

Optimal Power Management of Residential Customers in the Smart Grid

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Abstract—Recently intensive efforts have been made on the transformation of the world’s largest physical system, the power grid, into a “smart grid” by incorporating extensive information and communication infrastructures. Key features in such a “smart grid” include high penetration of renewable and distributed energy sources, large-scale energy storage, market-based online electricity pricing, and widespread demand response programs. From the perspective of residential customers, we can investigate how to minimize the expected electricity cost with real-time electricity pricing, which is the focus of this paper. By jointly considering energy storage, local distributed generation such as photovoltaic (PV) modules or small wind turbines, and inelastic or elastic energy demands, we mathematically formulate this problem as a stochastic optimization problem and approximately solve it by using the Lyapunov optimization approach. From the theoretical analysis, we have also found a good tradeoff between cost saving and storage capacity. A salient feature of our proposed approach is that it can operate without any future knowledge on the related stochastic models (e.g., the distribution) and is easy to implement in real time. We have also evaluated our proposed solution with practical data sets and validated its effectiveness.

Index Terms—Smart grid, optimal power management, Lyapunov optimization, energy storage, renewable energy generation, real-time pricing.

1 INTRODUCTION AND MOTIVATION

ELECTRIFICATION, as made possible by the electric power grid, has been selected as the most significant engineering achievement of the 20th Century by the US National Academy of Engineering [1]. However, not until recently has the imperative of revitalizing US electric infrastructures been realized and a lot of efforts are being put into the grid modernization, which transforms the century-old power grid to the “smart grid.” This transformation has been motivated by the following notable drivers: 1) The physical infrastructure of the electric grid is aging and overburdened. The electricity demand continues to rise while the investments in the power transmission and distribution infrastructure have been dwindling. 2) Concerns over global climate change (e.g., global warming) and carbon emissions have forced us to aim at more aggressive goals of deep integration of large amounts of renewable generation, especially wind and solar, to meet our electric energy needs. As stated in [2], the smart grid would be the enabler for meeting environmental targets, accommodating a greater emphasis on demand response (DR), and supporting widespread plug-in hybrid electric vehicles (PHEVs) as well as distributed generation and storage capabilities. To realize such vision for the smart grid, we have to seek help

from advanced communication, information, and control technologies in conjunction with advances in renewable energy generation, energy storage, materials, sensors, and power-electronics.

Although the smart grid is not a reality as yet, we can articulate how to design it to achieve the vision. We envision that the smart grid will consist of the following essential components in addition to the traditional power grid:

1. *Renewable energy generation*: Given the significant concerns regarding climate change, green energy such as solar and wind energy has become critical for our future energy sustainability. Most states in the US have developed their own renewable portfolio standards (RPSs), which require a predetermined amount of a state’s energy portfolio to come exclusively from renewable sources by the next decade [3]. However, the intermittency and variability of wind and solar energy impose a significant challenge to the grid operation when the penetration level increases [4].
2. *Energy storage*: Energy storage can alleviate the need to generate power at the time when needed and can smooth out the variations of energy utility due to random power demand and uncertain energy supply, which is desirable due to economic consideration and incorporation of more intermittent renewable sources. Examples of utility-scale energy storage include compressed air, pumped hydro, ultracapacitors, flywheels, fuel cells as well as batteries [5], [6]. In residential areas, energy storage is practically synonymous with batteries. Due to the popularity of the emerging PHEVs, the batteries in them may be treated as temporary electricity storages for residential customers [7].

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3. *Demand side management*: While traditional power system is designed for highly controllable supply to match a largely uncontrolled demand, a new energy balancing paradigm in the smart grid is needed in order to facilitate greater penetration of variable renewable energy sources. As noted in [8], over 10 percent daily energy consumption in the US is from the usage of appliances such as water heater, air conditioners, cloth dryers, and dish washers, which are envisaged to become “smart” and have the following distinct features: their energy demands are elastic and delay tolerant, i.e., as long as their energy demands are met within certain time limits, the customers would be satisfied. We call these appliances the *energy consumers* while other appliances, which should be powered whenever needed, are referred to as the *power consumers*. By utilizing the flexibility in the consumer side and providing appropriate incentives (such as real-time pricing), we can reduce the peak demand in the electric power grid and lower the need for expensive peak load generators.

Within the smart grid, advanced dynamic control will be required for simultaneous management of real-time pricing, flexible loads, electric vehicle charge, solar, wind, and other distributed generation sources, many forms of energy storage as well as microgrid management [9]. In the smart grid, we expect more and more renewable generators will be located at the side of residential customers due to environmental concerns. Moreover, by generating power close to the premises where the energy is needed, we can greatly reduce the transmission line losses associated with power delivery from remote power plants and significantly relieve the congestion due to limited transmission capacity of power lines. For example, residential customers may be interested in rooftop photovoltaic (PV) system because of its least environmental impact, scalable capacity, as well as decreasing cost. A basic PV cell converts sunlight of certain wavelengths into direct current (DC) using the “photoelectric effect.” Unfortunately, a basic PV cell typically generates only a small amount of power, which may not be enough to power a whole household. However, due to their modularity and portability, PV cells can be easily interconnected to form a PV panel to meet any electrical requirement, no matter how large or small it is. Although the current cost on PV systems is still high (around \$10 per watt installed), it is expected to reduce by two or three folds in the future [2]. Therefore, in this paper, we select a PV system as the renewable energy source for our study. However, our model is quite flexible and can be easily adapted to other forms of renewable energy sources. A practical system model consisting of the aforementioned essential components in the smart grid for residential customers is shown in Fig. 1.

Since solar energy cannot be dispatched and the fluctuations in solar irradiance may occur in a minute-to-minute time scale, the energy generating profile of a PV system does not coincide with residential energy demand profile for most of the time. There may be electricity spillage at daytime when the PV electricity generation is high and electricity shortage at nighttime when the PV electricity generation is low. To cope with this mismatch, energy storage may have to be

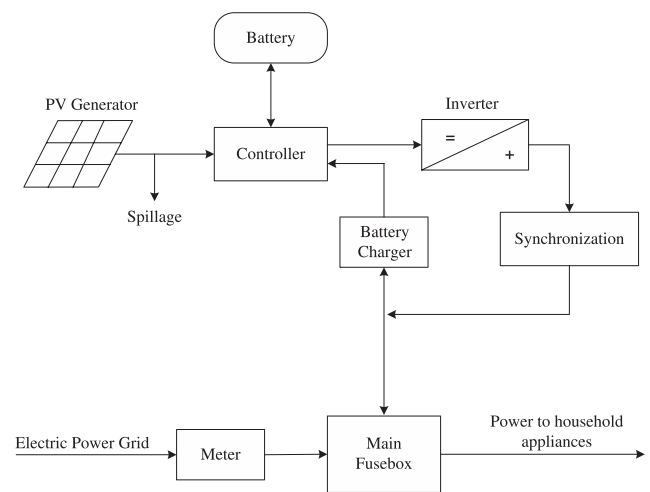


Fig. 1. A PV-utility grid system with the energy storage for residential customers in the smart grid.

used. By storing some excessive generated electricity at daytime, it can be released at nighttime to supplement the power usage for a household. Intuitively, through this method, the total amount of electricity drawn from the electric utility grid can be reduced. Unfortunately, battery charges and discharges will impact the operational life of a battery. In order to protect the battery from overcharge and overdischarge, a controller is needed to regulate the charging and discharging process [10]. Because of the finite capacity of energy storage, some PV generated electricity may still be spilled. As the power generated by PV panels is DC, an inverter is needed to convert DC into alternating current (AC) before it can be used by household appliances. Moreover, a synchronization device is required to adjust the voltage phase and magnitude of the output power from the inverter, so that the output power can be combined smoothly with the power drawn from the electric utility grid to supply electricity to household appliances together. This combination is usually completed at the main fusion box. In the smart grid, customers would be enrolled in a real-time electricity pricing environment, where the electricity price is time varying [11]. The electricity drawn from the power grid can also be stored in the battery through the battery charger so that it can be reused later. Intuitively, the total electricity cost can be reduced by recharging the battery from the electric power grid when the electricity price is low while discharging it during the high electricity price period.

Obviously, it is challenging to manage the use of both the traditional energy and the harvested renewable energy to overcome the variability in the energy supply from the renewable energy source and the energy demand from residential customers while minimizing the cost of traditional energy usage. In this paper, we take the first step to investigate the optimal power management for residential customers in the smart grid by utilizing the battery storage facilities. We consider two different types of energy demands: the inelastic energy demand and the elastic one. Based on the Lyapunov optimization techniques [12], we develop some interesting algorithms to solve our problems, respectively. We demonstrate that our algorithms can achieve close-to-optimal performance with tradeoff between

battery capacity and cost saving. Moreover, in the case for elastic energy demands, we show that our algorithm can guarantee finite worst case delay for any buffered elastic energy demand.

In summary, we have made following contributions in this paper:

- From the perspective of residential customers, we propose a comprehensive model to incorporate almost all essential components of the smart grid, including distributed renewable energy generation, energy storage, demand side management, and smart appliances.
- We present algorithms to approximately achieve the minimum time-average expected electricity cost for residential customers for both inelastic and elastic energy demands without the knowledge of the statistics of related stochastic models.
- Through theoretical analysis, we show that our algorithms can achieve better tradeoff between cost saving and energy storage capacity. Moreover, through extensive simulations and by using practical data sets, we validate the effectiveness of our proposed algorithms.

The rest of the paper is organized as follows: We first review some related work in Section 2. In Section 3, we describe the models for energy storage, renewable energy source, and electricity market we use in this paper. Besides, our control objective is presented. We first consider the case for inelastic energy demands in Section 4 and propose an algorithm to approximately solve the optimization problem. Then, we examine the case for elastic energy demands in Section 5. In Section 6, we employ real data sets to evaluate our algorithms in Section 6. The paper is concluded in Section 7.

2 RELATED WORK

Scheduling in the smart grid inspires intensive interests in the energy community. The problem of supplying renewable energy to demand-flexible customers is investigated in [13], [14]. Specifically, Papavasiliou and Oren [14] address the optimal allocation for renewable sources to demand-flexible customers in real-time pricing environment using dynamic programming, while in [13], the authors develop a Lyapunov optimization method. Both of these studies are from the perspective of the renewable energy source provider and neither of them consider energy storage. Another stream of research is residential load control in a real-time pricing environment. Mohsenian-Rad and Leon-Garci [11] formulate the optimal control of multiple flexible appliances as a linear program to achieve a desired tradeoff between the electricity payment and the waiting time for the operation of each appliance in a household, where customers are subject to a real-time pricing tariff combined with inclining block rates. Kim and Poor [15] investigate the problem of causally scheduling power consumption in a real-time pricing environment, which minimizes the expected cost for a single flexible appliance from the residential consumer's viewpoint and dynamic programming is used to find the optimal solution. Both of these studies consider scheduling of energy consumption of smart appliances using power only from the electric power grid, but our work incorporates distributed renewable

energy into energy sources. Once again, no energy storage is considered in these studies.

The utilization of energy harvested from renewable energy sources is well investigated in rechargeable wireless sensor networks, in which sensor nodes can be self-powered by harvesting energy from their environments [16], [17], [18], [19], [20]. Kansal et al. [16] consider the problem of the optimal power management for sensor nodes, under the assumption that the harvested energy satisfies a leaky-bucket type property. Optimal point-to-point data transmission with an energy harvesting transmitter subject to limited battery capacity and wireless fading channel is addressed in [17]. Finite-horizon energy allocation and routing scheme in rechargeable sensor networks is explored in [18], while infinite-horizon cross-layer resource allocation for wireless networks with rechargeable batteries is discussed in [19], [20]. All these studies give some hints on how to manage the energy consumption, but our problem is quite different and needs new schemes to deal with energy management.

The studies most relevant to ours are [21], [22], in which short-term resource scheduling for an integrated thermal and renewable generations with battery is used to minimize the total thermal generation cost. These studies are from the perspective of power generators and assume that future renewable generation profiles are known beforehand or can be forecasted. However, we consider the long-term time-average expected electricity cost from the viewpoint of residential customers and assume that future knowledge of all related stochastic models are unknown. Therefore, our problem is more challenging. The idea on using available energy storage to reduce electricity cost at a data center in real-time pricing environment is proposed in [23]. Guo et al. [24] extend the case for a single data center in [23] to a cloud provider with multiple data centers. However, no renewable energy source is considered in these studies.

3 SYSTEM MODEL

In this section, we describe the mathematical models for renewable energy generation, energy storage, and electricity market we use in this paper. We also present the control objective, which is to minimize the long-term time-average expected electricity cost. In the next two sections, we consider two different types of energy demand, i.e., the inelastic energy demand and the elastic one, and further analyze the electricity cost minimization problem.¹

3.1 Renewable Energy Generation

Let $S(t)$ denote the amount of renewable energy generated in slot t and we assume that this energy is first stored in battery before it can be used in the next time slot. A controller is to regulate the portion $\gamma(t)$ of the generated energy stored into battery for each slot t in order to prevent battery overflow. The other portion is spilled. Hence, we have

$$0 \leq \gamma(t) \leq 1. \quad (1)$$

Moreover, there is a maximum value S_{max} for $S(t)$, that is,

$$0 \leq S(t) \leq S_{max}. \quad (2)$$

1. We assume a time-slotted system as [13].

3.2 Energy Storage

In practice, the battery is not ideal and has the following physical properties as analyzed in [16], [23]. First, the battery lifetime depends on both the number of times it undergoes charging/discharging and the depth of discharge during its operation. This relationship is illustrated as battery lifetime chart [25]. Second, there is an energy conversion loss during the charging or discharging process, which is measured as charging/discharging efficiency. Finally, as the time goes, the battery will leak some energy stored in it. To simplify our analysis, we assume a battery model without any inefficiency in charging or discharging. As the time slot we choose is typically small (e.g., 5-minute period), energy leakage over time can be neglected. However, more complicated battery model can be easily incorporated into our model without significant impact on our analysis.

We assume that in each time slot t , energy amount $G_b(t)$ can be drawn from the traditional power grid (or simply power grid) to recharge the battery in order to utilize the time diversity of electricity price. The intuition is that if we recharge the battery when electricity price is low, the overall electricity cost may be reduced with proper design.

The state of charge (SOC) level $B(t)$ in the battery evolves according to the following equation:

$$B(t+1) = B(t) - D(t) + \gamma(t)S(t) + G_b(t), \quad (3)$$

where $D(t)$ is the amount of energy that is discharged from battery to supply demand in slot t . Obviously, we should have the following “energy availability” and finite capacity constraint for each time slot t :

$$D(t) \leq B(t) \leq B_{max}, \quad (4)$$

where B_{max} is the battery capacity. There is a maximum discharge rate D_{max} of the battery for one time slot, i.e.,

$$0 \leq D(t) \leq D_{max}. \quad (5)$$

The energy amount that can be drawn from the electric power grid to recharge battery for one time slot is also bounded by $G_{b,max}$, i.e.,

$$0 \leq G_b(t) \leq G_{b,max}. \quad (6)$$

3.3 Electricity Market

As shown in [26], electricity price in the real-time electricity market has both time diversity and location diversity. In this paper, as the proof of concept, we concentrate on one single residential customer (one household), who is subject to a time-varying electricity price. Assume that the time-varying electricity price, $C(t)$, is sent to the customer’s smart meter by the utility company at the beginning of each slot t . The cost of using renewable energy generated by the customer itself is assumed to be zero. Denote $G_l(t)$ as the power drawn from the electric power grid to directly supply the energy demand in slot t . Since the total electricity drawn from the electric power grid is $G_b(t) + G_l(t)$, the electricity cost for each time slot t is $(G_b(t) + G_l(t))C(t)$. In our analysis, the unit electricity price $C(t)$ does not depend on the total amount of energy drawn from the power grid. However, if the unit electricity price depends on the total power consumed, such as

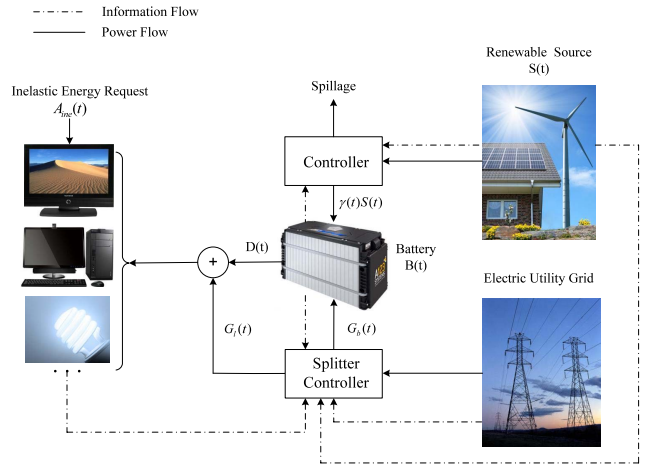


Fig. 2. A schematic of power management with inelastic energy demands in the smart grid.

inclining block rate in [11], it can be still integrated easily into our model as in [23].

3.4 Control Objective

In this paper, we are interested in long-term electricity cost. Hence, our objective here is to minimize the long-term time-average expected electricity cost as described below

$$P = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\}, \quad (7)$$

where the expectation is w.r.t. possibly randomized control actions as well as the distribution of electricity price $C(t)$.

4 INELASTIC ENERGY DEMAND

In the smart grid, some energy demands of residential household are inelastic, such as lighting, TV watching, as well as computers. For this kind of energy demands, the energy requests must be met exactly at the time t when needed. Based on the models presented in the previous section, we come up with a schematic of power management for inelastic energy demands depicted in Fig. 2, where both the power flow and the information flow are shown. The splitter controller manages the power drawn from the power grid to recharge the battery or directly supply the demand. The battery SOC level, energy demand, electricity price, and renewable energy generation can be directly monitored by the splitter controller. Another controller is used to determine the portion of renewable energy to be stored into the battery, which also monitors the status of renewable energy generation and battery SOC level. Due to the information and communication infrastructure deployed in the smart grid, a home area network, either wired or wireless, would be formed in a residential house, which enables communication between the components above for information gathering and dissemination.

We assume the inelastic energy demand generated in time slot t is $A_{ine}(t)$. For each time slot t , we have

$$G_l(t) + D(t) = A_{ine}(t). \quad (8)$$

Thus, our problem can be formulated as the following stochastic optimization, called **Problem One**:

$$\min_{D(t), G_b(t), G_l(t), \gamma(t)} P_1 = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\}, \quad (9)$$

subject to

$$\begin{aligned} B(t+1) &= B(t) - D(t) + \gamma(t)S(t) + G_b(t), \\ D(t) &\leq B(t) \leq B_{max}, \\ G_l(t) + D(t) &= A_{ine}(t), \\ 0 &\leq D(t) \leq D_{max}, \\ 0 &\leq G_l(t) \leq G_{l,max}, 0 \leq G_b(t) \leq G_{b,max}, \\ 0 &\leq \gamma(t) \leq 1. \end{aligned}$$

Define the optimal objective value of the optimization problem above as P_1^* . In the following, we apply the Lyapunov optimization techniques [12], [27] to find an approximate solution, which attains an analytical performance guarantee within $O(1/V)$ of the optimal objective value, where V is a tunable control parameter related to the battery capacity.

The problem above is challenging mainly because of the time-coupling property brought by the battery constraint (4). To be specific, in our problem, the current control action may impact the future control actions in the sense that a current action may overuse the battery and leave insufficient energy for future use, or the current action may leave less available capacity and the future generated renewable energy cannot be utilized efficiently. Previous methods to handle this time-coupling problem are usually based on dynamic programming, which suffers from the ‘‘curse of dimensionality’’ problem [28] and requires detailed knowledge of statistics of $C(t)$, $S(t)$, and $A_{ine}(t)$ in our problem. However, in reality, the statistics of $C(t)$, $S(t)$, and $A_{ine}(t)$ may be unknown or difficult to obtain, and we need to design an optimal control algorithm under uncertainty. We use the recently developed Lyapunov optimization techniques [12] and find a modified Lyapunov function to develop our algorithm. A salient feature of our algorithm is that it does not need any future knowledge of the system states and can be implemented in real time.

In the next section, instead of solving the above stochastic optimization problem exactly, we study a relaxed problem, whose solution is easy to characterize based on the framework of Lyapunov optimization [12], [27].

4.1 Relaxed Problem

We define the time-average expected value of utilized renewable energy, charging and discharging rate under any feasible control policy of **Problem One**, respectively, as follows:

$$\begin{aligned} \overline{\gamma S} &= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{\gamma(t)S(t)\}, \\ \overline{G_b} &= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{G_b(t)\}, \\ \overline{D} &= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{D(t)\}. \end{aligned}$$

Since the battery SOC level evolves according to (3), summing over all $t \in \{0, 1, 2, \dots, T-1\}$ and taking expectation on both sides, we have

$$\mathbb{E}\{B(T)\} - B_0 = \sum_{t=0}^{T-1} \mathbb{E}\{\gamma(t)S(t) + G_b(t) - D(t)\},$$

where $B(0) = B_0$ is the initial battery SOC level. As $0 \leq B(t) \leq B_{max}$ for any time slot t , dividing both sides with T and taking $T \rightarrow \infty$, we have $\overline{D} = \overline{\gamma S} + \overline{G_b}$. Hence, we obtain the following relaxed problem, called **Problem Two**:

$$\min_{D(t), G_b(t), G_l(t), \gamma(t)} P_1 = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\}, \quad (10)$$

subject to

$$\begin{aligned} \overline{D} &= \overline{\gamma S} + \overline{G_b}, \\ G_l(t) + D(t) &= A_{ine}(t), \\ 0 &\leq D(t) \leq D_{max}, \\ 0 &\leq G_l(t) \leq G_{l,max}, 0 \leq G_b(t) \leq G_{b,max}, \\ 0 &\leq \gamma(t) \leq 1. \end{aligned}$$

Denote the optimal objective value of **Problem Two** as $P_{1,rel}^*$. From the discussion above, we observe that any feasible solution to **Problem One** is also a feasible solution to **Problem Two**, i.e., **Problem Two** is less constrained than **Problem One**. Therefore, $P_{1,rel}^* \leq P_1^*$.

It is easy to find the optimal solution to **Problem Two** due to the removal of dependence between battery SOC levels across time slots. As given by the following lemma, the optimal solution to **Problem Two** can be obtained by a randomized, stationary control policy that only chooses $D(t)$, $G_l(t)$, $G_b(t)$, and $\gamma(t)$ every slot purely as a (possibly randomized) function of $C(t)$, $S(t)$, and $A_{ine}(t)$. That means the control policy is independent of battery SOC level. This fact is stated as below:

Lemma 1. *If the $\{A_{ine}(t), C(t), S(t)\}$ are i.i.d. over slots, then there exists a stationary and randomized policy that takes control decisions $\hat{D}_{ine}(t)$, $\hat{G}_{l,ine}(t)$, $\hat{G}_{b,ine}(t)$ and $\hat{\gamma}_{ine}(t)$ every slot t purely as a function (possibly randomized) of current system states $\{A_{ine}(t), C(t), S(t)\}$ while satisfying the constraints above and providing the following guarantees:*

$$\mathbb{E}\{\hat{D}_{ine}(t)\} = \mathbb{E}\{\hat{\gamma}_{ine}S(t)\} + \mathbb{E}\{\hat{G}_{b,ine}(t)\}, \quad (11)$$

$$\mathbb{E}\{C(t)(\hat{G}_{l,ine}(t) + \hat{G}_{b,ine}(t))\} = P_{1,rel}^*, \quad (12)$$

where the expectations are w.r.t. the stationary distribution of $\{A_{ine}(t), C(t), S(t)\}$ and randomized control decisions.

The proof is similar to that in [20], [23] and follows directly from the framework of Lyapunov optimization in [12], [27], which is omitted here for brevity.

To derive such a policy, we need to know the statistical distribution of all combinations of $\{A_{ine}(t), C(t), S(t)\}$, which usually has the ‘‘curse of dimensionality’’ problem [28] if solved by dynamic programming. Moreover, this control policy may not be a feasible solution to **Problem**

One. Instead, we use the existence of such a policy to help us design our control policy that meets all constraints of **Problem One** and derive the performance results for our algorithm.

4.2 Our Proposed Algorithm

Before presenting our algorithm, we define another variable $X_{ine}(t)$ as a shifted version of battery SOC level $B(t)$ for each time slot t as follows:

$$X_{ine}(t) = B(t) - V_{ine}C_{max} - D_{max}, \quad (13)$$

where V_{ine} is a control parameter to be specified later. $X_{ine}(t)$ is used to ensure that the constraint (4) of battery SOC level is satisfied in our algorithm. The intuition behind $X_{ine}(t)$ is to construct the algorithm based on a quadratic Lyapunov function, but carefully perturb the weights used for decision making, so as to push the SOC level in battery toward certain nonzero values to avoid underflow. According to (3) of $B(t)$, we have the same update equation for $X_{ine}(t)$

$$X_{ine}(t+1) = X_{ine}(t) - D(t) + \gamma(t)S(t) + G_b(t). \quad (14)$$

In the latter part of this paper, we will prove that through our algorithm, $X_{ine}(t)$ is bounded in some range so that the constraint (4) on $B(t)$ is always satisfied for each slot t .

The proposed algorithm for inelastic energy demand is shown in Algorithm 1. The algorithm is designed based on the Lyapunov optimization technique developed in [12], [27]. The idea of the algorithm is to greedily minimize a upper bound of the drift-plus-penalty function in (18). Note that the algorithm only uses the current system states $X_{ine}(t)$, $C(t)$, $S(t)$, and $A_{ine}(t)$, and does not require any knowledge of the statistics of renewable energy generation, electricity price, and energy demand arrival process.

Algorithm 1. Power management with inelastic energy demands.

```

foreach Time slot  $t$  do
1   Measure the system states  $X_{ine}(t)$ ,  $C(t)$ ,  $S(t)$  and  $A_{ine}(t)$ ;
2   Choose control decisions  $D_{ine}^*(t)$ ,  $G_{l,ine}^*(t)$ ,  $G_{b,ine}^*(t)$  and  $\gamma_{ine}^*(t)$  as the solution to the following optimization problem, called Problem Three:
   
$$\min [V_{ine}C(t) + X(t)]G_b(t) + [X(t)S(t)]\gamma(t) + [V_{ine}C(t)]G_l(t) - X(t)D(t)$$

   s.t.
       
$$D(t) + G_l(t) = A_{ine}(t),$$

       
$$0 \leq G_l(t) \leq G_{l,max}, 0 \leq G_b(t) \leq G_{b,max},$$

       
$$0 \leq D(t) \leq D_{max},$$

       
$$0 \leq \gamma(t) \leq 1;$$

3    $X(t+1) = X(t) - D_{ine}^*(t) + \gamma_{ine}^*(t)S(t) + G_{b,ine}^*(t)$ 
   ;
end

```

4.3 Algorithmic Properties

In this section, we summarize the properties of our proposed algorithm as follows:

Theorem 1. Assume that $G_{l,max} + G_{b,max} \geq A_{ine}^{max}$, then for any parameter V_{ine} satisfying $0 < V_{ine} \leq V_{ine}^{max}$ for all $t \in \{0, 1, 2, \dots\}$, where

$$V_{ine}^{max} \triangleq \frac{B_{max} - D_{max} - G_{b,max} - S_{max}}{C_{max} - C_{min}}, \quad (15)$$

our Algorithm 1 has the following properties:

1. The queue $X(t)$ is always lower and upper bounded for all slots t as follows:

$$X(t) \geq -V_{ine}C_{max} - D_{max},$$

and

$$X(t) \leq B_{max} - V_{ine}C_{max} - D_{max}.$$

2. All control decisions are feasible.
3. If $S(t)$, $C(t)$, and $A_{ine}(t)$ are i.i.d. over slots, then the time-average expected cost under our algorithm is within bound B_1/V_{ine} of the optimal value, i.e.,

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\} \leq P_1^* + B_1/V_{ine}, \quad (16)$$

where B_1 is a constant given by

$$B_1 \triangleq \frac{[(G_{b,max} + S_{max})^2, D_{max}^2]}{2}. \quad (17)$$

Proof. 1. It is obvious that the optimal solution to **Problem Three** has the following properties:

- If $X_{ine}(t) > -V_{ine}C_{min}$, $G_{b,ine}^*(t) = 0$ and $D_{ine}^*(t) = \min\{A_{ine}(t), D_{max}\}$.
- If $X_{ine}(t) < -V_{ine}C_{max}$, $G_{b,ine}^*(t) = G_{b,max}$ and $D_{ine}^*(t) = \max\{0, A_{ine}(t) - G_{l,max}\}$.

We now use induction to prove this result. When $t = 0$, as $X_{ine}(0) = B_0 - V_{ine}C_{max} - D_{max}$ and $0 \leq B_0 \leq B_{max}$, we have $-V_{ine}C_{max} - D_{max} \leq X_{ine}(0) \leq B_{max} - V_{ine}C_{max} - D_{max}$.

Now suppose that the above bound holds for time slot t . We need to prove that it also holds for time slot $t + 1$. First, suppose $-V_{ine}C_{max} - D_{max} \leq X_{ine}(t) < -V_{ine}C_{max}$, then

$$\begin{aligned} X_{ine}(t+1) &= X_{ine}(t) + G_{b,ine}^*(t) + S(t) - D_{ine}^*(t) \\ &\geq -V_{ine}C_{max} - D_{max} + G_{b,max} \\ &\quad - \max\{0, A_{ine}(t) - G_{l,max}\}. \end{aligned}$$

As $G_{l,max} + G_{b,max} \geq A_{ine}^{max}$, we have

$$X_{ine}(t+1) \geq X_{ine}(t) \geq -V_{ine}C_{max} - D_{max}.$$

Moreover,

$$\begin{aligned} X_{ine}(t+1) &\leq X_{ine}(t) + G_{b,max} + S_{max} \\ &\leq -V_{ine}C_{min} + G_{b,max} + S_{max} \\ &\leq B_{max} - V_{ine}C_{max} - D_{max}, \end{aligned}$$

where we have used

$$V_{ine} \leq \frac{B_{max} - D_{max} - G_{b,max} - S_{max}}{C_{max} - C_{min}}.$$

Second, suppose $-V_{ine}C_{max} \leq X_{ine}(t) \leq -V_{ine}C_{min}$, then

$$\begin{aligned} -V_{ine}C_{max} - D_{max} &\leq X_{ine}(t) - D_{max} \leq X_{ine}(t+1) \\ &\leq X_{ine}(t) + G_{b,max} + S_{max} \leq -V_{ine}C_{min} + G_{b,max} \\ &\quad + S_{max} \leq B_{max} - V_{ine}C_{max} - D_{max}, \end{aligned}$$

where we have used the same bound of V_{ine} as the case above. Third, suppose $-V_{ine}C_{min} < X_{ine}(t) \leq 0$, then $G_{b,ine}^*(t) = 0$. It is obvious that $X_{ine}(t+1) \geq X_{ine}(t) - D_{max} > -V_{ine}C_{max} - D_{max}$. Moreover,

$$\begin{aligned} X_{ine}(t+1) &\leq X_{ine}(t) + S_{max} \leq S_{max} \\ &\leq B_{max} - V_{ine}C_{max} - D_{max}, \end{aligned}$$

where we have used the upper bound of V_{ine} and $G_{b,max} \geq V_{ine}^{max}C_{min}$. Finally, suppose $0 < X_{ine}(t) \leq B_{max} - V_{ine}C_{max} - D_{max}$, then $G_{b,ine}^*(t) = \gamma_{ine}^*(t) = 0$. Hence, $-V_{ine}C_{max} - D_{max} \leq X_{ine}(t+1) \leq X_{ine}(t) \leq B_{max} - V_{ine}C_{max} - D_{max}$. From the induction, we conclude the proof of 1.

2. From 1 and the definition (13) of $X_{ine}(t)$, it follows immediately that $0 \leq B(t) \leq B_{max}$ holds for any time slot t . Further, we make our decisions to satisfy all constraints in **Problem Three**. Combining them together, all constraints of **Problem One** are satisfied. Therefore, our control decisions are feasible to **Problem One**.

3. We make use of the Lyapunov optimization techniques [12] to derive the performance bound for our algorithm. Define the Lyapunov function as $L(X_{ine}(t)) = \frac{1}{2}X_{ine}^2(t)$ and the conditional 1-slot Lyapunov drift as follows:

$$\Delta(X_{ine}(t)) = \mathbb{E}\{L(X_{ine}(t+1)) - L(X_{ine}(t)) | X_{ine}(t)\}.$$

From (14), squaring both sides, we obtain

$$\begin{aligned} \frac{X_{ine}^2(t+1) - X_{ine}^2(t)}{2} &= \frac{(D(t) - \gamma(t)S(t) - G_b(t))^2}{2} \\ &\quad - X_{ine}(t)(D(t) - \gamma(t)S(t) - G_b(t)). \end{aligned}$$

As $0 \leq D(t) \leq D_{max}$ and $0 \leq \gamma(t)S(t) + G_b(t) \leq G_{b,max} + S_{max}$, we have

$$\begin{aligned} &\frac{(D(t) - \gamma(t)S(t) - G_b(t))^2}{2} \\ &\leq \frac{1}{2} \max[(G_b^{max} + S_{max})^2, D_{max}^2]. \end{aligned}$$

Therefore, we can obtain the following upper bound on the Lyapunov drift for $X_{ine}(t)$:

$$\begin{aligned} \frac{X_{ine}^2(t+1) - X_{ine}^2(t)}{2} &\leq \frac{1}{2} \max[(G_b^{max} + S_{max})^2, D_{max}^2] \\ &\quad - X_{ine}(t)(D(t) - \gamma(t)S(t) - G_b(t)). \end{aligned}$$

Taking expectation w.r.t. $X_{ine}(t)$ and adding the penalty term $V_{ine}\mathbb{E}\{C(t)(G_l(t) + G_b(t)) | X_{ine}(t)\}$ to both sides of the inequality above, we obtain the following inequality:

$$\begin{aligned} \Delta(X_{ine}(t)) + V_{ine}\mathbb{E}\{C(t)(G_l(t) + G_b(t)) | X_{ine}(t)\} \\ \leq B_1 - X_{ine}(t)\mathbb{E}\{D(t) - \gamma(t)S(t) - G_b(t) | X_{ine}(t)\} \\ + V_{ine}\mathbb{E}\{C(t)(G_l(t) + G_b(t)) | X_{ine}(t)\}, \end{aligned} \quad (18)$$

where B_1 is defined as

$$B_1 \triangleq \frac{[(G_{b,max} + S_{max})^2, D_{max}^2]}{2}.$$

Comparing with the objective of **Problem Three**, it is obvious that our algorithm always attempts to greedily minimize the right hand side (R.H.S.) of the inequality above for each time slot t over all possible feasible control policies including the optimal, stationary policy given in Lemma 1. Plugging this policy $(\hat{D}_{ine}(t), \hat{G}_{l,ine}(t), \hat{G}_{b,ine}(t), \hat{\gamma}_{ine}(t))$ into the R.H.S. of the inequality above and using the fact that this policy is independent of queue state $X_{ine}(t)$, we obtain the following:

$$\begin{aligned} \Delta(X_{ine}(t)) + V_{ine}\mathbb{E}\{C(t)(G_l(t) + G_b(t)) | X_{ine}(t)\} &\leq B_1 \\ &\quad - X_{ine}(t)\mathbb{E}\{\hat{D}_{ine}(t) - \hat{\gamma}_{ine}(t)S(t) - \hat{G}_{b,ine}(t) | X_{ine}(t)\} \\ &\quad + V_{ine}\mathbb{E}\{C(t)(\hat{G}_{l,ine}(t) + \hat{G}_{b,ine}(t)) | X_{ine}(t)\} \\ &\leq B_1 + V_{ine}P_{1,rel}^* \leq B_1 + V_{ine}P_1^*, \end{aligned}$$

where the following facts have been used:

$$\begin{aligned} \mathbb{E}\{\hat{D}_{ine}(t) - \hat{\gamma}_{ine}(t)S(t) - \hat{G}_{b,ine}(t) | X_{ine}(t)\} &= 0, \\ \mathbb{E}\{C(t)(\hat{G}_{l,ine}(t) + \hat{G}_{b,ine}(t)) | X_{ine}(t)\} &= P_{1,rel}^*. \end{aligned}$$

The equations above follow from Lemma 1. Taking the expectation on both sides, using the law of iterative expectation, and summing over $t \in \{0, 1, 2, \dots, T-1\}$, we obtain

$$\begin{aligned} V_{ine} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\} &\leq B_1T + V_{ine}TP_1^* \\ &\quad - \mathbb{E}\{L(X_{ine}(T))\} + \mathbb{E}\{L(X_{ine}(0))\}. \end{aligned}$$

Dividing both sides by T , let $T \rightarrow \infty$, and using the facts that $E\{L(X_{ine}(0))\}$ are finite and $E\{L(X_{ine}(t))\}$ are nonnegative, we finally arrive at the following:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\} \leq P_1^* + B_1/V_{ine},$$

where P_1^* is the optimal objective value, B_1 is a constant given by (17), and V_{ine} is a control parameter which has the maximum value given by (15). This completes the proof of 3. \square

5 ELASTIC ENERGY DEMAND

While the previous section deals with inelastic energy demand, some household appliances in the smart grid can be made "smart," meaning that they can be controlled to adjust the times of their operations and the amount of their energy usage. In other words, as long as their energy requirements are met within certain deadlines, the residential customers will be satisfied. Some typical examples include dish washer, water heater, air conditioner, and

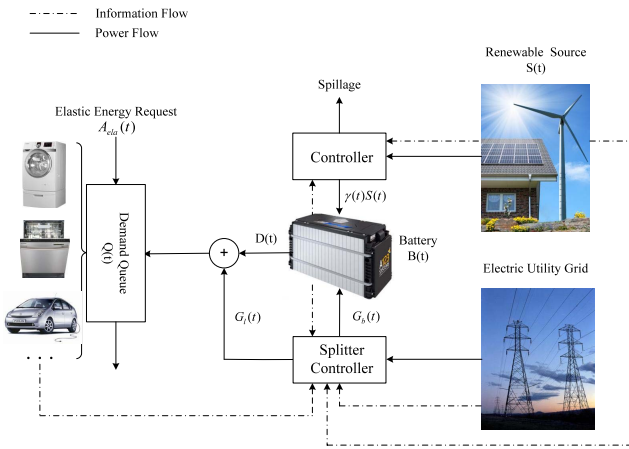


Fig. 3. A schematic for power management with elastic energy demands in the smart grid.

PHEVs. A schematic for the power management with elastic energy demands is shown in Fig. 3.

We assume that the amount of elastic energy demands requested at slot t are $A_{ela}(t)$. These energy demands are stored in an energy demand queue. In every slot t , the energy discharged from the battery is denoted as $D(t)$ and the energy amount drawn directly from the power grid is denoted as $G_l(t)$, which are determined from the buffered energy demands. The energy demands are served in a First-In-First-Out (FIFO) manner.

Let $Q(t)$ denote the total energy demands in the queue for time slot t , we have the following queuing equation:

$$Q(t+1) = \max\{Q(t) - D(t) - G_l(t), 0\} + A_{ela}(t). \quad (19)$$

As long as the waiting time of any buffered energy demand in this demand queue does not exceed a certain maximum deadline δ_{max} , the utility perceived by customers does not decrease. We use the same battery model (3) as in the case for inelastic energy demands. Our problem here is to minimize the time-average expected electricity cost subject to all constraints discussed before and to ensure finite average delay for any buffered energy demand, which can be stated below and is called **Problem Four**

$$\min_{D(t), G_b(t), G_l(t), \gamma(t)} P_2 = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\}, \quad (20)$$

subject to

$$\begin{aligned} B(t+1) &= B(t) - D(t) + \gamma(t)S(t) + G_b(t), \\ D(t) &\leq B(t) \leq B_{max}, \\ Q(t+1) &= \max\{Q(t) - D(t) - G_l(t), 0\} + A_{ela}(t), \\ 0 &\leq D(t) \leq D_{max}, \\ 0 &\leq G_b(t) \leq G_{b,max}, 0 \leq G_l(t) \leq G_{l,max}, \\ 0 &\leq \gamma(t) \leq 1, \\ \bar{Q} &< \infty, \end{aligned} \quad (21)$$

where \bar{Q} is the time-average expected energy demand queue backlog defined as

$$\bar{Q} = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{Q(t)\}.$$

5.1 Relaxed Problem

Similar to the case for the inelastic energy demands, we define a relaxed problem, called **Problem Five**, which can be stated as follows:

$$\min_{D(t), G_b(t), G_l(t), \gamma(t)} P_2 = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\}, \quad (22)$$

subject to

$$\begin{aligned} \bar{D} &= \bar{\gamma}\bar{S} + \bar{G}_b, \\ Q(t+1) &= \max\{Q(t) - D(t) - G_l(t), 0\} + A_{ela}(t), \\ 0 &\leq D(t) \leq D_{max}, \\ 0 &\leq G_b(t) \leq G_{b,max}, 0 \leq G_l(t) \leq G_{l,max}, \\ 0 &\leq \gamma(t) \leq 1, \\ \bar{Q} &< \infty. \end{aligned}$$

Denote the optimal objective value of **Problem Four** and **Problem Five** as P_2^* and $P_{2,rel}^*$, respectively. Similarly, any feasible solution to **Problem Four** is also a feasible solution to **Problem Five**, therefore, $P_{2,rel}^* \leq P_2^*$. Similar to Lemma 1, we have the following result:

Lemma 2. *If $\{A_{ela}(t), C(t), S(t)\}$ are i.i.d. over slots, then there exists a stationary and randomized policy that takes control decisions $\hat{D}_{ela}(t)$, $\hat{G}_{l,ela}(t)$, $\hat{G}_{b,ela}(t)$, and $\hat{\gamma}_{ela}(t)$ every slot t purely as a (possibly randomized) function of current system states $\{A_{ela}(t), C(t), S(t)\}$ while satisfying the constraints above and providing the following guarantees:*

$$\mathbb{E}\{\hat{D}_{ela}(t)\} = \mathbb{E}\{\hat{\gamma}_{ela}S(t)\} + \mathbb{E}\{\hat{G}_{b,ela}(t)\}, \quad (23)$$

$$\mathbb{E}\{\hat{D}_{ela}(t) + \hat{G}_{l,ela}(t)\} \geq \mathbb{E}\{A_{ela}(t)\}, \quad (24)$$

$$\mathbb{E}\{C(t)(\hat{G}_{l,ela}(t) + \hat{G}_{b,ela}(t))\} = P_{2,rel}^*, \quad (25)$$

where the expectations are w.r.t. the stationary distribution of $\{A_{ela}(t), C(t), S(t)\}$ and the randomized control decisions.

The proof is similar to that in [20], [23] and follows the framework of Lyapunov optimization in [12], [27], which is omitted here for brevity.

Note that the constraint (21) only ensures finite average delay without any guarantee for the worst case delay. In the following, we use the technique of ϵ -persistent queue [13] to guarantee the finite worst case delay for any buffered energy demand in the queue.

5.2 Delay-Aware Virtual Queue

We use the following virtual queue $Z(t)$ to provide the worst case delay guarantee on any buffered energy demand in $Q(t)$:

$$Z(t+1) = \max\{Z(t) - D(t) - G_l(t) + \epsilon 1_{\{Q(t) > 0\}}, 0\}, \quad (26)$$

where $1_{\{Q(t) > 0\}}$ is an indicator function that is 1 if $Q(t) > 0$ or 0 otherwise; ϵ is a fixed positive parameter to be specified

later. The intuition behind this virtual queue is that since $Z(t)$ has the same service process as $Q(t)$, but has an arrival process that adds ϵ whenever the actual backlog is nonempty, this ensures that $Z(t)$ grows if there is an energy demand in the queue $Q(t)$ that has not been serviced for a long time. The following lemma shows that if we can control the system to ensure that the queues $Q(t)$ and $Z(t)$ have finite upper bounds, then any buffered energy demand is served within the worst case delay.

Lemma 3. *Suppose we can control the system to ensure that $Z(t) \leq Z_{max}$ and $Q(t) \leq Q_{max}$ for all slots t , where Z_{max} and Q_{max} are some positive constants, then the worst case delay for all buffered energy demand is upper bounded by δ_{max} slots where*

$$\delta_{max} \triangleq \left\lceil \frac{(Q_{max} + Z_{max})}{\epsilon} \right\rceil. \quad (27)$$

Proof. The proof follows directly from the framework of Lyapunov optimization [12]. Consider any slot t for which $A_{ela}(t) > 0$. We will show that this energy request $A_{ela}(t)$ is served on or before time $t + \delta_{max}$ by contradiction. Suppose not, then during slots $\tau \in \{t + 1, \dots, t + \delta_{max}\}$ it must be that $Q(\tau) > 0$, otherwise, the energy request $A_{ela}(t)$ would have been served before τ . Therefore, $1_{Q(t)>0} = 1$, and from the update (26) of $Z(t)$, we have for all $\tau = \{t + 1, \dots, t + \delta_{max}\}$

$$Z(\tau + 1) \geq Z(\tau) - D(t) - G_l(t) + \epsilon.$$

Summing the above over $\tau = \{t + 1, \dots, t + \delta_{max}\}$ yields

$$Z(t + \delta_{max} + 1) - Z(t + 1) \geq - \sum_{\tau=t+1}^{t+\delta_{max}} [D(t) + G_l(t)] + \delta_{max}\epsilon.$$

Rearranging the terms and using the facts that $Z(t + 1) \geq 0$ and $Z(t + \delta_{max} + 1) \leq Z_{max}$ yields

$$\sum_{\tau=t+1}^{t+\delta_{max}} [D(t) + G_l(t)] \geq \delta_{max}\epsilon - Z_{max}.$$

Since the request $A_{ela}(t)$ are queued in a FIFO manner and $Q(t + 1) \leq Q_{max}$, it would be served on or before time $t + \delta_{max}$ whenever there are at least Q_{max} units of energy served during $\tau \in \{t + 1, \dots, t + \delta_{max}\}$. As we have assumed that the request $A_{ela}(t)$ are not served by time $t + \delta_{max}$, it must be that $\sum_{\tau=t+1}^{t+\delta_{max}} [D(t) + G_l(t)] < Q_{max}$. Comparing this inequality with (5.2) yields

$$Q_{max} > \delta_{max}\epsilon - Z_{max},$$

which implies that $\delta_{max} < (Q_{max} + Z_{max})/\epsilon$, contradicting the definition of δ_{max} in (27). \square

We will show that there indeed exist such constants Z_{max} and Q_{max} later.

5.3 Our Proposed Algorithm

Before presenting our algorithm, we define another variable $X_{ela}(t)$ as a shifted version of battery SOC level $B(t)$ for time slot t as follows:

$$X_{ela}(t) = B(t) - \Theta_{max} - D_{max}, \quad (28)$$

where Θ_{max} is a positive constant to be specified. $X_{ela}(t)$ is also used to ensure that the constraint (4) of battery SOC

level is satisfied in our algorithm. According to (3), we obtain the same update equation for $X_{ela}(t)$,

$$X_{ela}(t + 1) = X_{ela}(t) - D(t) + \gamma(t)S(t) + G_b(t). \quad (29)$$

The algorithm for elastic energy demands is shown in Algorithm 2. The algorithm is designed based on the Lyapunov optimization technique developed in [12], [27]. The idea of the algorithm is to greedily minimize a upper bound of the drift-plus-penalty function in (36). Similarly, the algorithm only makes use of the current system states $(X_{ela}(t), Q(t), Z(t))$, $C(t)$, $S(t)$, and $A_{ela}(t)$, and does not require any knowledge on the statistics of the renewable energy generation, the electricity price, and the energy demand arrival process.

Algorithm 2. Power management with elastic energy demands.

foreach Time slot t **do**

1 Measure system states $(X_{ela}(t), Q(t), Z(t))$, $C(t)$, $S(t)$ and $A_{ela}(t)$;

2 Choose control decisions $D_{ela}^*(t)$, $G_{l,ela}^*(t)$, $G_{b,ela}^*(t)$ and $\gamma_{ela}^*(t)$ as the solution to the following optimization problem, called **Problem Six**:

$$\begin{aligned} \min \quad & [V_{ela}C(t) + X_{ela}(t)]G_b(t) + \\ & [X_{ela}(t)S(t)]\gamma(t) + [V_{ela}C(t) - Z(t) - \\ & Q(t)]G_l(t) - [X_{ela}(t) + Z(t) + Q(t)]D(t) \\ \text{s.t.} \quad & \end{aligned}$$

$$0 \leq D(t) \leq D_{max},$$

$$0 \leq G_l(t) \leq G_{l,max}, 0 \leq G_b(t) \leq G_{b,max},$$

$$0 \leq \gamma(t) \leq 1;$$

3 $X(t + 1) = X(t) - D_{ela}^*(t) + \gamma_{ela}^*(t)S(t) + G_{b,ela}^*(t)$;

4 $Z(t + 1) = \max[Z(t) - D_{ela}^*(t) - G_{l,ela}^*(t) + \epsilon 1_{\{Q(t)>0\}}, 0]$;

5 $Q(t + 1) = \max[Q(t) - D_{ela}^*(t) - G_{l,ela}^*(t), 0] + A_{ela}(t)$;

end

5.4 Algorithmic Properties

Intuitively, by constructing the quadratic Lyapunov function as the square of $X_{ela}(t)$ and keeping the value small, we indeed push the value of $B(t)$ toward the shifted value in the definition (29) of $X_{ela}(t)$. Therefore, by carefully selecting the shifted value, we can ensure that the battery SOC level always satisfies the finite capacity constraint.

We summarize the properties of our proposed algorithm as follows:

Theorem 2. *Assume that $G_{l,max} \geq \max[A_{ela}^{max}, \epsilon]$. If $Q(0) = Z(0) = 0$, then for any fixed parameter $0 \leq \epsilon \leq \mathbb{E}\{A(t)\}$ and a parameter V_{ela} such that $0 < V_{ela} \leq V_{ela}^{max}$ for all $t \in \{0, 1, 2, \dots\}$, where*

$$V_{ela}^{max} \triangleq \frac{B_{max} - A_{ela}^{max} - \epsilon - D_{max} - G_{b,max} - S_{max}}{C_{max} - C_{min}}, \quad (30)$$

our Algorithm 2 has the following properties:

1. The queues $Q(t)$ and $Z(t)$ are deterministically upper bounded by Q_{max} and Z_{max} at every slot, where

$$Q_{max} \triangleq V_{ela}C_{max} + A_{ela}^{max}, Z_{max} \triangleq V_{ela}C_{max} + \epsilon. \quad (31)$$

Further, $Q(t) + Z(t)$ are upper bounded by Θ_{max} where

$$\Theta_{max} \triangleq V_{ela}C_{max} + A_{ela}^{max} + \epsilon. \quad (32)$$

2. The worst case delay of any buffered energy demand is given by

$$\delta_{max} = \left\lceil \frac{2V_{ela}C_{max} + A_{ela}^{max} + \epsilon}{\epsilon} \right\rceil. \quad (33)$$

3. The queue $X_{ela}(t)$ is always lower and upper bounded for all slots t by the following:

$$-\Theta_{max} - D_{max} \leq X_{ela}(t) \leq B_{max} - \Theta_{max} - D_{max}.$$

4. All control decisions are feasible.
5. If $S(t)$, $C(t)$, and $A_{ela}(t)$ are i.i.d. over slots, then the time-average expected electricity cost under our algorithm is within bound B_2/V_{ela} of the optimal value, i.e.,

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\} \leq P_2^* + B_2/V_{ela}, \quad (34)$$

where B_2 is a constant given by

$$B_2 \triangleq \frac{[(D_{max} + G_{l,max})^2 + A_{ela,max}^2]}{2} + \frac{\max[(D_{max} + G_{l,max})^2, \epsilon^2]}{2} + \frac{\max[(S_{max} + G_{b,max})^2, D_{max}^2]}{2}. \quad (35)$$

Proof. 1. First, we prove $Q(t) \leq Q_{max}$ for every time slot t . Once again, we will use induction method. Obviously, $Q(0) \leq Q_{max}$. Suppose it holds at time slot t , we need to show that it also holds at time slot $t+1$. As $Q(t+1) = \max[Q(t) - D(t) - G_l(t), 0] + A_{ela}(t)$, if $Q(t) \leq V_{ela}C_{max}$, then the maximum amount of energy demand arrival is A_{ela}^{max} , we have $Q(t+1) \leq V_{ela}C_{max} + A_{ela}^{max}$. If $V_{ela}C_{max} < Q(t) \leq V_{ela}C_{max} + A_{ela}^{max}$, then $V_{ela}C(t) - Z(t) - Q(t) < 0$. According to **Problem Six**, our algorithm will choose $G_{l,ela}^*(t) = G_{l,max}$. If $Q(t) - D_{ela}^*(t) - G_{l,max} > 0$, then, in time slot t the amount of energy demand being served is at least $G_{l,max}$, which is larger than the maximum amount of arrival during time slot t . Hence, the queue cannot increase, i.e., $Q(t+1) \leq Q(t) \leq V_{ela}C_{max} + A_{ela}^{max}$. If $Q(t) - D_{ela}^*(t) - G_{l,max} \leq 0$, then $Q(t+1) = A_{ela}(t) \leq A_{ela}^{max} \leq V_{ela}C_{max} + A_{ela}^{max}$. Therefore, we have proved $Q(t) \leq V_{ela}C_{max} + A_{ela}^{max}$.

Next, we prove $Z(t) \leq Z_{max}$ for every time slot t . Obviously, $Z(0) \leq Z_{max}$. Suppose it holds for time slot t , we need to show that it also holds in time slot $t+1$. As $Z(t+1) = \max[Z(t) - D(t) - G_l(t) + \epsilon 1_{Q(t)>0}, 0]$, if $Z(t) \leq V_{ela}C_{max}$, then the maximum amount of queuing increase is ϵ , we have $Z(t+1) \leq V_{ela}C_{max} + \epsilon$; if $V_{ela}C_{max} < Z(t) \leq V_{ela}C_{max} + \epsilon$, then $V_{ela}C(t) - Z(t) - Q(t) < 0$. According to **Problem Six**, our algorithm will choose $G_{l,ela}^*(t) = G_{l,max}$. If $Z(t) - D_{ela}^*(t) - G_{l,max} > 0$, then, in time slot t

the amount of energy demand being served is at least $G_{l,max}$, which is larger than the maximum amount of arrival ϵ during time slot t . Hence, the queue cannot increase, i.e., $Z(t+1) \leq Z(t) \leq V_{ela}C_{max} + \epsilon$. If $Z(t) - D_{ela}^*(t) - G_{l,max} \leq 0$, then $Z(t+1) \leq \epsilon \leq V_{ela}C_{max} + \epsilon$. Therefore, we have proved that $Z(t) \leq V_{ela}C_{max} + \epsilon$.

Finally, we prove $Q(t) + Z(t) \leq \Theta_{max}$. Obviously, $Q(0) + Z(0) \leq \Theta_{max}$. Suppose $Q(t) + Z(t) \leq \Theta_{max}$ holds for time slot t . If $Q(t) + Z(t) \leq V_{ela}C_{max}$, then, according to the queuing equations of $Q(t)$ and $Z(t)$, the maximum increase during one slot is $A_{ela}^{max} + \epsilon$. If $V_{ela}C_{max} < Q(t) + Z(t) \leq V_{ela}C_{max} + A_{ela}^{max} + \epsilon$, then $V_{ela}C(t) - Z(t) - Q(t) < 0$. According to **Problem Six**, our algorithm will choose $G_{l,ela}^*(t) = G_{l,max}$. Using the proof above, $U(t+1)$ and $Z(t+1)$ cannot increase. Hence, $U(t+1) + Z(t+1) \leq U(t) + Z(t) \leq \Theta_{max}$. This completes the proof for 1.

2. This is straightforward from Lemma 3.

3. It is obvious that the optimal solution to **Problem Six** has the following properties:

- If $X(t) > -V_{ela}C_{min}$, $G_{b,ela}^*(t) = 0$.
- If $X(t) < -[Q(t) + Z(t)]_{max} = -\Theta_{max}$, $D_{ela}^*(t) = 0$.

In the following, we prove this result by induction. When $t = 0$, as $X_{ela}(0) = B_0 - \Theta_{max} - D_{max}$ and $0 \leq B_0 \leq B_{max}$, we have $-\Theta_{max} - D_{max} \leq X(0) \leq B_{max} - \Theta_{max} - D_{max}$.

Now suppose that the above bound holds for time slot t . We need to show that it also holds for time slot $t+1$. First, suppose $0 < X_{ela}(t) \leq B_{max} - \Theta_{max} - D_{max}$, then $G_{b,ela}^*(t) = \gamma_{ela}^*(t) = 0$. As there is no recharge to the battery and the maximum discharge rate during one time slot is D_{max} , we have $-\Theta_{max} - D_{max} < -D_{max} < X_{ela}(t+1) \leq X_{ela}(t) \leq B_{max} - \Theta_{max} - D_{max}$. Second, suppose $-V_{ela}C_{min} < X_{ela}(t) \leq 0$, then $G_{b,ela}^*(t) = 0$ and the maximum recharge and discharge rate for the battery are S_{max} and D_{max} , respectively. Hence,

$$-\Theta_{max} - D_{max} < -V_{ela}C_{min} - D_{max} < X_{ela}(t+1) \leq X_{ela}(t) + S_{max} \leq B_{max} - \Theta_{max} - D_{max},$$

where we have used

$$V_{ela} \leq \frac{B_{max} - A_{ela}^{max} - \epsilon - D_{max} - G_{b,max} - S_{max}}{C_{max} - C_{min}},$$

and $V_{ela}^{max}C_{min} \leq G_{b,max}$. Third, suppose $-\Theta_{max} \leq X_{ela}(t) \leq -V_{ela}C_{min}$. As $X_{ela}(t) - D_{max} \leq X_{ela}(t+1) \leq X_{ela}(t) + S_{max} + G_{b,max}$, we have

$$-\Theta_{max} - D_{max} \leq X_{ela}(t+1) \leq -V_{ela}C_{min} + S_{max} + G_{b,max} \leq B_{max} - (V_{ela}C_{max} + A_{ela}^{max} + \epsilon) - D_{max} = B_{max} - \Theta_{max} - D_{max},$$

where we use the same bound of V_{ela} as the case before. Last, suppose $-\Theta_{max} - D_{max} \leq X(t) < -\Theta_{max}$, from **Problem Six**, we have $D_{ela}^*(t) = 0$, then

$$-\Theta_{max} - D_{max} \leq X_{ela}(t) \leq X_{ela}(t+1) < -\Theta_{max} + S_{max} + G_{b,max} \leq B_{max} - \Theta_{max} - D_{max}.$$

This completes the proof of 3.

4. From 3 and the definition (28) of $X_{ela}(t)$, it follows immediately that $0 \leq B(t) \leq B_{max}$ holds all slots t .

Further, we choose our decisions to satisfy all constraints in **Problem Six**. Combining them together, all constraints of **Problem Four** are satisfied. Therefore, our control decisions are feasible to **Problem Four**.

5. Here, we make use of Lyapunov optimization techniques to derive this result. Denote queue states $\vec{K}(t) \triangleq (Q(t), Z(t), X_{ela}(t))$. Define the Lyapunov function as $L(\vec{K}(t)) = \frac{1}{2}(Q^2(t) + Z^2(t) + X_{ela}^2(t))$ and the conditional 1-slot Lyapunov drift as follows:

$$\Delta(\vec{K}(t)) = \mathbb{E}\{L(\vec{K}(t+1)) - L(\vec{K}(t)) | \vec{K}(t)\}.$$

From the update (29), squaring both sides, we obtain

$$\frac{X_{ela}^2(t+1) - X_{ela}^2(t)}{2} = \frac{(D(t) - \gamma(t)S(t) - G_b(t))^2}{2} - X_{ela}(t)(D(t) - \gamma(t)S(t) - G_b(t)).$$

As $0 \leq D(t) \leq D_{max}$ and $0 \leq \gamma(t)S(t) + G_b(t) \leq G_{b,max} + S_{max}$, we have

$$\begin{aligned} & \frac{(D(t) - \gamma(t)S(t) - G_b(t))^2}{2} \\ & \leq \frac{1}{2} \max[(G_{b,max} + S_{max})^2, D_{max}^2]. \end{aligned}$$

Therefore, we can get the following upper bound for the Lyapunov drift for $X(t)$:

$$\frac{X_{ela}^2(t+1) - X_{ela}^2(t)}{2} \leq \frac{1}{2} \max[(G_{b,max} + S_{max})^2, D_{max}^2] - X_{ela}(t)(D(t) - \gamma(t)S(t) - G_b(t)).$$

From the update (26), we have

$$Z(t+1) \leq \max[Z(t) - D(t) - G_l(t) + \epsilon, 0],$$

then

$$Z^2(t+1) \leq (Z(t) - D(t) - G_l(t) + \epsilon)^2,$$

and we obtain the following inequality:

$$\begin{aligned} & \frac{Z^2(t+1) - Z^2(t)}{2} \\ & \leq \frac{(\epsilon - D(t) - G_l(t))^2}{2} + Z(t)(\epsilon - D(t) - G_l(t)) \\ & \leq \frac{\max[(D_{max} + G_{l,max})^2, \epsilon^2]}{2} + Z(t)(\epsilon - D(t) - G_l(t)). \end{aligned}$$

From the update (19), squaring both sides and using the following inequality:

$$\begin{aligned} & (\max[Q(t) - D(t) - G_l(t), 0] + A_{ela}(t))^2 \leq A_{ela}^2(t) \\ & + Q^2(t) + (D(t) + G_l(t))^2 + 2Q(t)(A_{ela}(t) - D(t) - G_l(t)), \end{aligned}$$

we obtain

$$\begin{aligned} & \frac{Q^2(t+1) - Q^2(t)}{2} \leq \frac{[(D_{max} + G_{l,max})^2 + A_{ela,max}^2]}{2} \\ & + Q(t)(A_{ela}(t) - D(t) - G_l(t)). \end{aligned}$$

Combining these three bounds together and taking the expectation w.r.t. $\vec{K}(t)$ on both sides, we arrive at the following inequality:

$$\begin{aligned} \Delta(\vec{K}(t)) & \leq B_2 + \mathbb{E}\{Z(t)(\epsilon - D(t) - G_l(t)) | \vec{K}(t)\} \\ & + \mathbb{E}\{Q(t)(A_{ela}(t) - D(t) - G_l(t)) | \vec{K}(t)\} \\ & - \mathbb{E}\{X_{ela}(t)(D(t) - \gamma(t)S(t) - G_b(t)) | \vec{K}(t)\}, \end{aligned}$$

where

$$\begin{aligned} B_2 & = \frac{\max[(S_{max} + G_{b,max})^2, D_{max}^2]}{2} \\ & + \frac{\max[(D_{max} + G_{l,max})^2, \epsilon^2]}{2} \\ & + \frac{[(D_{max} + G_{l,max})^2 + A_{ela,max}^2]}{2}. \end{aligned}$$

Adding penalty term $V_{ela} \mathbb{E}\{C(t)(G_l(t) + G_b(t)) | \vec{K}(t)\}$ to both sides of the above inequality, we obtain the following inequality:

$$\begin{aligned} & \Delta(\vec{K}(t)) + V_{ela} \mathbb{E}\{C(t)(G_l(t) + G_b(t)) | \vec{K}(t)\} \\ & \leq B_2 - X_{ela}(t) \mathbb{E}\{D(t) - \gamma(t)S(t) - G_b(t) | \vec{K}(t)\} \\ & + Z(t) \mathbb{E}\{\epsilon - D(t) - G_l(t) | \vec{K}(t)\} \\ & + Q(t) \mathbb{E}\{A_{ela}(t) - D(t) - G_l(t) | \vec{K}(t)\} \\ & + V_{ela} \mathbb{E}\{C(t)(G_l(t) + G_b(t)) | \vec{K}(t)\}. \end{aligned} \quad (36)$$

Comparing with the objective of **Problem Six**, it is obvious that our algorithm always attempts to greedily minimize the R.H.S. of the above inequality at each time slot t over all feasible control policies including the optimal, stationary policy given in Lemma 2. Plugging this policy $(\hat{D}_{ela}(t), \hat{G}_{l,ela}(t), \hat{G}_{b,ela}(t), \hat{\gamma}_{ela}(t))$ into the R.H.S. of the inequality above and using the fact that this policy is independent of queue state $\vec{K}(t)$, we obtain the following:

$$\begin{aligned} & \Delta(\vec{K}(t)) + V_{ela} \mathbb{E}\{C(t)(G_l(t) + G_b(t)) | \vec{K}(t)\} \leq B_2 \\ & - X_{ela}(t) \mathbb{E}\{\hat{D}_{ela}(t) - \hat{\gamma}_{ela}(t)S(t) - \hat{G}_{b,ela}(t) | \vec{K}(t)\} \\ & + Z(t) \mathbb{E}\{\epsilon - \hat{D}_{ela}(t) - \hat{G}_{l,ela}(t) | \vec{K}(t)\} \\ & + Q(t) \mathbb{E}\{A_{ela}(t) - \hat{D}_{ela}(t) - \hat{G}_{l,ela}(t) | \vec{K}(t)\} \\ & + V_{ela} \mathbb{E}\{C(t)(\hat{G}_{l,ela}(t) + \hat{G}_{b,ela}(t)) | \vec{K}(t)\} \\ & \leq B_2 + V_{ela} P_{2,rel}^* \leq B_2 + V_{ela} P_2^*, \end{aligned}$$

where the following facts have been used:

$$\mathbb{E}\{\hat{D}_{ela}(t) - \hat{\gamma}_{ela}(t)S(t) - \hat{G}_{b,ela}(t) | \vec{K}(t)\} = 0, \quad (37)$$

$$\mathbb{E}\{A_{ela}(t) - \hat{D}_{ela}(t) - \hat{G}_{l,ela}(t) | \vec{K}(t)\} \leq 0, \quad (38)$$

$$\mathbb{E}\{\epsilon - \hat{D}_{ela}(t) - \hat{G}_{l,ela}(t) | \vec{K}(t)\} \leq 0. \quad (39)$$

The first two equations follow from Lemma 2 and the last one follows from (38) together with $\epsilon \leq \mathbb{E}\{A_{ela}(t)\}$. Taking the expectation on both sides, using the law of iterative expectation, and summing over $t \in \{0, 1, 2, \dots, T-1\}$, we obtain

$$\begin{aligned} & V_{ela} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_l(t) + G_b(t))\} \leq B_2 T + V_{ela} T P_2^* \\ & - \mathbb{E}\{L(\vec{K}(T))\} + \mathbb{E}\{L(\vec{K}(0))\}. \end{aligned}$$

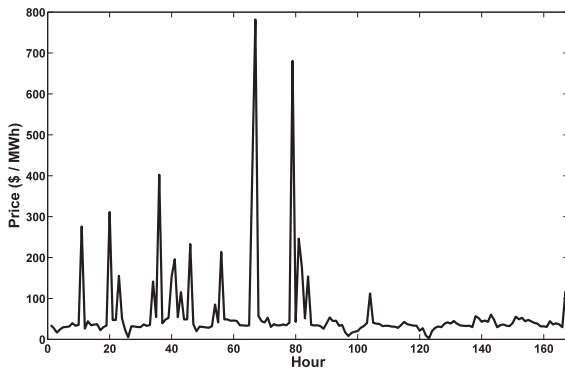


Fig. 4. Average hourly spot market price during the week of 01/01/2011 to 01/07/2011 at LA [29].

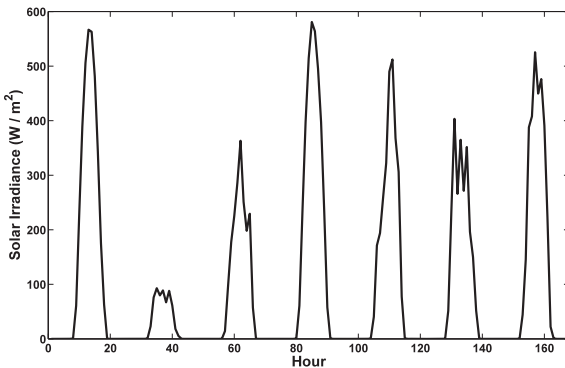


Fig. 5. Average hourly solar irradiance profile during the week of 01/01/2011 to 01/07/2011 at LA [30].

Dividing both sides by T , letting $T \rightarrow \infty$, and using the facts that $E\{L(\vec{K}(0))\}$ are finite and $E\{L(\vec{K}(t))\}$ are nonnegative, we arrive at the following result for our algorithm:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{C(t)(G_i(t) + G_b(t))\} \leq P_2^* + B_2/V_{ela},$$

where P_2^* is the optimal objective value, B_2 is a constant given by (35), and V_{ela} is a tunable control parameter which has a maximum value given by (30). This completes the proof. \square

6 PERFORMANCE EVALUATION

In this section, we evaluate the proposed algorithms using practical data sets of electricity price and renewable energy generation. We consider a single household with a battery, a PV panel and various appliances subject to real-time pricing.

6.1 Simulation Setup

The data set of electricity price we use is from the California Independent System Operator (CAISO) [29] for Los Angeles area, which consists of 5-min interval average spot market price $C(t)$. Meanwhile, we use the 5-min interval average solar irradiance data for Los Angeles area from the Measurement and Instrumentation Data center (MIDC) [30] at National Renewable Energy Laboratory. The period we consider in this paper is half year from January 1, 2011 to June 30, 2011. In total, this duration includes 181 days or

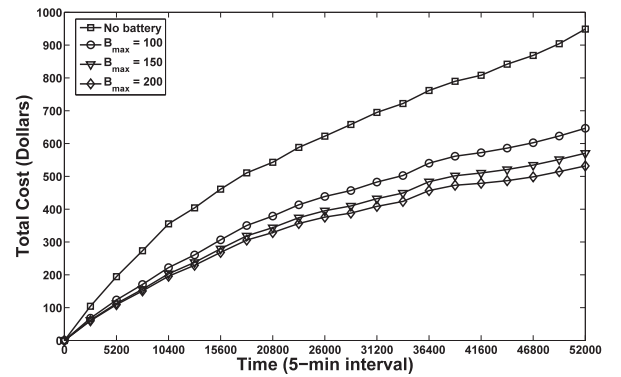


Fig. 6. Total Cost with i.i.d. $A(t)$ and different battery capacity B_{max} for inelastic energy demands.

52,128 5-min slots. The control interval is chosen to be 5-minute. A portion of average hourly spot market electricity price and solar irradiance during the first week of January 2011 are plotted in Figs. 4 and 5, respectively.

We execute our algorithms in 5-min time slots and conduct simulations with different values of parameters V , B_{max} , and ϵ . In our simulations, we set the energy demand arrival, either elastic or inelastic, during each time slot t as uniformly distributed from $[1, 24]$ KW-slot based on the practical home appliance usage in [11]. We fix the parameters $D_{max} = 30$ KW-slot, $G_{l,max} = 30$ KW-slot, and $G_{b,max} = 20$ KW-slot.

6.2 Results and Analysis

First, we consider the impact of storage capacity B_{max} on cost saving in the case for inelastic energy demands. We compare our algorithm against a simple algorithm without storage. The simple algorithm uses the renewable energy generation to meet the demand as much as possible; in the case of insufficiency, it would draw some power from the power grid to meet the energy demand. The result is illustrated in Fig. 6 during 6-month period with $B_{max} = \{100, 150, 200\}$ KW-slot and $V = V_{ine}^{max}$. From the figure, it is clear that the larger the battery is, the more saving our proposed algorithm can obtain. The saving comes from two aspects: one is by storing excessive renewable energy generated in current time slot for use at later time when renewable energy generation is insufficient; the other is by charging the battery when the price is low while discharging it when the price is high.

Next, we compare the cases for the inelastic energy demand and the elastic one when $B_{max} = 100$ KW-slot, $\epsilon = 1$, and $V = V_{ela}^{max}$. The result is shown in Fig. 7. The case when the battery is used in conjunction with elastic energy demand provides more spaces to optimize the cost saving, as illustrated in the figure. This result is intuitive as some elastic energy demands can be delayed to time when free renewable energy is sufficient or the electricity price is low.

Finally, we consider the impact of ϵ on the performance of our algorithm for the case for elastic energy demands. As explained before, ϵ is related to the worst case delay of queued energy demands. Smaller ϵ implies larger delay. We set $B_{max} = 100$ KW-slot and $V = V_{ela}^{max}$, and select different $\epsilon \in \{0, 0.3, 0.6, 1\}$. As observed in Fig. 8, the decrease in ϵ

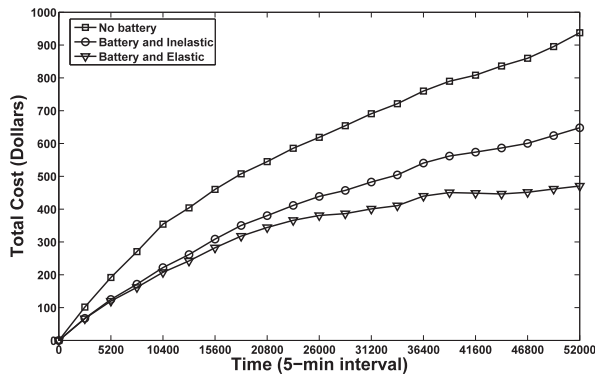


Fig. 7. Comparison of total cost for the cases when there is no battery, there is battery with inelastic energy demands, and there is battery with elastic energy demands.

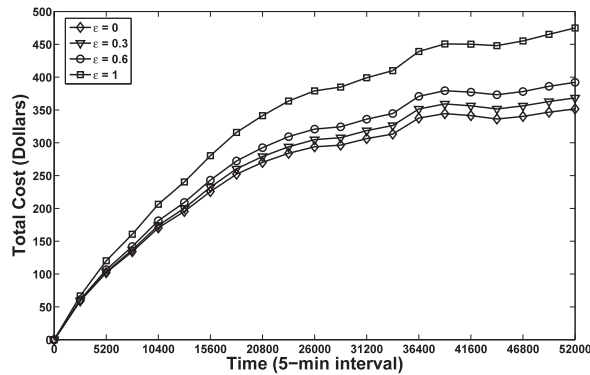


Fig. 8. Comparison of total cost for different ϵ with elastic energy demands.

gives lower cost with the tradeoff that the worst case delay is increased.

7 CONCLUSIONS

In this paper, we have proposed an approach to addressing the optimal management of real-time pricing, inelastic and elastic energy demands, renewable energy generation, and energy storage to reduce the electricity cost for a residential customer in the smart grid. The intuition behind our approach is to use energy storage to harvest excessive renewable generation for later use and to charge the battery when the electricity price is low while discharging it when the electricity price is high. By using the Lyapunov optimization techniques, we can achieve close to optimal cost with increased battery capacity. Specifically, our algorithm can find a solution achieving the cost deviated no more than $O(1/V)$ from the optimal cost where V is a tunable control parameter determined by the battery capacity. Moreover, we have also investigated the case for elastic energy demand and use the technique of virtual queue to guarantee the finite worst case delay for any buffered energy demand. Finally, we use practical data sets to evaluate the effectiveness of our algorithms.

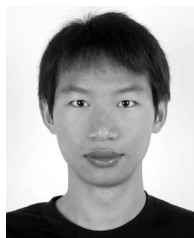
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