Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home

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***Abstract*—High quality demand side management has become indispensable in the smart grid infrastructure for enhanced energy reduction and system control. In this paper, a new demand side management technique, namely, a new energy efficient scheduling algorithm, is proposed to arrange the household appliances for operation such that the monetary expense of a customer is minimized based on the time-varying pricing model. The proposed algorithm takes into account the uncertainties in household appliance operation time and intermittent renewable generation. Moreover, it considers the variable frequency drive and capacity-limited energy storage. Our technique first uses the linear programming to efficiently compute a deterministic scheduling solution without considering uncertainties. To handle the uncertainties in household appliance operation time and energy consumption, a stochastic scheduling technique, which involves an energy consumption adaptation variable β, is used to model the stochastic energy consumption patterns for various household appliances. To handle the intermittent behavior of the energy generated from the renewable resources, the offline static operation schedule is adapted to the runtime dynamic scheduling considering variations in renewable energy. The simulation results demonstrate the effectiveness of our approach. Compared to a traditional scheduling scheme which models typical household appliance operations in the traditional home scenario, the proposed deterministic linear programming based scheduling scheme achieves up to 45% monetary expense reduction, and the proposed stochastic design scheme achieves up to 41% monetary expense reduction. Compared to a worst case design where an appliance is assumed to consume the maximum amount of energy, the proposed stochastic design which considers the stochastic energy consumption patterns achieves up to 24% monetary expense reduction without violating the target trip rate of 0.5%. Furthermore, the proposed energy consumption scheduling algorithm can always generate the scheduling solution within 10 seconds, which is fast enough for household appliance applications.**

***Index Terms*—Smart home, stochastic scheduling.**

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I. Introduction

THE electrical power grid is a complex adaptive system with significant amount of uncertainties. The integration of advanced technologies such as renewable energy generation including wind farms and solar cells introduces further complexity and challenge to various controllers at all levels of the power grid [1]. Salient communication and information technologies have been explored in utility industry to handle the increasing complexity [2].

In a smart grid infrastructure which targets to facilitate the modernization of the classical power grid, utility companies explore demand side management (DSM) technology to control the energy consumption at the user side [3]–[7]. It enables the integration of various renewable energy resources such as solar, wind and hydrate energy into the classical electrical power grid [6], [7]. Demand side management technology can help shift the energy consuming workload from peak time to off-peak time for the purposes such as load balancing and monetary expense reduction [8], which is critical in a smart home system.

There are multiple components in a smart home system such as household appliances, plug-in hybrid electric vehicles (PHEVs), energy storage component and renewable energy component such as photovoltaic (PV) arrays. Typical examples of household appliances include air conditioners, space heaters, washing machines, and refrigerators. Energy storage such as high capacity batteries are often used to store energy generated from photovoltaic arrays. Each residential customer is equipped with a smart meter that is connected to the power distribution system [5], [9], [10]. Each smart meter includes a scheduling unit which implements the workload shifting mentioned above. It periodically receives the updated pricing information from the utility companies, and its scheduling unit arranges different household appliances for operation during different time periods. It is effective in reducing the monetary expense charged to end users since different electricity rates can be applied at different time periods in the popular real-time pricing model [11]–[14]. Refer to Fig. 1 for a smart home scenario. This paper aims to minimize the monetary expense of a single customer through optimally scheduling the operation and energy consumption for each appliance under the real-time pricing environment.

Considerable research effort has been devoted to the investigation of the scheduling issue in the demand side management for reducing the monetary expense of the customer and peak-to-average ratio in load demand. Kim *et al.* [15] investigated the energy consumption scheduling problem with time-

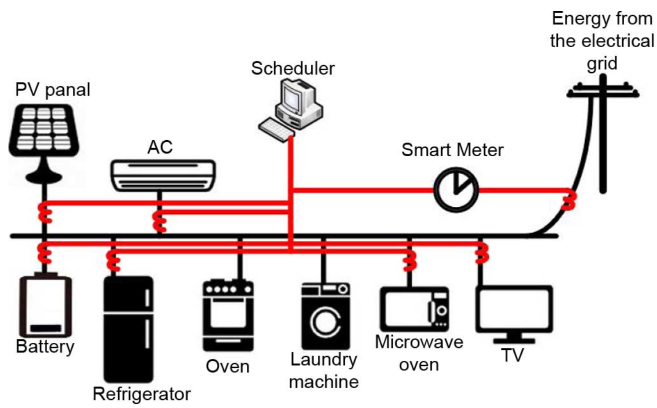


Fig. 1. A smart home scenario.

varying prices known in advance to customers. Optimal scheduling algorithms that bring significant gains to customers were derived to find a series of price thresholds by using stochastic dynamic programming. Mohsenian-Rad *et al.* [16] designed an interesting optimal and automatic residential energy consumption scheduling framework by combining a real-time pricing tariff with inclining block rates. The proposed framework attempts to achieve a desired trade-off between minimizing the monetary expense and minimizing the waiting time for the operation of each appliance in a household. In [17], [18], the authors presented an energy consumption scheduling heuristic to reduce the peak load in individual homes or buildings with reasonable computation time. The operations of household appliances are classified into preemptive and non-preemptive operations, and the scheduling for preemptive operations is based on the schedule of the non-preemptive operations. In [19], the authors proposed a power scheduling protocol for demand response in smart grid systems. A joint media access and appliance scheduling approach was developed to manage the power usage of appliances so that total power demand is kept below a target value. Extensive research on the demand side load management also has been performed for a neighborhood with multiple customers. In [4], [5], the authors considered the deployment of energy consumption scheduling devices in smart meters for demand side management in a neighborhood. Based on game theory, a distributed incentive-based energy consumption scheduling algorithm was proposed to find the optimal energy consumption schedule for each subscriber in the neighborhood. The presented algorithm aims to reduce the peak-to-average ratio, total energy costs, and electricity charges of individual customers. Caron and Kesidis [20] proposed a dynamic pricing scheme incentivizing consumers to achieve an aggregate load profile suitable for utilities. Based on the degree of information sharing, distributed scheduling algorithms were designed to reduce the total cost and peak-to-average ratio, and improve the overall load profile of the system. In [21], the authors proposed a three-step control methodology to manage the cooperation between technologies of energy production, consumption, and storage. A better matching of demand and supply can be achieved through using this methodology.

In the above recent research works which focus on reducing the monetary expense of customers and peak-to-average ratio of the system, the stochastic characteristics of customer energy consumption patterns are not considered, which is however quite important. Stochastic design technique itself has been investigated in the literature in varying contexts such as stochastic security constrained unit commitment (SCUC) design [22] and wireless base station construction [23]. In [22] and [23], the uncertain problem is directly approached using the stochastic programming technique, and the benders decomposition method is utilized to reduce the time to obtain the optimized results. In [24]–[26], the authors presented stochastic models that minimizes the total cost of operations of generation units and transmission network with the consideration of the power system uncertainties, which include the availability of generation units and transmission lines, and inaccuracies in load forecasting. Monte Carlo simulation is utilized to model the uncertainties, and the lagrangian relaxation method is applied to decompose the stochastic problem into subproblems. However, no related work on stochastic optimization has been found in the area of smart home design.

In addition, the energy storage and renewable generation such as wind and solar are not considered in most of the related research works. With emerging requirements for renewable portfolio standards, wind and solar generation become a must-take resources in many countries of the world and about 30 of 50 U.S. states [6], [27]. For instance, the State of California requires 33% of the total energy generated from renewable resources by 2020. However, there could be significant difference between the predicted energy generation and the actual energy generation from renewable resources. For example, the solar energy generated from a PV panel may vary with the changes in sun irradiation level, the angle of the sun, or even the lasting time of cloud shadow. This intermittent nature of renewable resources imposes significant challenge in designing salient scheduling techniques considering renewable generation [6].

Furthermore, most existing smart home energy scheduling works do not consider variable frequency drive (VFD) which is however a very important technique for expense minimization and load balancing. Basically, the typical execution time of a task is determined assuming that the task is scheduled to operate at a typical frequency level. The execution time varies with different frequencies. For example, if a micro-wave oven originally needs 10 minutes to cook a dish when operating at its nominal frequency 1.5 GHz, it might need only 5 minutes when operating at 3 GHz. As far as the performance is concerned, it is certainly desirable to schedule the household appliance to run at the high frequency.

Oftentimes, there is a limit on the total load demand for each household during a certain time interval. When the total load demand of household appliances exceeds the given load limit of the household, the home power network trips out. This will lead to degradation of customer comfortableness. *The probability that the home power network trips out during a time interval is defined to be the trip rate*. Or course, the scheduler should try to avoid tripping out. However, since there are uncertainties in the energy consumption of household appliances as well as renewable generation, one can only minimize the trip rate (to a very small value) in practice. Thus, it is desired for customers to set a trip rate constraint (e.g., 0.5%) such that the trip rate of the scheduling solution is no greater than the constraint.

In this paper, an energy efficient scheduling algorithm is proposed to minimize the monetary expense without compromising the comfortableness of customers. Precisely, the proposed operation scheduling algorithm takes as inputs the time-varying pricing information released by power utility companies ahead of time, distributed renewable generations and energy storage, and the customer-defined target trip rate. It generates an operation schedule over a pre-defined time domain (called horizon) that minimizes the customer monetary expense and meet the customer-defined trip rate. The major contribution of this paper is summarized as follows. Our algorithm features the consideration of the uncertainties in household appliance operation time and energy consumption and energy generated from the renewable resources. To handle the uncertainty in household appliances, a stochastic scheduling algorithm which involves an energy adaptation variable β to model the uncertainty in energy consumed by an appliance is designed. On the other hand, since the real-time energy generated from renewable energy resources is much more difficult to predict precisely, its uncertainty will be handled using online scheduling algorithm, which adapts the static operation schedules to the runtime intermittent behavior of renewable energy resources. The proposed algorithm can also handle the scheduling of operations of VFD-equipped appliances. The simulation results show that when compared to a worst case design where an appliance is assumed to consume the maximum amount of energy, the proposed design that considers the stochastic energy consumption patterns achieves up to 24% monetary expense reduction without violating the target trip rate of 0.5%. When compared to a natural greedy algorithm which models typical household appliance operations in the traditional home scenario, the proposed deterministic linear programming based scheduling scheme achieves up to 53% monetary expense reduction. Furthermore, the proposed energy consumption scheduling algorithm can always generate the scheduling solution within 10 seconds, which is fast enough for household appliance applications.

The rest of the paper is organized as follows. Section II describes the system architecture and models, and defines the optimization problem. Section III formulates the scheduling problem into a linear programming problem and proposes the offline operation scheduling algorithm that minimize the customer monetary expense. In Section III-C, the offline operation schedule is adapted to the intermittent behavior of the renewable generation. Section IV presents the simulation results, and Section V concludes the paper.

II. System Architecture and Models

This paper aims to minimize the monetary expense of the customer through optimally scheduling the operation and energy consumption for each appliance considering uncertainties under the real-time pricing environments. The following subsections describe the system models and problem definition.

A. Residential Customer Model

As is illustrated in Fig. 1, a residential unit may include various household appliances such as air conditioners, space heaters, washers, refrigerators, plug-in hybrid vehicles, etc. Let a denote an appliance and A denote the set of appliances. For each $a \in A$, an energy consumption scheduling vector $\mathbf{X}$ is defined as

$$\mathbf{X} \triangleq [x_a^1, \ldots, x_a^T],$$

where T is the scheduling horizon that denotes the number of time units ahead of which the scheduling decision on energy consumption is to be made. For a pricing structure that releases price information one day ahead [28], the scheduler arranges the operation of appliances for the next 24 hours. The scheduling horizon is 24 hours in this scenario. The resolution of scheduling horizon can be hours, minutes, or even seconds, depending on the available pricing information and the computing capability of the scheduler in the smart meter. For example, since the Ameren Illinois Power Corporation releases hourly price information one day ahead [28], the resolution of scheduling can be set to hourly in this case.

For each time unit $\tau \in \mathbf{T} \triangleq [1, 2, \ldots, T]$ in the horizon of scheduling, the element x_a^τ of the vector $\mathbf{X}$ denotes the energy consumed by the appliance a during the interval τ. Suppose that there are two user-defined time instants δ_a and θ_a which indicate the start time and end time of the operation of the appliance a, respectively. It is clear that $\delta_a < \theta_a$ holds and the appliance a consumes no energy beyond the interval of $[\delta_a, \theta_a]$. In other words, $x_a^\tau = 0$ for $\tau < \delta_a$ or $\tau > \theta_a$.

It is assumed that each appliance $a \in A$ has a maximum energy level in the interval of τ, which is defined to be the rated power and denoted by P_a. For example, let a denote a laundry machine and it may operate at the power of up to $P_a = 5.6\,\mathrm{kW\ per\ hour}$. It is clear that $x_a^\tau \le P_a$ holds, where x_a^τ is the actual energy consumed by the appliance a during the interval of τ. Oftentimes, there is a limit on the total energy consumed by various appliances of a household in the time interval of τ. Let L_A^τ denote the value of the energy limit, then the inequality

$$\sum_{a \in A} x_a^\tau \le L_A^\tau \tag{1}$$

holds for $\tau \in \mathbf{T}$. When the above constraint is violated, the home power network will be tripped out.

The total energy consumed by an appliance $a \in A$ during the scheduling horizon T is given by $\sum_{\tau \in \mathbf{T}} x_a^\tau$ and denoted by E_a^T. E_a^T is essentially a random variable. For instance, the laundry time of an advanced laundry machine depends on the load, which is usually a Gaussian distribution. As a result, the energy consumed by the machine follows the Gaussian distribution of the probability.

Let μ denote the mean and σ denote the standard deviation of the random variable, and let $\gamma_a^{\min}$ and $\gamma_a^{\max}$ denote the minimum and maximum value of the random variable, respectively. For a random variable following a Gaussian distribution, with more than 99% confidence its maximum deviation from the mean is bounded by 3σ. Thus, we set $\gamma_a^{\min} = \mu - 3\sigma$ and $\gamma_a^{\max} = \mu + 3\sigma$.

During our optimization, since it is difficult to directly solve a mathematical program with uncertainty the energy optimization problem is transformed into a set of deterministic optimization problems without random variables (refer to Section III). In this work, motivated from [29], a variable β, referred to as energy adaptation variable, is introduced to model the uncertainty in

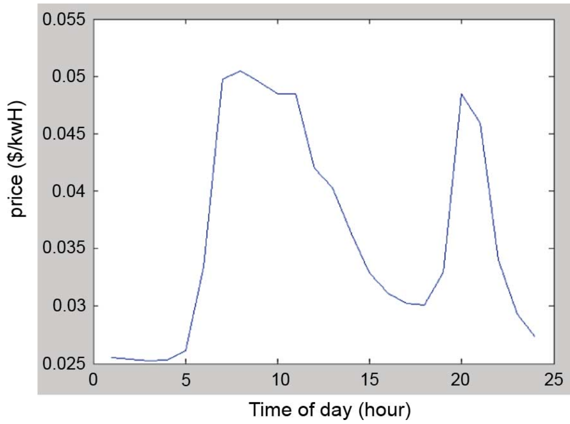


Fig. 2. An example of the one day ahead pricing structure [28].

energy consumed by an appliance. The actual energy consumption of the appliance $a \in A$ during the scheduling horizon T can be expressed as a function of β, $\gamma_a^{\min}$, and $\gamma_a^{\max}$, that is,

$$E_a^T = (1-\beta) \times \gamma_a^{\min} + \beta \times \gamma_a^{\max}, \tag{2}$$

where $0 \leq \beta \leq 1$. The energy consumption of appliance a during T is $\gamma_a^{\max}$ if $\beta = 1$ and is $\gamma_a^{\min}$ if $\beta = 0$.

B. Pricing Model

In the literature, numerous time-differentiated pricing models have been proposed which include real-time pricing (RTP), day-ahead pricing (DAP), time-of-use pricing (TOU), critical-peak pricing (CPP), inclining block rates (IBR), etc. [16]. Among them, the RTP and IBR models have been extensively investigated from various perspectives [30]–[37]. Basically, in RTP pricing model prices could be different for different time intervals while they are flat within each time interval. In contrast, in IBR pricing model prices remain the same over time while incuring an increase when the energy consumption of a residential unit reaches a pre-determined threshold. Combining RTP and IBR pricing models, which can reflect both the fluctuating wholesale price and the energy consumption level, would lead to the promising replacement model of the current flat rate tariffs [16].

As is in [16], let $c^\tau(E_A^\tau)$ denote the price of the energy consumed by all household appliances in the interval of τ, then $c^\tau(E_A^\tau)$ can be formulated as

$$c^\tau(E_A^\tau) = \begin{cases} b_1^\tau & 0 \leq E_A^\tau \leq l_{th}^\tau \\ b_2^\tau & E_A^\tau > l_{th}^\tau \end{cases} \tag{3}$$

where b_1^τ, $b_2^\tau > 0$ are differentiated price and l_{th}^τ is the energy consumption threshold in the time interval of τ.

It is assumed that real-time pricing parameters b_1^τ, b_2^τ, and l_{th}^τ are known for users ahead of time. For example, one day ahead pricing data released by Ameren Illinois Power Corporation [28] are available online (refer to Fig. 2). These data can be utilized to schedule the operation of appliances for monetary expense optimization.

Note that the proposed energy consumption scheduling scheme is independent of pricing models or pricing prediction models as is described in [38], [39]. Thus, the proposed scheme can be combined with other pricing models to minimize the customer monetary expense.

C. Photovoltaic (PV) Model

With the increasing the penetration of grid-connected photovoltaic systems, extensive research has been conducted on obtaining the maximum power output from an PV array and on the efficient use of fluctuating solar energy. For example, various photovoltaic array Maximum Power Point Tracking (MPPT) techniques are summarized and compared in [40]. It is shown that the two-stage IncCond [41], [42] and the current sweep [43] MPPT methods are appropriate for residential areas, which can be further combined with the irradiance forecasting scheme presented in [44] to estimate the energy output. Taking the PV array output energy as input, the proposed energy consumption algorithm attempts to maximize the benefit from solar energy so as to minimize the overall monetary expense of the residential customer.

Note that the proposed scheme is also independent of specific solar power prediction models. In other words, the proposed scheme can be jointly utilized with any other solar power prediction approach. For the illustration purpose, in this work the power generated from a photovoltaic system is assumed to follow the probabilistic distribution function derived from historical data.

III. The Proposed Stochastic Scheduling Algorithm for Household Appliances

Our algorithm consists of three parts. The first part is a linear programming based deterministic scheduling algorithm. The second part is a stochastic scheduling technique based on the deterministic linear programming scheduling technique to handle the uncertainty in energy consumption and runtime of household appliances. The last part is the online runtime scheduling, which can effectively handle the uncertainty in the energy generation from the photovoltaic system.

A. Linear Programming Based Deterministic Scheduling

A residential unit consumes solar energy in addition to the energy from electrical grid. The solar energy from PV could be consumed by a residential unit, stored in a battery, or wasted if the battery is full. It is assumed that the price of energy from electrical grid is higher than that of the per-unit cost of solar operation and maintenance, and customers prefer to use solar energy.

Let y_u^τ and e_s^τ denote the energy from electrical grid and the energy produced by the PV system in the time interval of τ, respectively, and let c_u^τ and c_s^τ denote the unit price of the energy from electrical grid and solar energy, respectively, in the time interval of τ, then the objective function is given by (4), where T is the scheduling horizon. b_c denotes the cost of battery and I_c denotes the one-time installation cost of solar panel, both normalized to the scheduling horizon T. Note that the unit price of the solar energy (c_s^τ) essentially indicates the per-unit cost of solar operation and maintenance.

The energy consumed by all appliances in the interval of τ is typically upper bounded by a constant value L_A^τ, which is explained in (1) and rewritten in (5). If the total energy consumption in a residential unit exceeds the limit L_A^τ, then the electricity supply to the unit trips out.

It is assumed that the energy consumed by an appliance $a \in A$ during the scheduling horizon of T follows a distribution of probability. The mean of the energy consumption is denoted by E_a^T. In the offline scheduling, this mean value is taken as the energy consumed by the appliance in the time span of T, as is given in (6). Equation (7) shows that the energy consumed by an appliance $a \in A$ in the interval of τ, which is denoted by x_a^τ, is less than or equal to the rated power of the appliance, which is denoted by P_a. Equation (8) indicates that an appliance does not consume any energy beyond the interval defined by its operation start time δ_a and operation end time θ_a.

Let y_s^τ and y_b^τ denote the solar energy and the battery energy consumed by all appliances in the time interval of τ, respectively. Then the energy consumed by all appliances in a residential unit in the interval τ is the sum of the energy from the grid, the solar energy directly from the PV system, and the battery energy, which is given in (9), where y_u^τ is the energy from the grid.

As is described in (10), part of the solar energy, which is denoted by y_s^τ, is provided to household appliances, and the remaining solar energy, which is denoted by z_s^τ, is stored in the battery. Since there could be waste of solar energy, the solar energy e_s^τ produced by the PV system is greater than or equal to the sum of the consumed and stored solar energy.

Equation (11) describes the energy constraint on the battery. Let z_b^τ denote the remaining energy in the battery at the beginning of the interval τ, and $z_b^{\tau-1}$ denote the remaining energy in the battery at the beginning of the immediate previous interval $(\tau - 1)$. Similarly, the $z_s^{\tau-1}$ and $y_b^{\tau-1}$ denote the solar energy stored in the battery and the battery energy consumed by all appliances in the immediate previous interval of $(\tau - 1)$, respectively. Equation (11) indicates that the current battery energy in the time interval of τ (z_b^τ) equals the remaining battery energy $(z_b^{\tau-1})$ plus the solar energy stored in the battery $(z_s^{\tau-1})$, and minus the battery energy provided for appliances in the immediate previous time interval $(y_b^{\tau-1})$.

In general, the lifetime and price of a battery depends on the total energy throughput of the battery, which is a fixed value by ignoring other aging effects. As a result, the price of a battery can be normalized to the scheduling interval of τ. Let b_u^τ denote the price of the battery with respect to the interval of τ and b_c denote the price of the battery with respect to the scheduling horizon T. The b_c is then given by (12), where z_s^τ is the solar energy charged to the battery in the interval of τ.

Considering the grid electricity cost $(y_u^\tau \times c_u^\tau)$, the solar operation and maintenance cost $(e_s^\tau \times c_s^\tau)$, the battery cost (b_c), and the one-time installation cost of solar panel (I_c), the optimization for the customer monetary expense is hence formulated as a linear programming problem, which is given as follows.

$$\text{minimize:} \quad \sum_{\tau \in \mathbf{T}} (y_u^\tau \times c_u^\tau + e_s^\tau \times c_s^\tau) + b_c + I_c \tag{4}$$

$$\text{subject to:} \quad \sum_{a \in A} x_a^\tau \leqslant L_A^\tau,\ \forall \tau \in \mathbf{T} \tag{5}$$

$$\sum_{\tau \in \mathbf{T}} x_a^\tau = E_a^T,\ \forall a \in A \tag{6}$$

$$x_a^\tau \leqslant P_a,\ \forall a \in A,\ \tau \in \mathbf{T} \tag{7}$$

$$x_a^\tau = 0,\ \forall a \in A,\ \tau \notin [\delta_a, \theta_a] \tag{8}$$

$$\sum_{a \in A} x_a^\tau = y_b^\tau + y_s^\tau + y_u^\tau,\ \forall \tau \in \mathbf{T} \tag{9}$$

$$y_s^\tau + z_s^\tau \leqslant e_s^\tau,\ \forall \tau \in \mathbf{T} \tag{10}$$

$$z_b^\tau = z_b^{\tau-1} + z_s^{\tau-1} - y_b^{\tau-1},\ \tau \in [2, \ldots, T] \tag{11}$$

$$b_c = \sum_{\tau \in \mathbf{T}} z_s^\tau \times b_u^\tau. \tag{12}$$

Variable Frequency Drive (VFD) technology has been widely adopted in household appliances such as air conditioner and fans to obtain smooth speed control and achieve significant energy savings [45]. For an appliance with VFD, its power consumption for different scheduling intervals is different while the power consumption for a single scheduling interval τ is the same. For an appliance without VFD, its power consumption in different scheduling intervals remains the same. The above energy consumption scheduling formulation handles the household appliances with VFD. That is, an appliance does not change operating frequency within an interval but can operate at different frequencies in different scheduling intervals.

B. *Energy Adaptation Variable Based Offline Stochastic Scheduling*

In this paper, motivated from [29], a systematic trip rate-driven stochastic scheduling algorithm is proposed to derive the desired energy adaptation variable β and generate the operation schedule for a given set of household appliances with trip rate requirements. Note that this is an offline scheduling (to handle the uncertainty in household appliances) and the online scheduling scheme is described in Section III-C (to handle the uncertainty in renewable generation).

As described in Fig. 3, for a given set of appliances $a \in A$ and the target trip rate ρ_t, a value of the energy adaptation variable β is iteratively picked, and the actual energy consumed by each appliance in the scheduling horizon T is derived using (2) based on the selected β (step *A*). The operation schedule of the appliance set is then generated through solving the linear program (step *B*). Finally, the trip rate ρ of the resultant operation schedule is derived using Monte Carlo simulation (step *C*). If the trip rate of the schedule does not satisfy the stop-condition of the algorithm, the energy adaptation variable β is adjusted and the above process is repeated. If the trip rate of the operation schedule satisfies the stop-condition of the algorithm, the valid operation schedule is generated and its trip rate meets the system trip rate requirement. In other words, the output operation schedule is the desired operation schedule if $(\rho_t - \rho) \geqslant \epsilon > 0$ holds, where ϵ is an arbitrarily small positive number. The design flow of the algorithm is illustrated in Fig. 4. Each step of the offline scheduling algorithm is described in details in the following subsections.

Input: γ_a^{min} and γ_a^{max} for $a \in A$; target trip rate ρ_t
Output: the desired β; expense efficient operation schedule
pick a value of β in $0 \leq \beta \leq 1$
repeat
  A: update E_a^T for $a \in A$ based on β
  B: generate an operation schedule by solving the LP
  C: derive ρ for the operation schedule using Monte Carlo simulation; update β
until $(\rho_t - \rho) \geq \epsilon > 0$

Fig. 3. The Offline stochastic scheduling algorithm to iteratively derive the energy adaptation variable β and generate the monetary expense efficient operation schedule.

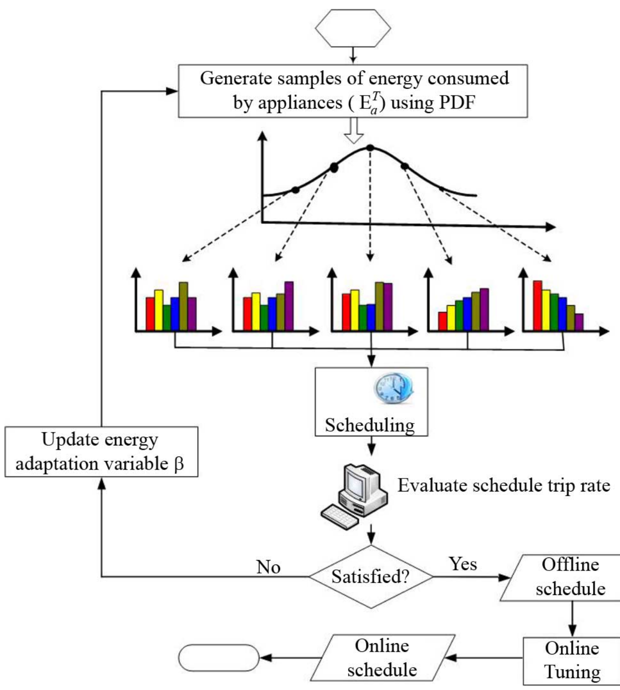


Fig. 4. The design flow of the household appliance energy consumption scheduling algorithm.

1) β-Enabled Parallel Appliance Operation Scheduling: The energy adaptation variable β can adapt energy consumed by an appliance to the Gaussian probability distribution of energy consumption patterns. It enables the trip rate-driven scheduling of appliance operation based on pricing information released ahead of time. Since $0 \leqslant \beta \leqslant 1$, the energy consumed by an appliance $a \in A$ during the scheduling horizon T ranges from $\gamma_a^{\min}$ to $\gamma_a^{\max}$, as is shown in (2).

Due to the statistical property of energy consumption patterns, there exists no fixed relationship between the energy adaptation variable β and the trip rate of a schedule. Although the current trip rate ρ of the operation schedule can not be directly used to find the value of β in the next iteration, the energy consumed by a household appliance is linear with the energy adaptation variable β according to (2). Therefore, it is natural to use a step search strategy to derive the desired β that minimize the customer monetary expense. The β is initialized to 0 and the the step length depends upon the time requirements to generate the desired operation schedule.

The introduction of the energy adaptation variable β in fact makes the proposed algorithm parallelization friendly through utilizing the powerful computing capacity of modern computers. The iterative appliance operation scheduling algorithm shown in Fig. 3 is essentially a pipelined processing stages, each of which consists of using β to adapt energy consumed by an appliance to energy consumption patterns, solving linear program to generate an operation schedule, and evaluating the resultant operation schedule. This pipelining property of the algorithm naturally facilitates the concurrent generation of operation schedules and strikingly reduces the time to generate the desired β and operation schedule. The key fact is that the above procedure with different β can be performed independently. For example, for a given a dual core processor, if the current value of β is β_0 and current trip rate does not meet the specified stop-condition, the next iterations of the algorithm with $\beta = \beta_0 + \xi$ and $\beta = \beta_0 + 2\xi$ can be run simultaneously on core 1 and core 2, respectively, where ξ is the specified step length.

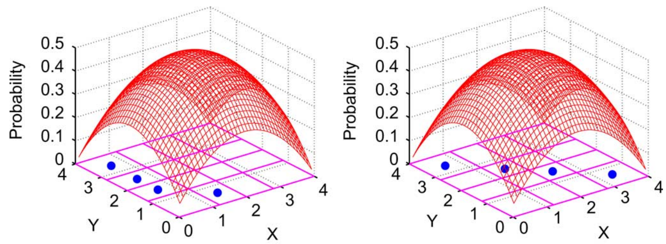
2) Derive the Trip Rate Using Monte Carlo Simulation and Latin-Hypercube Sampling: The trip rate of an operation schedule for a given set of appliances is evaluated using Monte Carlo simulation under the assumption that the energy consumption patterns follows the Gaussian probability distribution. Oftentimes, the trip rate of an operation schedule is obtained in two major steps. In the first step, the energy consumed by an appliance during the scheduling horizon is generated based on the probability distribution of the energy consumption patterns. In the second step, the sum of the energy consumed by all appliances in a household unit is derived, and whether the operation schedule trips out is verified.

The first step is the Monte Carlo sample generation and the second step is the Monte Carlo sample evaluation. Repeat the two steps to take a sufficiently large number of (say 10,000) Monte Carlo samples, and the trip rate of the current operation schedule can be estimated as the ratio of the number of samples where the system trips out to the total number of Monte Carlo samples. If the current trip rate is less than and yet close enough to the target trip rate, the resultant operation schedule is the desired schedule and the execution of the algorithm exits. Otherwise, the algorithm jumps from step C to step A and continues its execution, as is described in Fig. 3.

Although the Monte Carlo simulation described above exhibits relative generality and insensitivity to stochastic characteristics of energy consumption patterns, it is expensive for accurate trip rate estimation of an operation schedule. Therefore, the Latin Hypercube sampling method is adopted in this work to improve the efficiency of trip rate estimation for an operation schedule by sampling energy consumption more systematically.

The Latin Hypercube sampling (LH), first described by McKay *et al.* in [46], has been utilized in uncertainty analysis to generate multivariate samples of statistical distributions. For a one-dimensional variable-sampling, it starts by estimating the uncertainty of a variable using a probability distribution, dividing the range of the variable into intervals of equal probability, and generating a sample value for the variable in each interval.

A two-dimensional variable-sampling is used to illustrate the idea of LH sampling. Given two random variables (x, y) that are to be simulated. 4 simulation samples of the variable can be



(a) (b)

Fig. 5. Random sampling versus Latin Hypercube sampling (a) Random sampling (b) Latin Hypercube sampling.

obtained by randomly generating 4 pairs of (x, y). As is shown in Fig. 5(a), these samples cannot well represent the simulation space.

LH sampling technique can be utilized to tackle the above non-representative sampling issue. In LH sampling, the range of each variable is divided into equally probable intervals, each of which can associate with one and only one simulation sample. As is illustrated in Fig. 5(b), the simulation domain is first divided into 4×4 grids of equal probability. When one grid is selected to generate a simulation sample, grids with the same row or column can not be the candidate grids for future sample generation. The samples in Fig. 5(a) represent the standard Monte Carlo samples. They cover only a small part of the simulation space, and thus a large number of samples are needed. In contrast, LH sampling can use much smaller number of samples to cover the simulation space. As a result, the simulation time can be significantly reduced.

C. Adaptation of Offline Operation Schedules to Online Scheduling

The proposed energy consumption scheduling algorithm consists of two parts, that is, the offline scheduling algorithm and the online adaptation algorithm. The offline scheduling algorithm is first designed assuming that all inputs of the algorithm are given. In other words, it is assumed that the energy consumed by household appliances and the energy produced by the solar panel are known in advance. As a result, the offline operation schedule is optimum. However, when the system is in operation, the energy consumed by household appliances and the energy produced by the solar panel deviate from the values utilized to optimize the offline operation schedule. Thus, the optimality of the offline operation scheduling is lost and the online operation needs to be tuned to compensate for the optimality loss.

Let $\Delta \sum_{a\in A} x_a^\tau$ denote the runtime variation (increase) in the energy demand of appliances $a \in A$ in the interval of τ, and let Δe_s^τ the runtime variation (increase) in the harvested solar energy, then the combined variation (increase) in grid energy attributed to the concerned household appliances and the solar energy is denoted by ΔP^τ and can be expressed as $\Delta P^\tau = \Delta e_s^\tau - \Delta \sum_{a\in A} x_a^\tau$. The ΔP^τ is essentially the modified variation in the solar energy by considering the offset to the variation in energy demand of household appliances. The ΔP^τ could be greater than, less than, or equal to 0. For each case, the battery status is checked before disposal of solar energy. The solar energy could be consumed, stored in the battery for future use, or wasted due to limitation of battery capacity, as is detailed as follows.

- $\Delta P^\tau > 0$: If battery is full, and the consumption of energy from electrical grid is not scheduled, that is, only solar energy is scheduled at the moment, then discard the extra solar energy; if battery is full and the consumption of energy from electrical grid is scheduled, then use solar instead of utility energy. If battery is not full, and the current price of utility electricity is higher than the average utility electricity price, then use the solar energy; else if the current electricity price is lower than the average electricity price, then store the solar energy to battery.
- $\Delta P^\tau < 0$: If battery is empty, then use the energy from electrical grid. If battery is not empty and the current utility electricity price is higher than the average utility electricity price, then use batter energy, else use the utility energy.
- $\Delta P^\tau = 0$: Follow the offline appliance operation schedule.

It is worth noting that the online tuning algorithm is an integral part of the proposed scheduling scheme. The uncertainty in the energy demand of household appliances has been handled by the offline scheduling algorithm, thus, the runtime variation in the energy demand has minimal impact to the scheduling results. With respect to the solar energy, it in general accounts for a small portion of the total energy consumed. Therefore, the runtime variation of the solar energy is much smaller and its impact to the scheduling results is negligible. In fact, the online tuning algorithm aims at maximizing the benefit of the solar energy instead of dealing with the impact of the above variations to the scheduling results. The online algorithm prioritizes the solar energy and the energy from the grid, and utilizes solar energy at a higher priority.

IV. Simulation Results and Discussions

Extensive simulation experiments have been performed to validate the proposed scheme, which aims to reduce customer monetary expenses by utilizing the grid energy at off-peak times and maximizing the benefit from the solar energy. Sets of household appliances are carefully designed and generated. The number of appliances in each set ranges from 5 to 30, which is the typical number of household appliances [47]. The operation start time δ_a and end time θ_a of an appliance $a \in A$ are typically defined by customers. These values are such designed and generated in the scheduling horizon that they conform to human being's practice pattern. The scheduling horizon is assumed to be 24 hours. It is assumed that the mean and standard deviation of the energy consumed by an appliance during the scheduling horizon are known in advance. The mean of the energy consumed by an appliance is generated according to power characteristics of the appliance, and the standard deviation is set to 20% of the μ which is the mean. Hence, the maximum energy value $\gamma_a^{\max}$ and minimum energy value $\gamma_a^{\min}$ of the appliance $a \in A$ during the scheduling horizon T can be derived based on the given mean and standard deviation. The one day ahead pricing data released by Ameren Illinois Power Corporation [28] are available online, and are taken as the price input in the experiment.

TABLE I
COMPARISON OF THE DETERMINISTIC LP-BASED APPROACH AND THE TRADITIONAL SCHEDULING APPROACH

Appliance set size	Traditional		Deterministic LP-based		
	Runtime(s)	Expense(¢)	Runtime(s)	Expense(¢)	Expense reduction
5-10	0.02	102.7	0.8	60.0	41.7%
11-15	0.03	220.5	1.2	128.4	41.8%
16-20	0.05	294.5	1.8	174.6	40.7%
21-25	0.08	330.0	2.3	185.7	43.7%
26-30	0.11	393.6	2.9	220.5	44.1%

In the simulation, two sets of the KD200–54 P series PV modules from the Kyocera Solar Incorporation [48] are taken to construct a solar station for a residential unit. The total cost of the two sets is 502 \$ [49]. Assuming the lifetime of the PV system is 20 years [50], the PV installation cost normalized to the scheduling horizon T, which is 24 hours in the experiment, is $I_c = 0.055$ \$. A battery of 845 kW throughput is taken as energy storage. The battery costs 75 \$, thus, the cost per kW is $b_u = 0.089$ \$ [51].

The peak power of the module in the data sheet is 220 W. For the offline scheduling, the energy produced by the solar station in each hour from 10:00 AM to 18:00 PM is assumed to be 100 Wh, 210 Wh, 300 Wh, 400 Wh, 400 Wh, 300 Wh, 210 Wh, and 100 Wh, respectively. The solar energy e_s^τ produced in the interval of τ could be derived from these data. The solar operation and maintenance cost is assumed to be $c_s^\tau = 0.01$ \$ per kWh, which is mostly due to washing the modules to remove dirt and dust instead of due to the rare occurrence of technical failure [52]. In the runtime, the generated solar energy is assumed to deviate from the energy produced offline by 6%.

The proposed scheme was implemented in C++ and tested on a Pentium Dual Core machine with 2.3 GHz T4500 CPU and 3 GB main memory. Simulation was run 1000 times on each set of appliances, and the reported results are the results averaged over all the runs.

Two approaches, referred to as the traditional scheduling approach and the deterministic LP-based approach, are compared in scheduling time and monetary expense of energy. The traditional scheduling approach represents a typical scenario of energy consumption pattern for the traditional grid while the deterministic LP-based scheme is the basis for the proposed scheduling algorithm.

In the traditional scheduling approach, an appliance is switched on by the customer whenever it is needed and switched off when the customer finishes using it. For simplicity, it is assumed that the appliance operates at its rated power. In this simulation of the experiment, the appliance $a \in A$ with the feasible interval of $[\delta_a, \ \theta_a]$ is supposed to be switched on at the instance δ_a, operate at its rated power, and is switched off before the instance θ_a. This arrangement of the appliance operation does not consider the time-varying electricity price in the execution duration of the appliance, thus incurring high customer monetary expenses.

In the deterministic LP-based approach, the operation schedule is generated by running the LP solver only once other than running the LP solver iteratively. As is shown in Table I, for a residential unit with different number of household appliances, the deterministic LP-based approach achieves significant savings while taking longer scheduling time. For instance, for a household with 5–10 appliances, the monetary expense of energy for the traditional scheduling approach and the deterministic LP-based approach is 102.7 and 60.0, respectively, while the scheduling time of the two schemes is 0.02 s and 0.8 s, respectively. The deterministic LP-based approach reduces the monetary expense of energy by about 42%.

Three cases of β-based energy consumption scheduling schemes, that is, the worst case ($\beta = 1$), the best case ($\beta = 0$), and the proposed stochastic case ($0 < \beta < 1$), were implemented. In the worst case where an appliance $a \in A$ is assumed to consume the maximum amount of energy $\gamma_a^{\max}$, the operation schedule is generated by running the LP solver only once. Similarly, in the best case, the LP solver takes as input the minimum energy value $\gamma_a^{\min}$ for each appliance $a \in A$, and runs only once to produce the operation schedule. On the contrary, the proposed stochastic design approach takes as input the β-based energy budget for each appliance $a \in A$, and runs the LP solver iteratively to generate an expense efficient operation schedule under a given trip rate requirement.

The three design cases are then compared in the expense of energy consumption and scheduling time. The scheduling time of the worst case and best case design is less than that of the stochastic design. This is because the worst case and the best case designing approaches run the LP solver only once while the proposed stochastic approach iteratively runs the LP solver to generate the operation schedule. The monetary expense of the worst case design is greater than that of the stochastic design, which is in turn greater than that of the best case design. This is because that the worst case design overestimates the energy consumed by individual appliances while the best case design underestimates the energy consumption. This misestimate of the energy consumed by individual appliances also leads to the discrepancy in trip rate of different designing approaches. Although the best case solution has the minimum monetary expense, it leads to significant tripping out which is useless in practice. As is illustrated in Table II, for a residential unit with 16–20 household appliances and with trip rate requirement of 0.5%, the scheduling time of the worst case, the best case, and the proposed stochastic design is 1.8 s, 1.8 s, and 7.6 s, respectively, and the expense of utility energy of the three designs is 238.3, 116.1, and 211.4, respectively. Due to the overestimation and underestimation of the energy consumed by individual appliance in the residential unit, the trip rate of the worst case and the best case design is 0% and 25.1%, respectively. The trip rate of the proposed stochastic design is 0.5% for the residential unit, which satisfies the given trip rate requirement.

The traditional scheduling and the stochastic scheduling approach are compared in terms of monetary expenses and scheduling time, and the results are presented in Table III. The proposed stochastic design achieves up to 41% reduction in monetary expenses at the cost of longer scheduling time. Note that the proposed scheduling algorithm can always generate a monetary expense efficient operation schedule within 10 seconds, which is fast enough for household appliance applications.

Due to uncertainty of the renewable energy source and the variation of energy demand of household appliances, the offline operation schedule need to be tuned to fully utilize the benefit from the solar energy and guarantee the customer satisfaction

TABLE II
COMPARISON OF THE WORST CASE, THE BEST CASE, AND THE STOCHASTIC DESIGN IN TERMS OF MONETARY EXPENSE AND SCHEDULING TIME

Appliance set size	Worst case design ($\beta = 1$)			Best case design ($\beta = 0$)			Proposed stochastic design ($0 < \beta < 1$)			
	Trip rate	Run time(s)	Expense(¢)	Trip rate	Run time(s)	Expense(¢)	Trip rate	Run time(s)	Expense(¢)	Expense reduction
5-10	0%	0.7	79.0	3.8%	0.7	41.7	0.5%	2.8	60.7	23.2%
11-15	0%	1.1	172.4	15.9%	1.2	86.5	0.5%	3.5	149.7	13.2%
16-20	0%	1.8	238.3	25.1%	1.8	116.1	0.5%	7.6	211.4	11.3%
21-25	0%	2.3	256.0	29.5%	2.4	121.4	0.5%	8.8	226.3	11.6%
26-30	0%	2.8	301.0	39.0%	2.8	143.8	0.5%	9.6	270.8	10.0%

TABLE III
COMPARISON OF THE PROPOSED STOCHASTIC DESIGNING APPROACH WITH THE TRADITIONAL SCHEDULING APPROACH

Appliance set size	Traditional		Proposed stochastic design		
	Runtime(s)	Expense(¢)	Runtime(s)	Expense(¢)	Expense reduction
5-10	0.02	102.7	2.8	60.7	40.9%
11-15	0.03	220.5	3.5	149.7	32.1%
16-20	0.05	294.5	7.6	211.4	28.2%
21-25	0.08	330.0	8.8	226.3	31.4%
26-30	0.11	393.6	9.6	270.8	31.2%

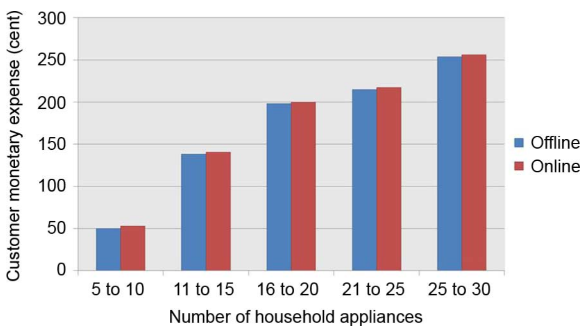


Fig. 6. Compare the monetary expense of online and offline operation schedule.

without violating the system trip rate requirement. Fig. 6 shows a comparison of the customer monetary expense for online and offline operation schedule. For various number of household appliances, the customer monetary expense of online operation schedule is close to that of the optimized offline operation schedule.

V. CONCLUSIONS

This paper proposes a stochastic energy consumption scheduling algorithm based on the time-varying pricing information released by utility companies ahead of time. The proposed energy consumption scheduling algorithm is featured by an energy adaptation variable β that models the stochastic property of customer energy consumption practices. It takes as input the minimum and maximum amount of energy consumed by individual appliances and the pre-defined target trip rate. The output of the proposed algorithm is the desired β that approximates the probability distribution of customer energy consumption practice, and the expense efficient appliance energy consumption schedule. The proposed appliance operation scheduling algorithm also accelerates the generation of the desired operation schedule by paralleling the computing process. Simulation results show that the proposed energy consumption scheduling scheme achieves up to 41% monetary expenses reduction when compared to the traditional scheduling scheme that models typical appliance operations in traditional home scenario. The results also demonstrate that when compared to a worst case design where an appliance is assumed to consume the maximum amount of energy, the proposed design that considers the stochastic energy consumption patterns achieves up to 24% monetary expenses reduction without violating the target trip rate of 0.5%. The monetary expense of the runtime operation schedule is close to that of the offline optimized operation schedule. Furthermore, the proposed scheduling algorithm can always generate a monetary expense efficient operation schedule within 10 seconds, which is fast enough for household appliance applications. The future work seeks to investigate the game theory based scheduling to reduce peak-to-average ratio for a smart community based on the scheduling technique proposed in this paper.

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