Cost-Comfort Balancing in a Smart Residential Building with Bidirectional Energy Trading

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***Abstract*—The increasing integration of new technologies for power generation into the smart grid systems calls for novel demand response (DR) algorithms, which schedule the appliances to minimize cost and maximize comfort for the users. Traditionally, the formulations of the DR problem consider unidirectional energy flow from the power grid (energy supplier) to the user in a residential building (energy consumer). In this paper, we argue for an extended model of a smart residential building with bidirectional energy trading. This model allows the user to sell the surplus energy, obtained from local renewable energy sources, so as to partially recover the electricity cost. We further study an efficient linear model for appliance scheduling, under the assumption of bidirectional energy trading. To balance the user comfort and electricity cost, we introduce a comfort demand function based on declining block rates (DBR) and discuss the microeconomic meaning of this function. We evaluate our method with several case studies and analyze how energy selling and comfort demand affect the total cost and the schedule. We also show that our scheduler is fast enough to allow for nearly real-time scheduling adjustments ahead of each period, to minimize the impact of forecast deviations.**

I. Introduction

Smart power grids employ information technology to improve the efficiency, reliability and security of the power generation, transmission and distribution processes under the increasing energy demands. In smart systems, the energy providers usually adopt dynamic pricing strategies, such as Real-time Pricing (RTP), penalizing consumption during peak periods and varying the unit price of electricity depending on the customer demand [1]. Demand response (DR) strategies address the reduction in the utility cost for the customer by curtailing or shifting the electricity usage during the periods of high rates, as set by the energy provider. In a typical smart grid infrastructure, DR is an integral part of the energy management system (EMS) in a smart home.

These days increasingly more residential buildings are becoming equipped with local energy production units, such as photo-voltaic panels, as the renewable energy brings many benefits in terms of economic, environmental and social perspectives [2]. Furthermore, the encouraging progress in the energy storage technology [3] projects batteries to become indispensable components of EMS in smart homes. Due to the enhanced possibility of producing and storing energy locally, energy consumers are increasingly becoming energy producers (i.e. prosumers) as the surplus energy can be traded to the local grid or neighborhood [4]–[6]. This fact motivates us to consider *bidirectional energy trading* between the residential building and the energy grid to further increase the economic benefits from DR strategy.

In addition to cost minimization, DR often aims at maximizing the user comfort (or user satisfaction) [7]. The level of comfort obtained from the services of home appliances (e.g. air conditioner) can be traded-off with the cost or revenue in response to the buying or selling prices of energy. In a bidirectional energy trading system, comfort model can allow a user to sell the energy instead of receiving services from low-priority appliances while ensuring the services of high-priority appliances. While comfort modeling is a hard problem, frequently involving nonlinear functions [8], in this paper we seek for a fast scalable, yet realistic linear model for appliance scheduling. We therefore introduce and provide motivation for a DBR-based *comfort demand function*, balancing the electricity cost and user comfort in the model objective. The contributions of this paper can be summarized as follows:

- We argue for the need to consider bidirectional energy trading in DR and present an efficient linear model for appliance scheduling in a residential building with a hybrid power supply system and an energy storage unit.
- We introduce a DBR-based comfort demand function to balance the electricity cost and user comfort in a linear model. We discuss the microeconomic meaning of the comfort function, and explain how it can be obtained.
- We evaluate the effectiveness of our model in reducing the cost for the user while maximizing the comfort level. The scalability of the model is also demonstrated by generating the schedules for hundreds of appliances within a few seconds.
- We show that our model is robust against forecasting errors in the amount of generated renewable energy as well as in the energy selling price.

II. Related Work

A substantial amount of research has been conducted in the field of DR to minimize either the peak-to-average ratio or the aggregate load demand [9]–[12]. Logenthiran et al. [9] presented a heuristic-based evolutionary algorithm for day-ahead demand side management, which allows the customers to choose their own strategic actions in response to time-varying prices. In [10], Mohsenian-Rad et al. proposed a game theory-based distributed energy scheduling algorithm to

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find the optimal consumption schedule for each subscriber in the neighborhood. In [11], the authors designed a residential energy scheduling framework considering an RTP tariff with inclining block rates (IBR). The framework attempts to achieve the desired trade-off between the cost and waiting time for the operation of household appliances, and finds the schedule using the interior-point method. Zhao et al. [12] solved a similar type of problem using genetic algorithms.

The latest research in the field of DR has marked the trend to consider renewable energy sources and energy storage units as well as to address the concerns of user comfort. Along these lines, the works in [7] and [13] proposed robust scheduling algorithms to handle the uncertainties of renewable energy generation. Although our developed model is similar to the model in [7], our work differs by the consideration of bidirectional energy trading aspect along with the proposal of a comfort demand function to explicitly model the relation between cost and comfort. Several recent papers presented DR algorithms taking into account the use of air conditioning systems, either without considering the user comfort [8], or by doing so with highly non-linear models [14], [15], substantially affecting the complexity of the scheduling algorithm.

The importance of bidirectional energy trading has been emphasized in [4]–[6]. The authors in [4], [5] primarily focused on the potential market models for the energy trading. While the authors in [6] paid little attention to the user's inconvenience in the cost-effective residential appliance-scheduling, here we address the challenge of finding the balance between the revenue and the comfort of the user.

III. System Architecture and Models

This section describes the underlying models and assumptions of the DR strategy considered in this work.

A. System Modeling

The system architecture is illustrated in Fig. 1. It encapsulates a number of smart appliances, including renewable energy sources supplied with 24-hour forecast of energy production. The system allows to trade energy in both directions, i.e. both buying and selling energy from and to the grid. EMS receives day-ahead RTP from the provider through the smart meter. Besides, EMS also receives a task-list from the user including priorities and deadlines of the tasks. Afterwards, the integrated DR algorithm of the EMS schedules the tasks within the defined time frames to minimize the utility costs, while maximizing the user-comfort. To reduce the impact of day-ahead forecasting errors, the schedule is recalculated at fine intervals, allowing for practically real-time incorporation of the energy price and production volume.

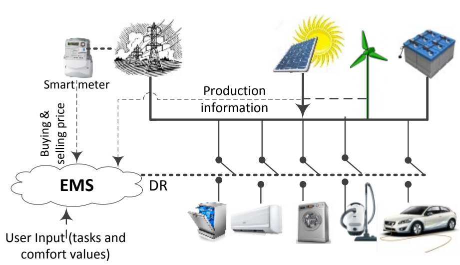


Fig. 1: The architecture of an EMS in a smart home.

B. Residential Load Modeling

We assume that the scheduling horizon of the appliances is divided into T slots, indexed by $t \in \{1, 2, \ldots, T\}$. Let A denote the set of all appliances. The scheduling task for each appliance $a \in A$ is defined by the user in the form of a tuple (α_a, β_a, E_a), where α_a is the task earliest starting time slot, β_a is the latest ending time slot and E_a is the energy consumption required to accomplish the task. We assume that each appliance a has a number of operating states, including the off-state, and each state is associated with the index ω. The total number of states for appliance a is δ_a and the power consumption in the state ω is $p_{a,\omega}$. Depending on the type of appliances and corresponding tasks, we differentiate the load demand into the following categories:

- *Fixed load:* For some appliances, such as television (TV), the load cannot be shifted or curtailed and therefore is termed as fixed load (i.e. category A_1).
- *Non-interruptible load:* Some appliances can only be deferred, but cannot be stopped and resumed (e.g. rice cooker) once the task has started (i.e. category A_2).
- *Interruptible load:* For some appliances, such as plug-in hybrid electric vehicle (PHEV), the task can be deferred to a later time, or it can be stopped and resumed as long as it is completed before the deadline (i.e. category A_3).
- *Comfort load:* Some appliances such as air conditioners (A/C) represent flexible interruptible load and deliver a certain level of comfort to the user (i.e. category A_4).

C. Power Supply System Modeling

We consider a hybrid power supply system consisting of a traditional electric grid (G) as well as renewable energy sources (R) installed locally in the residential unit. We assume that the forecasts of the renewable energy are given by the vector, $\vec{e} = [e_s^1, \ldots, e_s^T]$, where e_s^t is the available renewable energy (in kWh) at time t.

The considered system is equipped with an energy storage unit of capacity B_{max} kWh, that can be charged from any of the available sources. R_{max} defines the maximum amount of energy in kW that can be charged or discharged in one hour.

D. Price Modeling

1) Buying Price: We consider an RTP tariff with IBR as the price model for buying energy from the electric grid [11]. A 2-step IBR model is adopted to vary the price of a unit of

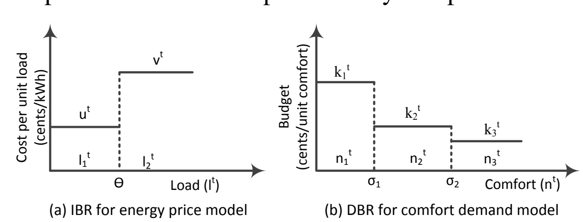
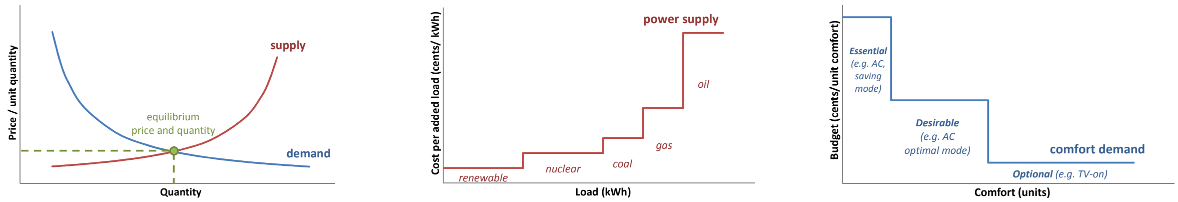


Fig. 2: A 2-step IBR pricing model for buying energy from the grid (a); a 3-step DBR comfort demand function (b).



(a) An abstract supply-demand model (b) Power supply model with IBR (c) Comfort demand model with DBR

Fig. 3: An analogy between the microeconomic supply-demand model (a) and the cost-comfort models in a smart grid (b), (c).

electricity, depending on the level of consumption within the time period (Fig. 2a). The unit price of energy at time t at source s is:

$$C^t_{s\in G}(l^t_s) = \begin{cases} u^t, & if \quad 0 \leq l^t_s < \theta, \\ v^t, & if \quad l^t_s \geq \theta, \end{cases} \tag{1}$$

where u^t and v^t denote the real time price and the price of the second level of IBR in the time slot t, respectively, l^t_s is the load at source s, and θ is the IBR threshold. For the renewable energy sources, we assume that the user only pays the operation and maintenance costs ($C^t_{s\in R}$), which are constant throughout the scheduling period.

2) Selling Price: Our model accepts the energy selling price as an input through the smart meter [16]. As for the selling price of energy to the grid, we assume day-ahead dynamic pricing scheme which is set by the grid provider. The selling price at time t is denoted as P^t.

E. User Comfort Level Modeling

An important issue for modeling the user comfort is how to find the right balance between the total cost of the electricity and the desired level of comfort. To address this problem, in this work we propose to introduce a comfort demand function, indicating the willingness of the user to pay for the certain level of comfort. In this section we define and discuss the economic meaning of this function.

Let us consider Fig. 3(a), which depicts an abstract supply-demand model for some product in a market [17]. The supply curve defines the price of a product unit at which the manufacturer is ready to supply the given quantity. The demand curve shows how much the user is willing to pay to acquire the given quantity. The supply-demand model is convenient for studying the market equilibrium, in which the user demand meets the manufacturer supply.

In Fig. 3(b) an analogy of the supply curve for a smart grid market is given, with electricity being the supplied product. The curve is defined in terms of inclining block rates and shows the cost of an *added* unit of load as the overall load increases. The price per unit load is relatively low while using the cheapest energy sources (e.g. renewable), however it raises gradually as more expensive sources (e.g. gas and oil) are employed to provide the desired load. An example of this price model has been discussed in Sect. III-D.

We further draw an analogy between the user comfort requirement and the demand curve, which we term as the *comfort demand function*, depicted in Fig. 3(c). Since the additional comfort can be gained by paying an extra cost, it is convenient to consider the notion of *budget per added unit of comfort*, emphasizing how much the customer is ready to pay for an additional unit of comfort. The comfort demand function defined via declining block rates aims at indicating the *saturating effect* of the user comfort preference. It is likely that the user will agree to pay a relatively high amount of money to get an essential minimum comfort (e.g. an A/C working in a saving mode on a hot day).

The benefit of using the comfort demand function is that it takes a holistic view of comfort, by merging the comfort gains from individual appliances. It therefore allows modeling substitutes (e.g. the comfort from watching a TV can be substituted by the comfort from an A/C) [17]. In addition to that, it reflects the readiness of the user to pay for comfort and, when defined in terms of DBR, provides a linear relation between the comfort and the electricity cost. This allows to solve a multi-objective optimization problem and find a balance between cost minimization and comfort maximization. The comfort demand function can be obtained in different ways. The straightforward option is to question the user preferences via surveys [15].

To formalize the definition of the comfort demand function for our problem, let us assume that $n^t_{a,\omega}$ denotes the level of comfort from appliance a operating in mode ω at time t. Then the 3-step DBR comfort function $\mathcal{K}^t(n^t)$ (Fig. 2b) to express the cost budget for an added unit of comfort is given by:

$$\mathcal{K}^t(n^t) = \begin{cases} \kappa^t_1 & if \quad 0 \leq n^t < \sigma_1, \\ \kappa^t_2 & if \quad \sigma_1 \leq n^t < \sigma_2, \\ \kappa^t_3 & if \quad n^t \geq \sigma_2. \end{cases} \tag{2}$$

where n^t is the total comfort at time t.

IV. The ILP Problem for Appliance Scheduling

In this section we describe an integer linear programming (ILP) model of the system for solving the DR problem.

A. Problem Variables

Let us consider a binary activity variable, $x^t_{a,\omega}$, which is set to 1 iff appliance a is scheduled to operate during time slot t in mode ω. For each appliance $a \in A$, we introduce an activity vector $\vec{x}_{a,\omega} = [x^1_{a,\omega}, \ldots, x^T_{a,\omega}]$, which defines the operating mode of the appliance in every period throughout the scheduling horizon.

For each source $s \in \{G \cup R\}$, we define a load demand vector $\vec{l}_s = [l^1_s, \ldots, l^T_s]$, where scalar $l^t_s \in \mathcal{R}$ denotes the scheduled load for source s in time slot t. To formalize the IBR price model (1) in terms of linear variables, we further

TABLE I: A summary of variables in the ILP model.

Variable	Type	Description
$x^t_{a,\omega}$	Binary	Activity status of appliance a in time slot t and mode ω
$l^t_s, l^t_{s,i}$	Real	Scheduled load and its components, source s, time slot t
m^t	Real	Energy sold to the grid in time slot t
b^t	Real	Energy remaining in the storage unit at the end of t
r^t	Real	Energy change in the storage unit during time slot t
n^t, n^t_j	Real	User comfort and its components in time slot t

divide the load l^t_s into 2 components, which correspond to the blocks of IBR. In this way, $l^t_{s,1}$ is the non-negative fraction of load within the threshold, θ, while $l^t_{s,2}$ is the non-negative fraction of load above the threshold, and so that $\sum_{i=1}^{2} l^t_{s,i} = l^t_s$.

In addition, we define an energy selling vector $\vec{m} = [m^1, \ldots, m^T]$, where scalar $m^t \in \mathcal{R}$ denotes the amount of energy sold in time slot t ($m^t \geq 0$).

We introduce variables b^t to indicate the energy remaining in the storage unit at the end of time slot t. We use $r^t \in \mathcal{R} := [-R_{max}, R_{max}]$ to represent the energy stored to ($r^t \geq 0$) or withdrawn from ($r^t < 0$) the unit during the time slot t, where R_{max} and $-R_{max}$ are the charge and discharge limits within the period, respectively. The capacity of the unit is B_{max} kWh.

For each appliance in the comfort group, $a \in A_4$, we define a comfort vector $\vec{n}_a = [n^1_a, \ldots, n^T_a]$, where scalar n^t_a denotes the level of comfort that a user receives from the service of appliance a in time slot t. Therefore, the total comfort n_t in time slot t is given by $\sum_{a \in A_4} n^t_a = n^t$. Similar to the load demand, to model DBR via linear variables, we decompose n^t into 3 different steps, where each step n^t_j corresponds to the j-th budget block of the comfort demand function (2). A summary of the defined variables is given in Table I.

B. Problem Objective and Constraints

The scheduling objective is to minimize the total electricity cost and to maximize the overall user comfort:

$$min \sum_{t=1}^{T} \sum_{s \in \{G \cup R\}} \sum_{i=1}^{2} (C^t_{s,i} \times l^t_{s,i}) - \sum_{t=1}^{T} \sum_{j=1}^{3} (\kappa_j \times n^t_j) - \sum_{t=1}^{T} (P^t \times m^t) \tag{3}$$

The first term in the objective is the cost of the electricity acquired from all sources, while the second term is the budget recovered by selling the electricity to the grid. The last term expresses the overall comfort that the user enjoys, weighed by the comfort demand function. The problem constraints are formalized below.

1) Task Completion: All tasks, except for the comfort tasks, have to finish within their time frames (i.e. $[\alpha_a, \beta_a]$):

$$\sum_{t=\alpha_a}^{\beta_a} \sum_{\omega=0}^{\delta_a - 1} (x^t_{a,\omega} \times p_{a,\omega}) = E_a, \quad \forall a \in \{A_1 \cup A_2 \cup A_3\}.$$

2) Task Activity: The tasks have to be inactive outside their time frames:

$$\begin{aligned} \sum_{t=1}^{\alpha_a - 1} \sum_{\omega=0}^{\delta_a - 1} (x^t_{a,\omega} \times p_{a,\omega}) &= 0, \quad \forall a \in \{A\}, \\ \sum_{t=\beta_a+1}^{T} \sum_{\omega=0}^{\delta_a - 1} (x^t_{a,\omega} \times p_{a,\omega}) &= 0, \quad \forall a \in \{A\}. \end{aligned}$$

TABLE II: Parameters of the selected appliance set.

Load Type	Appliance	Total Energy (kWh)	Service Time (h)	Starting Time	Ending Time	Number of Modes	Power Modes (kW)	Comfort Level
Fixed	TV	0.39	3	6:00 pm	8:59 pm	2	0.00/0.13	-
Non-Interruptible	Toaster	1.00	1	6:00 am	6:59 am	2	0.00/1.00	-
	Kettle	0.90	1	6:00 am	8:59 am	2	0.00/0.90	-
	Rice Cooker	2.80	2	10:00 am	11:59 am	2	0.00/1.50	-
	Washing Machine	1.50	3	12:00 pm	5:59 pm	2	0.00/0.50	-
	Dryer	8.00	4	6:00 pm	5:59 am	2	0.00/0.50	-
	Dishwasher	4.20	3	8:00 pm	5:59 am	2	0.00/1.40	-
	Vacuum Cleaner	3.60	3	9:00 am	1:00 pm	2	0.00/1.20	-
	Oven	3.90	3	6:00 pm	10:00 pm	2	0.00/1.30	-
Interruptible	Computer	1.20	4	11:00 am	8:00 pm	2	0.00/0.30	-
	PHEV	4.00	4	9:00 pm	5:00 am	4	0.00/1.00/1.30/5.70	-
Comfort	A/C-1	[0-16]	8	9:00 am	4:00 pm	4	0.00/0.75/1.50/2.00	0.0/2.0/4.0/5.0
	A/C-2	[0-12]	8	10:00 pm	5:00 am	4	0.00/0.75/1.50/2.00	0.0/1.0/2.0/5.0

3) Task State: An appliance can take only one of its states in one time slot:

$$\sum_{\omega=0}^{\delta_a - 1} x^t_{a,\omega} = 1, \;\; \forall \; a \in \{A\}.$$

4) Non-interruptible Tasks: Following set of equations are used to express non-interruptible tasks ($\forall a \in A_2$):

$$\begin{aligned} & t^{end}_a - t^{start}_a + 1 = ts_a, \\ & t^{start}_a \leq t + \eta \times (1 - x^t_{a,1}), \quad t^{end}_a \geq t - \eta \times (1 - x^t_{a,1}). \end{aligned}$$

Here t^{start}_a and t^{end}_a are the variables denoting the task starting and ending times, $ts_a = E_a / p_{a,1}$ is the task duration in periods and η is a large constant to model an OR-relation. Recall that non-interruptible tasks have one active state ($\omega = 1$), hence $x^t_{a,1} = 1$ iff the task is active.

5) System Energy Balance: The difference between the purchased and sold energy during time slot t is either used for powering the appliances or stored in the unit:

$$\sum_{s \in S} \sum_{i=1}^{2} l^t_{s,i} - m^t = \sum_{a \in A} \sum_{\omega=0}^{\delta_a - 1} (x^t_{a,\omega} \times p_{a,\omega}) + r^t.$$

6) Load Bounds: IBR-step bounds for the grid and production capacity bounds for renewable sources:

$$\begin{aligned} 0 \leq l^t_{s,1} \leq \theta, \quad l^t_{s,2} \geq 0, \qquad & \forall s \in \{G\}, \\ l^t_{s,1} + l^t_{s,2} \leq e^t_s \times a^t_s, \qquad & \forall s \in \{R\}. \end{aligned}$$

7) Storage Unit: Balance, charging limits and capacity of the energy storage unit:

$$b^t = b^{t-1} + r^t, 0 \leq b^t \leq B_{max}, -R_{max} \leq r^t \leq R_{max}.$$

8) Appliance Comfort Contribution: The level of comfort delivered by an appliance if defined by its active state, $x^t_{a,\omega}$:

$$n^t_a = \sum_{\omega=0}^{\delta_a - 1} (x^t_{a,\omega} \times n^t_{a,\omega}), \quad \forall a \in A_4.$$

9) Aggregate Comfort: The overall comfort experienced by the user is the aggregate comfort from all appliances:

$$n^t = \sum_{a \in A_4} n^t_a.$$

The aggregate comfort is defined via 3-DBR comfort components and the bounds for every component are specified:

$$n^t = \sum_{j=1}^{3} n^t_j, 0 \leq n^t_1 < \sigma_1, \quad 0 \leq n^t_2 < \sigma_2 - \sigma_1, \quad n^t_3 \geq 0.$$

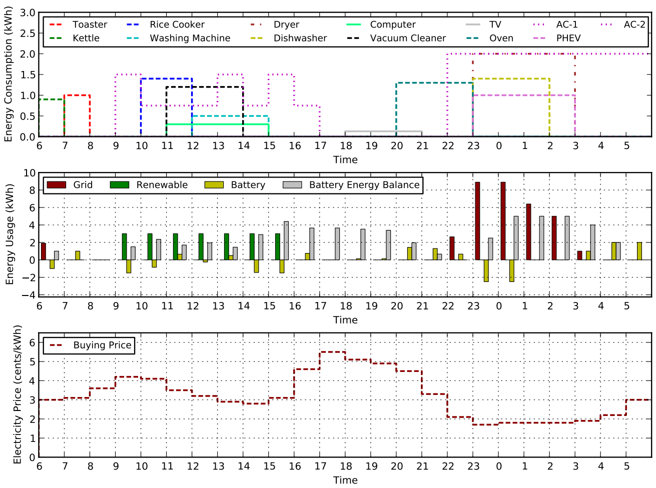


Fig. 4: Demand response with user comfort.

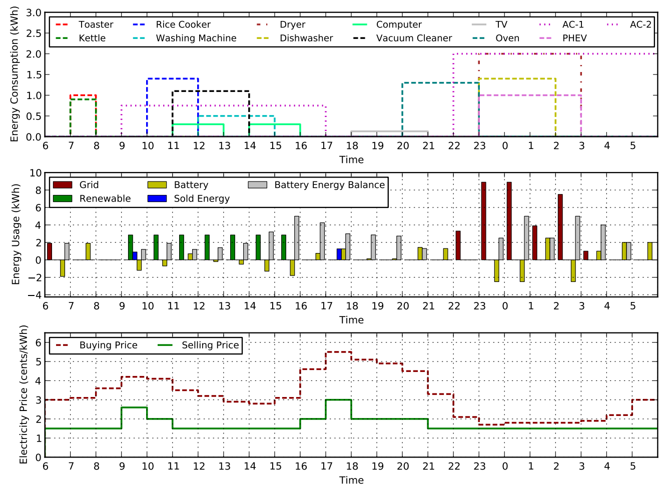


Fig. 5: Demand response with energy selling and comfort.

V. Evaluation

In this section we present several experiments to validate the ILP model and to study the impact of energy selling and comfort demand on the total cost and the schedule.

A. Experimental Setup

We use Gurobi 5.6.2 solver [18] to generate solutions to the ILP model and find the appliance schedule. The solver is executed on Intel® Core™ i7-2600 desktop system with 16 GB RAM, running 64-bit Microsoft Windows 7 OS.

Appliance Setup: We carefully choose a set of household appliances that resembles a typical household setup for our experiments [8]. The scheduling horizon is assumed to be 24 hours (from 6:00 am to 5:59 am next day) and is divided into 24 time slots. The parameters of the appliances (in Table II) are distributed within the scheduling horizon to match a common human schedule [19].

Energy Buying and Selling Prices: For the RTP pricing scheme as the buying price, we have used the day-ahead pricing information given by the Ameren Illinois Power Corporation [20] in our experiments. For IBR, the threshold value, θ, is set to 10 kWh and v^t is set to 8 ¢$/kWh$. Energy selling price is assumed to be constant throughout the day, and is set to 1.5 ¢$/kWh$, except from 9:00-11:00 and 16:00-21:00 when the electricity buying price is high.

Renewable Energy Sources: We consider a solar panel as the only renewable energy source in our system, and e^t is set to 3 kWh between 9:00 and 16:00. The panel operation and maintenance cost is set to 0.1 ¢$/kWh$.

Energy Storage Unit: The storage unit has the capacity of 5.0 kWh. The charging and discharging rate limits are set to 2.5 kW per hour.

Comfort Modeling: We assume that perceived comfort level from the service of individual appliances is defined by the user as presented in Table II. For the 3-step DBR comfort function, we set $\kappa_1^t = 1.5$, $\kappa_2^t = 0.75$ and $\kappa_3^t = 0.25$ respectively to represent the willingness of the user to pay for the comfort. The threshold values σ_1 and σ_2 are set to 2.0 and 4.0 respectively.

PHEV Modeling: This study considers a compact sedan with the battery capacity of 4.1 kWh. Three charging modes are available: slow, normal and quick. The slow mode is the standard PHEV charging mode from a 120V/15A/1 kW outlet [21]. The normal and the quick modes correspond to charging from 120V/20A/1.3 kW and 240V/40A/5.7 kW outlets, respectively.

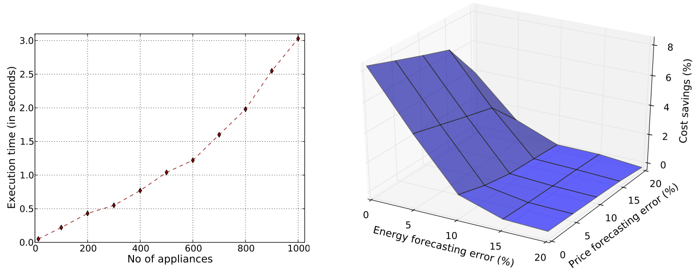
B. Results and Discussion

1) Demand Response with User Comfort: This experiment aims at demonstrating the effectiveness of the proposed comfort demand function in comfort maximization in accordance with the dynamic price of electricity.

Fig. 4 presents the generated appliance schedule (top), the energy consumption at every source, including the storage unit/battery (middle), and the RTP price (bottom) in time. From the figure, we can observe that the operating modes of the comfort appliances (AC-1, AC-2) vary depending on the willingness of the user to to pay for the comfort. For instance, AC-1 operates at low-power mode when the load demand (i.e. 10:00-13:00) or the electricity cost (e.g. 16:00-17:00) is high. This is due to the fact that the cost of maximum level of comfort is more than the user is willing to pay (*comfort level*$\times$*cost per unit of comfort*) for the comfort. In contrast, the scheduler provides maximum comfort to the user from 22:00 to 6:00. It is important to note that during this period, not only the price of the electricity is low, but also the discomfort-level of the user (i.e. low comfort) is very high in the low-power modes of AC-2. Therefore, we can conclude that the proposed *comfort demand function* seeks to maximize the comfort level in accordance with the willingness of the user to pay for it.

2) Demand Response with Energy Selling and Comfort: The second study considers the scheduler which encompasses the ability to minimize the electricity cost while maximizing the profit from energy selling and optimizing the user comfort. The obtained schedule is presented in Fig. 5.

Guided by the comfort demand function and the energy price, the scheduler is now able to decide how to use the surplus energy in the best way. This energy can either be used



(a) Scalability test (b) Robustness test

Fig. 6: The tests of the scheduling algorithm for scalability and robustness against forecasting errors.

to deliver extra comfort or it can be sold to compensate for the user expenses, if that appears more lucrative. This trend is reflected in the diagrams as the scheduler sells energy at 9:00 and at 17:00 when the selling price is high. It is important to note that the comfort level is not changed from 22:00 to 6:00 as the selling price is low during this period. The total electricity cost in this scenario is 60.08¢, which is 7.5% less than the cost in the previous case study, after recovering 6.12¢ with the sold energy. The comfort is only reduced by 5.7%, leading to an overall improvement in the objective function (3).

3) Performance Scaling: With this experiment, we show that our ILP model is very efficient in schedule generation. Fig. 6(a) illustrates the time to create a schedule as a function of the number of appliances. The plot is generated by taking the average execution times of 100 randomly generated appliance sets of the given size. An optimal schedule for a 1000-appliance set can be generated in approximately 3 seconds.

4) Robustness Against Forecasting Errors: In the last study, we emphasize the robustness of the model against forecasting errors in the amount of renewable energy and in the energy selling price. To perform a fair comparison, we first compute the *traditional* user expense (f_t) using a basic DR scheduler with *ideal* energy and price forecasting, however without energy selling [12]. Next, we compute the user expense using the *proposed* scheduler (f_p), parameterizing the degree of forecasting errors, however including the energy selling feature. Fig. 6(b) shows how the savings in user expenses change with the forecasting errors, in the range of [0-20]%. Along the vertical axis we depict the *lower bound* of the cost savings, calculated as $((f_t - f_p) \div f_t) \times 100\%$. The baseline for this study (i.e. the 0% error-case) is the configuration in Fig. 5, providing 8.3% of cost savings. The plot shows that the error in the amount of renewable energy has a greater impact on the cost savings as it reduces the amount of energy to be sold to earn revenue. The model is therefore more robust against the selling price error. However, the model tolerates the presence of both errors within the considerable range, without degrading the user comfort or increasing the cost, w.r.t. idealistic traditional schedulers.

VI. Conclusion and Future Work

In this paper, we present an energy management system in a residential building which extends the prior works in two important directions. First, we introduce a demand response model with bidirectional energy trading in presence in a hybrid power supply system and illustrate the economic impetus of such model. Second, we propose an ILP-based scheduling algorithm for the presented model that minimizes the cost of energy consumption while maximizing the comfort satisfaction in accordance with the user-willingness to pay for comfort.

We show the ability of the model to generate the schedules for hundreds of appliances within a few seconds. This fact suggests an extension of the proposed algorithm to develop a real-time DR scheduler, which is left for the future work. Another planned extension is the integration of learning techniques for the extraction of user comfort preferences as a function of multiple variables (e.g. electricity price, weather conditions).

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