_j} = True$

$M_{D_j}^n = ADJUST$

**elseif** $P_{D_j}^n > 0$ and $INTRP_{D_j} = False$

$M_{D_j}^n = SKIP$

*Cat3 Appliances:* Thermostatically controllable appliances such as WH and AC are considered in this category. Variation of water temperature is modeled using (4). First, second, and third terms in (4) represent compensation of thermal losses to ambient, process of heating inlet cold water replacing used hot water and input heat energy, respectively [18]:

$$C\frac{dT_w(t_n)}{dt_n} = SA^*U\left(T_a(t_n) - T_w(t_n)\right) + H_d(t_n).\rho.\psi_p. \left(T_{in} - T_w(t_n)\right) + K_{wh}(t_n).Q_{wh} \quad (4)$$

where $T_w(t_n)$ is water temperature at time $t_n$, $T_a$ is ambient temperature, $T_{in}$ is inlet cold water temperature, $SA$ is surface area of the tank, $U$ is standby heat loss coefficient, $H_d$ is water consumption rate, $\rho$ is density of water, $\psi_p$ is specific heat of water, $K_{wh}$ is binary signal for thermostat settings, and $Q_{wh}$ is energy input rate of WH:

$$\frac{dT_{room}(t_n)}{dt_n} = \frac{U_a}{\psi_{ac}}\left(T_a(t_n) - T_{room}(t_n)\right) + \frac{H_m}{\psi_{ac}}\left(T_m^n - T_{room}(t_n)\right) + \frac{Q_{ac}}{\psi_{ac}}K_{ac}^n. \quad (5)$$

Furthermore, thermodynamic equation for AC is shown in (5). Here, $T_{room}(t_n)$ is the room temperature at time $t_n$. $U_a$-heat loss coefficient, $\psi_{ac}$ is equivalent heat capacity, $H_m$-interior mass conductance of the house, $Q_{ac}$ is energy input rate of AC, and $K_{ac}$ is binary signal for thermostat settings [19]. For *Cat3* appliances, if customer input, $INTRP_{Dj}$, is false, then the set point is adjusted to reduce for power consumption of the appliance and is assigned "*ADJUST*" status. Otherwise, appliance is assigned "*SKIP*" status. This is summarized in Algorithm 2.

### *B. Stochastic Scheduling (STS) Phase*

Although, real-time monitoring of appliances' usage and price information gives the details of current status of various appliances, it is not sufficient to make a decision for appropriate selection. It is due to uncertainties in electricity price variation, appliance operation, user behavior and preferences. Hence, STS includes the uncertainties in decision making at each control time step. This phase helps in identifying the appropriate appliances to be controlled.

*Stochasticity in RTP and Demand of Electricity:* An infinite horizon discrete time dynamic model is formulated for the stochastic control process where time steps are indexed by $\{n = 0, 1, 2, \ldots\}$. This scheduling problem focuses on CoEC at each time step. The total CoEC ($C_n^{total}$) of a house at the $n$th time step from $t_{n-1}$ to $t_n$ is the product of RTP of electricity, $\pi_n$, total power consumption, $P_n^{total}$, and the time step, $dt$, i.e., $(t_n - t_{n-1})$ as shown in (6):

$$C_n^{total} = \pi_n.P_n^{total}.dt \tag{6}$$

$$P_n^{total} = \sum_{j=1}^{N} P_n^{D_j} + P_n^{other}. \tag{7}$$

Here, total power consumption, $P_n^{total}$ at the $n$th time step is calculated as in (7). It is the sum of power of adjustable $(\Sigma P_n^{Dj})$ and non-adjustable $(P_n^{other})$ appliances.

CoEC is considered as a time varying stochastic variable and its behavior is analyzed in this study. Initially, a discrete time stochastic process for $C_n^{total}$ is created as $C^{total} = \{C_n^{total}, n = 0, 1, 2, \ldots\}$, where $C_n^{total} \in S$. A set of states is represented by $S = \{S_k, k = 1, 2, \ldots k_{max}\}$ for the above stochastic process. The $k$th state $S_k$ (for all$k$) is defined by a range of predefined CoEC in a house so that $C_n^{total}$ lies within a range of a particular state $S_k$. Let us consider discrete cost variables $\{C_0^{total}, C_1^{total}, C_2^{total}, \ldots\}$ to occupy a value in a set of states $S$. The sequence of $C^{total} = \{C_n^{total}, n = 0, 1, 2, \ldots\}$, is considered as a Markov chain as the future CoEC is independent of the past CoEC, conditioned on the present value. It can be further elaborated by a transition probability, i.e., if the chain is in state, $S_x$, the transition probability, $Prob_{xy}(n+1)$, represents how the chain chooses to jump to next state, $S_y$, at the time step $(n+1)$ as in (8):

$$\text{Prob}_{xy}(n+1) = \text{Prob}\left(C_{n+1}^{total} \to S_y | C_n^{total} \to S_x\right). \tag{8}$$

As CoEC satisfies dynamics of Markov dependent structure, MDP is a suitable method for optimal scheduling of appliances within a house [20], [21]. MDP can be defined as five tuples $< L, S, A, Tr, R >$, where $L$ represents length of planning horizon, $S$ is a finite state space of discrete states reflecting CoEC, $A$ is for a finite action space and $Tr :\to Prob(S)$, is a transition function describing probability of distribution of next states as in (8). Further, $C^{total} : SxA \to R$ is cost of executing an action in a state and it represents $R$, which is a state dependent reward function.

*Problem Formulation:* MDP is used to minimize CoEC via optimal scheduling of appliances. Expected outcome of this process is optimal STS of appliances. An infinitely repeated 24-h cycles are considered and is discretized into intervals of 5 min with a time horizon of $n = \{1, 2, 3, \ldots\}$.

*State Space:* State space is defined to replicate a range of CoEC. For this purpose, CoEC of a house is observed at every time step for an entire season. A probability density function for $C_{total}$ is formed to define boundaries of CoEC for states from the data obtained. $B_k$ and $B_{k+1}$ are boundaries for CoEC for the $k$th state, $S_k$ as defined in (9):

$$S_k = [B_k, B_{k+1}) = \left\{C^{total} | B_k \le C^{total} < B_{k+1}\right\}. \tag{9}$$

Boundaries $B_k$ and $B_{k+1}$ can be found by cumulative distribution function (CDF) of CoEC. It is considered as 50%, 10% for $k = 1$ and $k = \{2, 3, 4, 5, 6\}$, respectively, as in Fig. 4 and the state space is defined as $S = \{S_k, k = 1, 2, \ldots, 6\}$.

*Action Space*: An action space $A_n$, contains a set of actions $A_n^q : S \to \sigma(A_n)$. $A_n^q(S_k) \subseteq A_n$ denotes the $q$th set of actions that can be applied in the $k$th state, $S_k$, at the $n$th time instant. $\sigma(A_n)$ is power set of the action space $A_n$. An action is considered as a set of appliances that can be curtailed at a given time step.

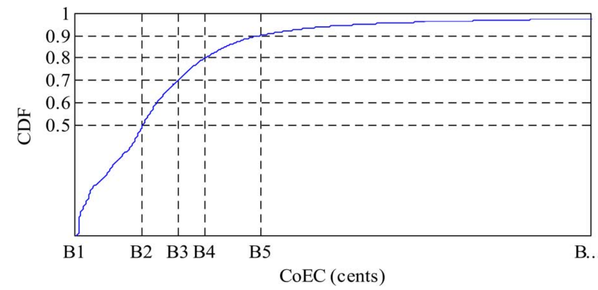


Fig. 4. Defined boundaries of states.

Consider a set $D$, consisting of $N$ number of controllable appliances in a house as in (10). A subset $D_n^{av}$ can be defined as the available appliances connected to HEMS at the $n$th time instant. Then, an action, $A_n^q(S_k)$ (i.e., a set of possible curtailment of appliances), is defined as a subset of $D_n^{av}$ as in (11). The power set, $\sigma(A_n)$, denotes number of all possible subsets of $D_n^{av}$ or number of actions as in (12):

$$D = \{D_1, D_2, \ldots\ldots D_N\}; \quad D_n^{av} \subseteq D \tag{10}$$

$$A_n^q(S_k) \subseteq D_n^{av} \tag{11}$$

$$\sigma(A_n) = 2^{\eta(D_n^{av})}. \tag{12}$$

In this study, seven $(N = 7)$ controllable appliances are considered in a house. For instance, if two appliances $D_4$ and $D_6$ are connected to HEMS at the $n$th time step, then $D_{av}^n = \{D_4, D_6\}$, $\eta(D_n^{av}) = 2$ and $\sigma(A_n) = 2^2$. Hence, four actions are possible which are $\{\}$, $\{D_4\}$, $\{D_6\}$ and $\{D_4, D_6\}$. Empty set $\{\}$ represents action of no curtailment. $\{D_4\}$ and $\{D_6\}$ represents when only one appliance, either $D_4$ or $D_6$, is selected for curtailment, respectively. When both appliances are selected, action $\{D_4, D_6\}$ is possible.

*Transition Probability:* Transition function is a function of probability that CoEC jumps from state $S_x$ to $S_y$ at the $(n+1)$th time step during the $q$th action and is defined as $Tr : SxAxS \to Prob_{n+1}(S_y|S_x, A_nq)$,[0,1]. As the probability depends on states and actions, an action and state dependent transition probability block is defined. Initially, daily power consumption profile of each appliance in a house is observed for a particular season. Daily variation of RTP is also observed for the given time frame. Then, Algorithm 3 is repeated for each action to calculate transition probabilities as summarized below. Algorithm 3 starts with the calculation of CoEC $(C_n^{Aq})$ at $n$th time step for $q$th action as defined in (13):

$$C_n^{A_q} = \pi_n \left\{ \left( P_n^{total} - \sum_{j=1}^{N_{A_q}} P_n^{Dj} \right) .dt \right\}. \tag{13}$$

Here, sum of power of appliances that can be curtailed during the $q$th action is subtracted from total power consumed $(P_n^{total})$ to find total power consumption during the $q$th action. This value is multiplied by $\pi_n$ and $dt$, the RTP and length of time interval, respectively, to obtain $C_n^{Aq}$. Here, $N_{Aq}$ is the

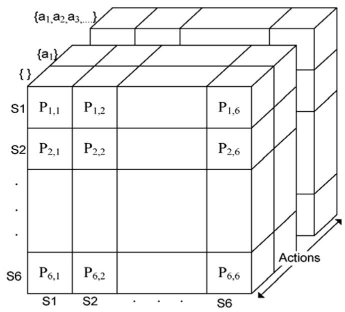


Fig. 5. Block of transition probability $(Tr)$.

number of appliances in the $q$th action. State change of $C_n^{Aq}$ at the $q$th action from $S_x$ to $S_y$ from subsequent time steps $n$ and $n+1$ are observed on daily basis. Number of days is counted for this specific jump $(N_{ij}^{Aq})$. It is divided by the total number of days where states changes from $S_x$ to the other states $S_k$ from 1 to 6. $(\sum N_{ik}^{Aq})$ to obtain the transition probability $Prob_{n+1}(S_y|S_x, A_n^q)$. This process is repeated at each time step. Further, Algorithm 3 is repeated for each action to obtain the transition probabilities of all possible state changes or jumps for the whole action space and is shown in Fig. 5.

**Algorithm 3**—Computation of transition probability block

fortime $t_n = 0$ to 24hrs(4minincrement)
initializecount $N_{ij}^{A_q} = 0$
    forday $d = 1$ to 90
    Calculate CoEC $C_n^{A_q}(d)$ as in (18)
        for state $i = 1$ to 6
            for state $j = 1$ to 6
                if $C_n^{A_q}(d) \in S_i \cap C_{n+1}^{A_q}(d) \in S_j$
                $N_{ij}^{A_q} = N_{ij}^{A_q} + 1$
                end if
            end for loop of state $j$
            $\Pr ob_{n+1}(S_j|S_i, A_p) = N_{ij}^{A_q} / (\sum_{k=1}^{6} N_{ik}^{A_q})$
        end for loop of state $i$
    end for loop of day $d$
end for loop of time $t_n$

*Reward Function:* Accurate definition of reward function $(r_{xy}^{Aq} \in R)$ is vital in MDP due to its importance in decision making. It helps to choose best possible action, $A_n^q$, for appropriate selection of appliances. A reward value is defined as in (14), which is four tuples,$< S_i/S_j, \beta_k, P_k, W_k >$ as follows.

1) Reward component 1 $(S_i/S_j)$—Ratio of state change from $S_x$ to $S_y$ as an effect on jumps from one state to another. Purpose of this component is to provide less reward for a state changing from low to high value (for $i < j$) and to provide more reward for a state changing from high to low value (for $i > j$). As an effect of this reward component, an action which causes furthest state change from high to low value will be chosen.
2) Reward component 2 $(\beta_n^{Dj})$—Status of appliances which are "*WAIT*"/"*OPERATION*"/"*ADJUST*". Appliance in "*WAIT*" status is given with a higher reward value comparing to the other statuses "*ADJUST*" and "*OPERATION*". In our study, values for $\beta_n^{Dj}$ for *WAIT*, *OPERATION*, and *ADJUST* are considered as 1, 0.5, and 0.75, respectively. Purpose of appliance status $\beta_n^{Dj}$ in reward function is to prioritize appliances which are in "*WAIT*" status and still not in operation rather than appliances which are in operation. It allows in maintaining appliance comfort and reduces the possibility of appliances being interrupted in the middle of their operation.
3) Reward component 3 $(\sum P_{Dj}^{rating})$—Summation of power ratings of appliances, involved in a particular action. Reward depends on the availability of power curtailment in a particular action. Purpose of this component is to provide higher reward for an action with more curtailment of loads comparing to actions with less curtailment of loads. Therefore, an action with highest available power for curtailment will be prioritized for control.
4) Reward component 4 $(1 - W_{Dj}^n / W_{Dj}^{max})$—A function of waiting time of an appliance. Appliance which is delayed more is considered to have less reward comparing to appliance which is delayed less. Time varying term $(1 - W_{Dj}^n / W_{Dj}^{max})$ provides this function. Here, $W_{Dj}^{max}$ is the maximum allowable waiting time of appliance $D_j$. Purpose of this component is to prioritize appliance which is delayed less comparing to other appliances which are delayed more. As an effect, appliance that can be sufficiently delayed is chosen to be controlled:

$$r_{xy}^{A_q}(n) = \begin{cases} \alpha \frac{S_x}{S_y} \sum_{j=1}^{N_{A_q}} \beta_n^{D_j}.P_{D_j}^{rating}.\left(1 - \frac{W_{D_j}^n}{W_{D_j}^{\max}}\right) & (\forall A_n \cap \{\} \notin A_n) \\ \alpha \frac{S_x}{S_y} & A_n^q = \{\}. \end{cases} \quad (14)$$

Coefficient $\alpha$ is chosen by utility according to their requirement. However, when there is no curtailment (i.e., $A_n^q = \{\}$), reward is considered only as the ratio of jump in states. Overall, reward function is designed so that it provides benefit to customer by satisfying their need and by reducing cost.

*Markov Decision Process (MDP):* Objective of MDP in this study is to maximize the reward function, so that HEMS minimizes CoEC. Reward of execution $(R)$ is the sum of all rewards along the path from $S_{initial}$ (initial state) to the first goal state. $S_G \subseteq$ S is the set of goal states (i.e., $S_g^G \subseteq S^G$ which terminates an execution) [22]. Here, transitions are managed stochastically by transition block, $Tr$. A policy $\lambda_n : S \rightarrow A_n$ is defined as a mapping from state space $S$ to action space $A_n$ and at $n$th time step, an optimal action is mapped to all possible states. An optimal policy $(\lambda_n^* : S \rightarrow A)$ is obtained from MDP. A value iteration algorithm is used to evaluate optimal policy to satisfy the objective. Algorithm 4 explains the value iteration and is summarized below.

The value function is initialized based on dynamic programming. A value function is defined as a mapping from state $S(V_\lambda : S \rightarrow R)$ as in (15). Bellman operator is used to update the values iteratively for having successive approximation at each state per iteration. A Bellman equation related to value functions with an objective function is created as in (16) using reward and transition blocks. Dynamic-programming algorithm is used to search the solution space by using the recursive structure of the Bellman equation which is more efficient than exhaustive-search algorithms.

**Algorithm 4—Value Iteration**

**Input a MDP** $=< S, A_n, Tr, R >$,$\delta$ **threshold value**

**Initialize** $V$, $Bellman\ error_{initial} (> \delta)$

$Bellman\ error_{initial} \leftarrow Bellman\ error$

**While** $Bellmanerror > \delta$

**for each state** $S_y \in S$

$V_{prev} \leftarrow V(S_y)$

$V(S_y) = \max\limits_{a \in A_q(S_y)} [R(S_y, A_q) + \sum Tr_{A_q}(S_y|S_x)V^*(S_x)]$

$Bellman\ residual(S_y) = |V(S_y) - V_{prev}|$

$Bellman\ error \leftarrow \max(Bellman\ error, Bellman\ residual(S_y))$

**end while**

**return** $V$

Here, a Bellman residual of a state is defined as the absolute difference of a state value before and after Bellman operation. Value iteration stops after convergence. The largest Bellman residual of all states becomes less than a predefined threshold $\delta$. Finally, optimal policy is obtained from value function is as in (17). In real-time, if CoEC lies in state $S_y$, the optimal action mapped in the proposed policy will be chosen for control. Ultimately, optimal policy gives the optimal curtailment schedule of appliances shown in (15)–(17) at the bottom of the page.

### C. Real-Time Control (RTC) Phase

In RTM phase, the status of appliances are determined which helps to find the optimal policy or the optimal action with a set of selected appliances in STS phase. Then in RTC phase, HEMS send signals to adjust selected set of appliances. Fig. 6 illustrates the change in operating statuses of *Cat1* and *Cat2* appliances. Appliances can be in any of the five conditions as shown in Fig. 6 (conditions represent "*if*" clauses in algorithm 1). **Condition 1** shows an appliance connected to HEMS within time $t_{n-1}$ to $t_n$ and identified to be in "*WAIT*" status during RTM. It has an initial waiting time of $W_{initial}$. If this appliance is selected for control during RTC, it will be delayed for another 5 min. Hence, operating status of this appliance again becomes "*WAIT*". This is true irrespective of customer input "*INTRP*". Then, at next time step, $t_{n+1}$, utility connects this appliance in offline STS program to check whether reconnection is possible. If reconnection is possible at $t_{n+1}$, appliance is connected, otherwise, it is delayed until next time step. **Condition 2** shows appliances which cannot be interrupted in the middle and are already in operation during RTM. Then, it is considered to be in "*SKIP*" status and continuously connected to utility without subjecting to RTC. **Condition 3** shows appliance in "*OPERATION*" status during RTM. If this appliance is chosen to be controlled, it is interrupted after 1 min from a time step for next 3 min and goes to "*WAIT*" status after RTC. **Condition 4** illustrates an appliance which is already delayed in time step $t_{n-1}$ and is in "*WAIT*" status. If the maximum waiting time and maximum number of interruptions are not exceeded, it can be further delayed at $t_n$ and again stays in "*WAIT*" status. **Condition 5** shows an appliance already in "*WAIT*" status during RTM. It will be reconnected during RTC and will go into "*SKIP*" status if and only if the maximum limits for waiting time and interruptions are exceeded.

RTC of *Cat3* appliance, however, is different. If a *Cat3* appliance is identified to be in ADJUST status during RTM, then the set point of the appliance is adjusted during RTC. AC set point is increased and WH set point is decreased by 2°C. A HEM scheduler in utility should have the capability to switch on, switch off or delay appliances connected to relevant HEMS in order to reduce overall energy consumption cost of a house.

## III. Test System and Simulation Results

A single house with seven controlled appliances connected to HEMS is taken as test system (as shown in Fig. 1). RTP of electricity is considered as the reflection of electricity spot price in

$$V^\pi(S_y) = R\left(S_y, \lambda(S_y)\right) + \sum_{S_y \in S} Tr_{\lambda(S_y)}\left(S_y|S_x\right) V^\pi(S_x) \tag{15}$$

$$V^*(S_y) = \begin{cases} 0 & if\ S_y \in S^G \\ \max\limits_{a \in A_q(S_y)} \left[R(S_y, A_q) + \sum Tr_{A_q}\left(S_y|S_x\right) V^*(S_x)\right] & else \end{cases} \tag{16}$$

$$\lambda^*(S_y) = \arg\max_{a \in A_q(S_y)} \left[R(S_y, A_q) + \sum Tr_{A_q}\left(S_y|S_x\right) V^*(S_x)\right] \qquad \forall S_y \in\ S - S^G \tag{17}$$

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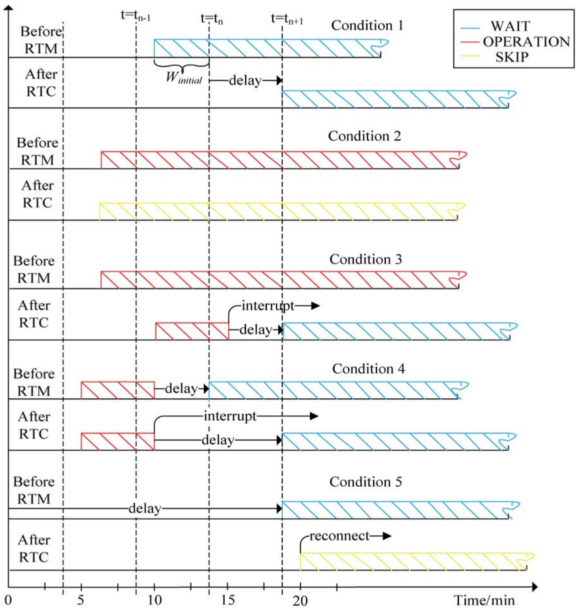


Fig. 6. Operating statuses of appliances before RTM and after RTC phase.

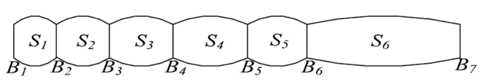


Fig. 7. Definition of states for CoEC.

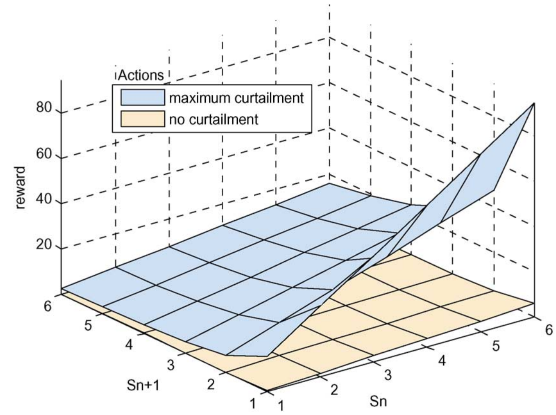


Fig. 8. Reward when there is no curtailment and maximum curtailment.

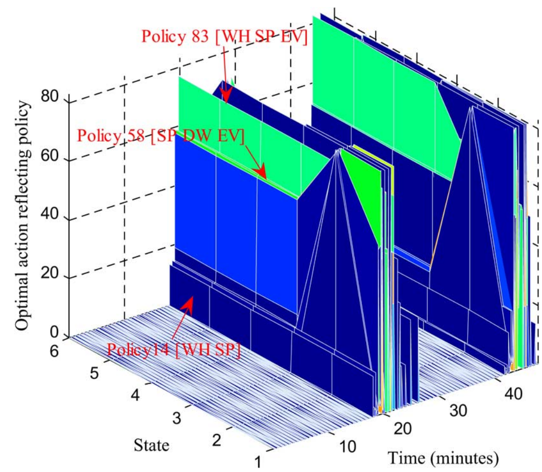


Fig. 9. Optimal policy values for two consecutive days.

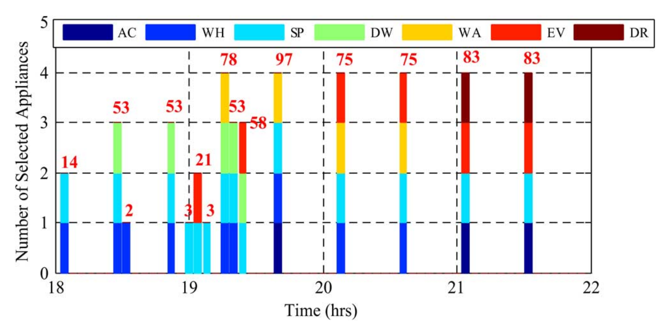


Fig. 10. Optimal policy values for two consecutive days.

electricity market during simulation and is broadcasted to individual HEMS. Electricity market spot price for a typical summer period (i.e., 3 months) in Australia is taken for this study [23].

As discussed in Section II-B, state space $S = \{S_k, k = 1, 2, 3, 4, 5, 6\}$ represents a range of CoEC. Its boundaries are defined by finding CDF of CoEC data as in (9). As CoEC lies in the range of 0–300 cents, the boundaries of states B1-B7 are 0.00, 1.00, 1.50, 2.00, 3.50, 20, and 300 cents, respectively, and is shown in Fig. 7. A state dependent reward function is defined for each time step as in (14). Change in reward is observed when there is no curtailment (i.e., $A_n^q = \{\}$) and when all seven appliances are controlled ($\alpha$ is taken as 1 and component of waiting time ($W_n^{Dj}$) is omitted). Reward gets a higher value when the state changes from 6 to 1 in the next time step and it has the least value when there is a jump from state 1 to 6 as shown in Fig. 8. This ensures that there is higher reward for larger curtailment. The optimal action is plotted as in Fig. 9. During 1800–2000 h, policy values are higher and hence allow more curtailment. If policy reaches 14, the 14th set of action or the appropriate combination of available appliances is subjected to control to reduce CoEC (i.e., WH and SP). Similarly policy value 58 and 83 represent a combination of [SP, DW, EV] and [WH, SP, EV], respectively. Each policy value represents a set of appliances that can be curtailed at that time step.

The details of selected appliances during 1800 to 2200 h are shown in Fig. 10. Before each control action, HEMS evaluates the current state of CoEC and matches with the corresponding policy value to select appliances appropriately. WH and SP are selected at 1804 h and the respective policy value is 14. The 14th action represents the availability of only WH, and SP (i.e., [0 1 1 0 0 0 0] is the binary representation of second (WH) and third (SP) appliance) representing policy value.

The change in appliances statuses, when they are subjected to control, is summarized in Table I. If a *Cat* 1 or 2 appliance is subjected to control which was initially under "*WAIT*" or "*OPERATION*" status, it is again kept at "*WAIT*" status confirming that the waiting time and the maximum number of interruptions are not exceeded.

Similarly, if a Cat 3 appliance is subjected to control, which was initially under "*ADJUST*" status, it is again kept at "*ADJUST*" status confirming that the set point limit and the maximum number of interruptions are not exceeded. Table II shows

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TABLE I
CHANGES IN APPLIANCE STATUSES WHEN THEY ARE SUBJECTED TO CONTROL

| Appliance | Conditions | Initial status | Status after control |
|---|---|---|---|
| *Cat* 1 and Cat 2 | $W_{Dj} < W_{Dj}^{max}$ and $INTRP_{Dj} = true$ | *WAIT* | *WAIT* |
| | | *OPERATION* | *WAIT* |
| *Cat* 3 | $P_{Dj}^{n} > 0$ and $INTRP_{Dj} = true$ | *ADJUST* | *ADJUST* |

TABLE II
APPLIANCE STATUS CHANGES AT 1940 h

| Appliances | Availability | Selected for control | Status at 1940 hrs | Status at 1944 hrs |
|---|---|---|---|---|
| AC | Yes | Yes | *ADJUST* | *ADJUST* |
| WH | Yes | Yes | *ADJUST* | *ADJUST* |
| SP | Yes | Yes | *WAIT* | *WAIT* |
| DW | No | - | - | - |
| WA | Yes | Yes | *OPERATION* | *WAIT* |
| EV | Yes | No | *WAIT* | *OPERATION* |
| DR | No | - | - | - |

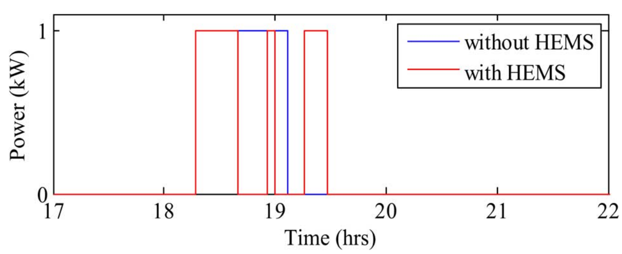


Fig. 11. Dish washer power profile of the house with HEMS (*Cat* 1).

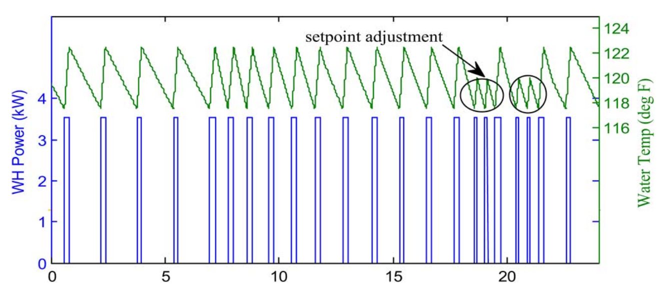


Fig. 12. Water heater power profile of the house with HEMS (*Cat* 3).

the changes in statuses of appliance at 1940 hours in a particular day. Here, AC, WH, SP, WA, and EV were available for control during this time and AC, WH, SP, and WA are selected for control in STS phase. Their respective status changes are shown in Table II. For example, WH which was already in "*OPERATION*" is switched off and kept in "*WAIT*" status. Operation of *Cat 1* appliance happens by switching ON and OFF during the control process. As an example, a dishwasher operation with and without HEMS is illustrated in Fig. 11. Here, a constant power consumption is assumed during different functions of a dishwasher such as washing, drying and disinfection. The power profile and the temperature variation of water heater is shown in Fig. 12. Here, the set point adjustments are shown when there is an increase in CoEC.

TABLE III
ENERGY AND COEC SAVINGS WITH HEMS

| Seasons | Energy Savings due to HEMS (kWh) | | CoEC savings ($) | |
|---|---|---|---|---|
| | One day | 3 months | One day | 3 months |
| Winter | 2.10 | 364.4 | 0.85 | 77.8 |
| Fall | 0.70 | 98.6 | 0.32 | 31.32 |
| Summer | 0.79 | 99.8 | 0.59 | 41.39 |
| Spring | 1.76 | 22.4 | 0.38 | 36.53 |
| Annual | -- | 791.2 | -- | 187.03 |

The effect of HEMS on the seasonal variation is summarized in Table III. Although on a daily basis, there is no significant energy reduction as the appliances are shifted rather than curtailed, a considerable reduction in energy consumption (791.2 kWh) and CoEC ($187.03) on an annual basis using HEMS (11% reduction in annual CoEC).

The efficacy of HEMS on the electricity cost in a day due to uncertainties in RTP or power consumption is summarized in Table IV. It also shows the electrocity cost when uncertainties in both RTP and power consumption exist. Firstly, the mean value of RTP is varied during 1800–2000 h (with a variance of 0.1) while keeping a constant power consumption profile. With HEMS, the variations in RTP does not affect the cost of energy consumption in a day (maintained at 335 cents). Similarly, HEMS effect due to uncertainties in power consumption profile is observed. The RTP profile is fixed and the uncertainty in power consumption is modeled by varying the mean while keeping the variance constant at 0.1. Again, the variation in electricity cost is suppressed and is maintained at fixed cost of 352 cents in a day with HEMS. Furthermore, the uncertainties in both RTP and appliance power consumption are considered using variable mean and constant standard deviation of 0.1 and electricity cost is maintained at 348 cents. It can be concluded that that HEMS achieves the aim of maintaining the reduced daily electricity cost of consumption.

Moreover, the computation time for STS phase of HEMS is approximately 7.5 s for a house with seven controllable appliances (using MATLAB software in a 64-bit operating system with a 2.10-GHz processor), which is well within the RTP time intervals.

## IV. CONCLUSIONS AND DISCUSSION

This paper focuses on an algorithm for a home energy management unit for reducing the cost of energy consumption, which operates in three subsequent phases namely RTM, STS, and RTC.

During RTM phase, HEMS obtains the operating statuses of each controllable appliances as well as RTP data from the utility, which is used in the STS phase to schedule the appliances. In STS phase, MDP is used to minimize cost of energy consumption by predicting the appropriate curtailment of appliances based on the stochastic behavior of cost of consumption. The STP phase incorporates the uncertainties in RTP and appliance consumption profile intrinsically and helps in optimizing the cost of energy consumption. Finally, selected appliances are

TABLE IV
EFFECT OF HEMS ON COEC DUE TO UNCERTAINTY IN RTP AND POWER CONSUMPTION (TYPICAL WINTER DAY)

| Effect of Uncertainty in RTP | | | Effect of Uncertainty in Appliance power consumption | | | Effect of Uncertainty in both RTP and Appliance power consumption | | |
|---|---|---|---|---|---|---|---|---|
| Mean of RTP ($\mu_{RTP}$) | CoEC (cents) in a day | | Mean of power consumption ($\mu_{ApplPower}$) | CoEC (cents) in a day | | Mean of RTP and Appliance power consumption ($\mu_{RTP}$, $\mu_{ApplPower}$) | CoEC (cents) in a day | |
| | Without HEMS | With HEMS | | Without HEMS | With HEMS | | Without HEMS | With HEMS |
| 0.8 | 349.13 | 334.51 | 0.5 | 362.96 | 351.91 | (0.8,0.5) | 357.96 | 348.31 |
| 0.9 | 352.13 | 335.63 | 0.75 | 363.85 | 352.08 | (0.9,0.75) | 359.85 | 348.53 |
| 1.0 | 353.87 | 335.73 | 1.0 | 366.41 | 352.13 | (1.0,1.0) | 360.41 | 348.83 |
| 1.1 | 364.51 | 336.14 | 1.5 | 368.07 | 352.51 | (1.1,1.5) | 364.07 | 349.15 |
| 1.2 | 368.16 | 336.71 | 2.0 | 371.12 | 352.85 | (1.2,2.0) | 369.12 | 349.25 |

controlled in RTC phase. The number of control commands are reduced through appropriate appliance categorization in RTM phase, which helps in optimal scheduling process in STS phase. Hence, these three phases complement each other and are necessary to achieve optimal cost of energy consumption in a house.

Furthermore, as the control of appliances is dependent on the individual HEMS, the network scalability is not an issue and it is easy to implement regardless of the size of the distribution network. This process is made possible with the advanced metering infrastructure and there are no additional communication requirements for the proposed algorithm. HEMS collect the relevant information about the appliances at regular intervals using home area networks such as Zigbee, HomePlug Wifi, Z-wave, etc. The demand aggregator/retailers broadcast the RTP signal to respective customers, who use HEMS to adjust the loads using the proposed algorithm. As HEMS only communicate to demand aggregators/retailers, the current low power radio frequency transmitters should be sufficient.

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