Decentralized Coordination of Energy Utilization for Residential Households in the Smart Grid

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***Abstract*—In this paper, we investigate the minimization of the total energy cost of multiple residential households in a smart grid neighborhood sharing a load serving entity. Specifically, each household may have renewable generation, energy storage as well as inelastic and elastic energy loads, and the load serving entity attempts to coordinate the energy consumption of these households in order to minimize the total energy cost within this neighborhood. The renewable generation, the energy demand arrival, and the energy cost function are all stochastic processes and evolve according to some, possibly unknown, probabilistic laws. We develop an online control algorithm, called Lyapunov-based cost minimization algorithm (LCMA), which jointly considers the energy management and demand management decisions. LCMA only needs to keep track of the current values of the underlying stochastic processes without requiring any knowledge of their statistics. Moreover, a decentralized algorithm to implement LCMA is also developed, which can preserve the privacy of individual household owners. Numerical results based on real-world trace data show that our control algorithm can effectively reduce the total energy cost in the neighborhood.**

***Index Terms*—Demand response, energy management, energy storage, inelastic and elastic energy loads, Lyapunov optimization, renewable generation, smart grid.**

I. Introduction

THE GROWING demands of electricity and concerns over global climate change and carbon emission have motivated the grid modernization, which transforms the current power grids to the future "smart grid." As stated in [1], the smart grid will enable deep penetration of renewable generation, customer driven demand response, widespread adoption of electric vehicles, and electric energy storage. Sensing, communication, computation, and control technologies in conjunction with advances in renewable generation, energy storage, power electronics, etc., are critical to realizing the vision and promise of the smart grid.

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Within the smart grid, demand side management (DSM) is a key component, which can help reduce peak load, increase grid reliability, and lower generation cost [2]. There are mainly two types of demand side management techniques: direct load control (DLC) and demand response based on time-varying pricing [3]. In DLC, the load serving entity, usually a utility company, enters into a contract with the consumers beforehand, so that certain amount of energy load can be curtailed during the peak hours in order to release the congestion on the power grid or to avoid the operation of high cost peak generators. Currently, it is mainly employed by large industrial and commercial customers. On the other hand, the demand response based on time-varying pricing encourages the customers to either reduce or shift their normal energy consumption based on the pricing signal issued by the load serving entity (LSE) in return for some benefits, such as electricity bill reduction. Several popular schemes already exist in this regard, such as critical-peak pricing (CPP), time-of-use (TOU) pricing, and real-time pricing (RTP). With the introduction of the advanced metering infrastructure (AMI), which can provide two-way communication between utility companies and smart meters, it is expected that there will be a widespread deployment of such demand response programs for residential and business customers in the smart grid [4].

Meanwhile, nearly 7% of electricity is lost during transmission and distribution (T&D) from remote power plants to distant homes [5]. Distributed generation (DG) from many small on-site energy sources deployed at individual homes and businesses can be used to decrease both T&D losses and carbon emissions. Typical examples of these small on-site energy sources include rooftop solar panels, fuel cells, microturbines, and micro-wind generators. Distributed energy storage devices are usually used in combination with these renewable sources to better utilize them. We envision residential households in the smart grid which use on-site renewable generation, modest energy storage, and the electric grid to meet their energy demands, within which some are elastic and can be served in a flexible manner. How to simultaneously manage these components for households within a neighborhood in order to reduce the total energy cost as well as the impact on the distribution network of the power grids is a challenging problem, especially considering the random dynamics in the system.

There have been many previous studies on energy consumption scheduling in households, renewable energy integration, and demand response schemes. On the residential energy consumption scheduling side, Mohsenian-Rad *et al.* [6] formulate the optimal control of multiple flexible appliances as a linear program to achieve a desired trade-off 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. A game theory based approach is proposed in [7] to handle the case of multiple households. Kim *et al.* [8] use dynamic programming to solve the problem of scheduling power consumption of a single appliance in order to minimize the expected cost. On the side of renewable energy integration, the problem of supplying renewable energy to demand-flexible customers is investigated in [9], [10]. Specifically, Papavasiliou *et al.* [10] address the optimal allocation for renewable sources to demand-flexible customers in a real-time pricing environment using dynamic programming, while in [9], the authors develop a Lyapunov optimization based method. Bitar *et al.* [11] consider optimal selling strategies for uncertain and variable wind production into the current electricity market. On the demand response side, Li *et al.* [12] consider the problem of optimal demand response as a convex optimization problem and study the role of dynamic pricing. Jiang *et al.* [13] propose a model that integrates two-period electricity markets, uncertainty in renewable generation, and real-time dynamic demand response, and derive the optimal control decisions to optimize the social welfare. However, most of the previous studies either only consider optimization for one household, or assume perfect future information, or do not consider on-site distributed generation and energy storage.

This paper extends the single household case in our previous work [14] to that of multiple households within a smart grid neighborhood. In our work, not only does the energy cost of an individual household matter, but also the total energy cost in a neighborhood is of equal importance. We show that, through our collaborative and decentralized energy consumption scheduling algorithm in multiple households, the impact of the household energy consumption on the power system and the total energy cost can be greatly reduced. Due to the decentralized and online properties of our proposed algorithm, it can be easily implemented in the smart grid. In summary, our paper makes the following contributions:

- In the setting of multiple households within a neighborhood, we propose a new system architecture to incorporate the following essential components in the smart grid: distributed renewable generation, energy storage, demand response, and smart appliances.
- We develop a decentralized online algorithm, called Lyapunov-based cost minimizing algorithm (LCMA), to approximately minimize time-average total energy cost for households within a neighborhood without the knowledge of the statistics of related stochastic models.
- Through theoretical analysis, we show that our algorithm can obtain an explicit trade-off between cost saving and energy storage capacity. Moreover, through extensive simulations based on real-world data sets, we demonstrate the effectiveness of our proposed algorithms.

The paper is organized as follows. In Section II, we describe our system model and formulate the problem as a stochastic programming problem. We describe the design principle behind our algorithm and present an online algorithm in Section III. We then analyze our algorithm in Section IV. We present numerical results based on real-world data in Section V. Finally, some concluding remarks are presented in Section VI.

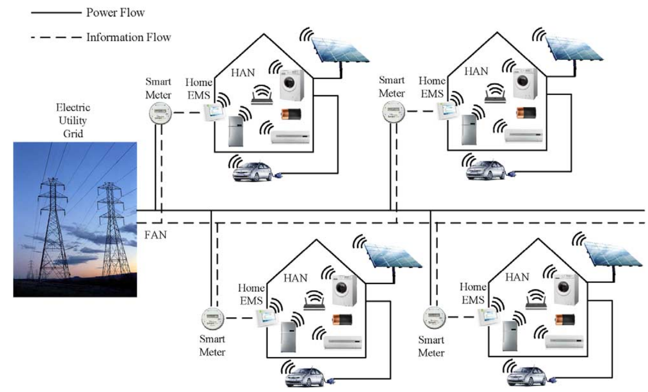

Fig. 1. A schematic diagram of household energy management in a smart grid neighborhood.

II. System Model and Problem Formulation

In this section, we provide mathematical descriptions for the load serving entity (LSE), energy load, energy storage, and distributed renewable generation in residential households. Based on these definitions, we will formulate our control problem as a stochastic program.

Consider a set of N households/customers that are served by the LSE in a smart grid neighborhood setting as depicted in Fig. 1. The LSE may be a utility company and the smart grid neighborhood may cover all households connected to a step-down transformer in the distribution network. The LSE may participate into wholesale electricity markets (day-ahead, hour-ahead, real-time balancing, ancillary service) to purchase electricity from power generators and then sell it to the N customers in the retail market. The electricity price in the retail market is typically set at a fixed level that reflects the broad average of the hourly costs to serve customers over a year or season. However, it does not encourage efficient usage of electricity, causing high peak demand and low load factor. We consider a time-slotted model with an infinite horizon. Each slot represents a suitable period for control decisions (e.g., 1 hour or 15 min) and is indexed by $t = \{0, 1, \ldots\}$.[1]

A. Load Serving Entity

The LSE serves as an agent that is responsible for purchasing enough electricity from wholesale electricity markets to serve the energy demand of the households in its service area. The retail price is set in order to at least recover the running cost of the LSE. In the future smart grid, a field area network (FAN) would be deployed, which can provide convenient communications between utility companies and smart meters of residential households. For simplicity, we make the assumption that the cost of the LSE can be represented by a cost function $C(D)$ that specifies the cost of providing amount D of electricity to the N customers during one period. We assume that the cost function $C(D)$ is increasing, continuously differentiable, and convex in

[1]In this paper, all power quantities such as $r_i(t), s_i(t), y_i(t), d_{i,1}(t), d_{i,2}(t)$ are in the unit of energy per slot, so the energy produced/consumed in time period t is $r_i(t), s_i(t), y_i(t), d_{i,1}(t), d_{i,2}(t)$, respectively.

D with a bounded first derivative. We use α^{min} and α^{max} to denote the minimum and the maximum first derivatives of $C(D)$, respectively.

B. Energy Load

In general, the energy loads in a household can be roughly divided into two categories: inelastic and elastic loads. Examples of inelastic energy loads include lights, TVs, microwaves, and computers. For this type of energy loads, the energy requests must be met exactly at the time t when needed. In contrast, there are some energy loads in households that are elastic in the sense that they can be controlled (using smart appliances, for example,) to adjust the times of their operations and the amount of their energy usage without impacting the satisfaction of customers. Examples include refrigerators, dehumidifiers, air conditioners, and electric vehicles. As observed in [15], while the elastic energy loads comprise less than 7.5% of the total loads in a household, they account for 59% of the average energy consumption. Therefore, there is great hidden potential in exploiting the inherent flexibility of such elastic loads for various important individual and system level objectives.

Inside a household, electric loads can communicate with the smart meter via the home area network (HAN), which may be Wi-Fi or ZigBee. For each household $i \in N$, denote by $d_{i,1}(t)$ the inelastic energy loads (in unit of kWh) and by $d_{i,2}(t)$ the elastic energy loads (in unit of kWh) at time t. As in [9], we assume that the elastic energy loads are "buffered" (i.e., the energy requests are held or delayed) first in a queue $Q_i(t)$ before being served. Denote by $y_i(t)$ the amount of energy that is used for serving the queued energy loads at time t. Then the dynamics of $Q_i(t)$ are as follows:

$$Q_i(t+1) = \max\{Q_i(t) - y_i(t), 0\} + d_{i,2}(t), \quad \forall i. \quad (1)$$

For each i, we assume that

$$0 \le y_i(t) \le y_i^{max}, \quad (2)$$

where $y_i^{max} \ge d_{i,2}^{max}$ so that the queue Q_i can always be stabilized. For any feasible control decision, we need to ensure that the average delay of the elastic loads in the queue is finite. In other words, the service of elastic energy loads cannot be delayed for an arbitrarily long time. This can be stated as follows:

$$\overline{Q_i} \doteq \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{Q_i(t)\} < \infty. \quad (3)$$

C. Energy Storage

In addition to energy loads, each household may have some kind of energy storage device, possibly in the form of the battery in the PHEV. For each household i, we denote by E_i^{max} the battery capacity, by $E_i(t)$ the energy level of the battery at time t, and by $r_i(t)$ the power charged to (when $r_i(t) > 0$) or discharged from (when $r_i(t) < 0$) the battery during slot t. Assume that the battery energy leakage is negligible and batteries at households operate independently of each other. Then we model the dynamics of the battery energy level by

$$E_i(t+1) = E_i(t) + r_i(t). \quad (4)$$

For each household i, the battery usually has an upper bound on the charge rate, denoted by r_i^{max}, and an upper bound on the discharge rate, denoted by $-r_i^{min}$, where r_i^{max} and $-r_i^{min}$ are positive constants depending on the physical properties of the battery as well as the charging infrastructure. Therefore, we have the following constraint on $r_i(t)$:

$$r_i^{min} \le r_i(t) \le r_i^{max}. \quad (5)$$

The battery energy level should always be nonnegative and cannot exceed the battery capacity. So in each time slot t, we need to ensure that for each household i,

$$0 \le E_i(t) \le E_i^{max}. \quad (6)$$

However, the cost of battery use cannot be ignored. In practice, batteries can only be charged a finite number of times. Besides, conversion loss occurs both in charging and discharging processes. Stored energy is also subject to leakage with time. All these factors depend on how fast/much/often it is charged and discharged. Instead of modeling these factors exactly, we use an amortized time-invariant cost function $F_i(r_i)$ (in unit of dollars) to model the impact of charging or discharging operation r_i on the battery during one slot for household i. Each battery cost function $F_i(r_i)$ is assumed to be continuously differentiable in r_i with a bounded first derivative and $F_i(0) = 0$. We use β_i^{min} and β_i^{max} to denote the minimum and the maximum first derivatives of $F_i(r_i)$ for each household i, respectively.

D. Renewable Distributed Generation (DG)

Each household i may possess a distributed renewable generator installed on its site, such as rooftop PV panel or small wind turbine. Since renewable sources such as wind and solar, are usually intermittent, uncertain, and uncontrollable, we model the renewable energy generated by the renewable DG by a discrete time random process $s_i(t)$, which has the maximum value given by its nameplate capacity s_i^{max}. Therefore, we have

$$0 \le s_i(t) \le s_i^{max} \quad \forall i, t. \quad (7)$$

Note that the power generation from a renewable generator is usually lower than the normal power consumption of residential households. Residential households need to connect to the utility electric grid for backup power and, therefore, are mostly grid-tied systems. In this paper, we assume that the marginal cost of renewable energy is zero and should be utilized as much as possible.

E. Problem Formulation

With the above models for the battery and the distributed renewable generator, at each time t, the total power demand of household i needed from the utility electric grid is

$$g_i(t) \doteq \max\{d_{i,1}(t) + y_i(t) + r_i(t) - s_i(t), 0\}. \quad (8)$$

Note that in the formula above, we have assumed that power cannot be fed from the household into the utility electric grid through, for example, net metering. Since we assume that each household has an energy storage device, excess renewable energy generation can be stored into it without spillage as long as the storage has enough capacity. We plan to incorporate the option of two-way energy flow in our future investigation.

In this paper, we are interested in minimizing the LSE's total cost of providing the electricity to the whole smart grid neighborhood in a sufficiently long horizon. Note that reducing the cost of supplying electricity for the LSE is both beneficial to the LSE as well as individual customers since the cost will be finally transferred to the customer's electricity bill. Therefore, the control problem can be stated as follows: for the dynamic system defined by (1) and (4), design a control strategy which, given the past and present random renewable supplies, the battery energy levels, the energy demands, and the energy cost function, chooses the battery charge/discharge vector $\mathbf{r}$ and the elastic load serving rate vector $\mathbf{y}$ such that the time-average total energy cost of the whole smart grid neighborhood is minimized. It can be formulated as the following stochastic programming problem, called $\mathbf{P1}$:

$$\min_{\mathbf{y},\mathbf{r}} : \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\left\{ C\left(\sum_{i=1}^{N} g_i(t)\right) + \sum_{i=1}^{N} F_i\left(r_i(t)\right)\right\}, \tag{9}$$

subject to constraints (1), (2), (3), (4), (5), and (6).

Here the expectation in the objective is w.r.t. the random renewable generation $s_i(t)$, the random inelastic energy loads $d_{i,1}(t)$, and the random elastic energy loads $d_{i,2}(t)$ for each household. Define $\mathbf{P1}^*$ as the infimum time average cost associated with $\mathbf{P1}$, considering all feasible control actions subject to the queue stability and the finite battery energy level. We will design a control algorithm, parameterized by a constant $V > 0$, that satisfies the constraints above and achieves the average cost within $O(1/V)$ of the optimal value $\mathbf{P1}^*$, while guaranteeing that the worst-case delay is within $O(V)$.

III. Online Decentralized Algorithm

In this section, we design algorithms to solve $\mathbf{P1}$. One challenge of solving the stochastic optimization problem above is the uncertainty of future renewable generation, time-varying cost function, inelastic or elastic energy loads. Moreover, the constraints on $E_i(t)$ bring the "time-coupling" property to the stochastic optimization problem above. That is to say, the current control action may impact the future control actions, making it more challenging to solve. Our solution is based on the technique of Lyapunov optimization [16] and requires minimum information on the random dynamics in the system.

A. Delay-Aware Virtual Queue

Since the constraint $\overline{Q_i} < \infty$ only ensures finite average delay for the elastic energy loads in household i, worst-case delay guarantee is usually desired in practice. For this purpose, we leverage the technique of "virtual queue" in the Lyapunov optimization framework. Specifically, the following virtual queues $Z_i(t)$, $i = 1, 2, \ldots, N$ are defined to provide the worst-case delay guarantee on any buffered elastic energy loads in $Q_i(t)$:

$$Z_i(t+1) = \max\left\{Z_i(t) - y_i(t) + \epsilon_i 1_{\{Q_i(t)>0\}}, 0\right\}, \tag{10}$$

where $1_{\{Q_i(t)>0\}}$ is an indicator function that is 1 if $Q_i(t) > 0$ or 0 otherwise; ϵ_i is a fixed positive parameter to be specified later. The intuition behind this virtual queue is that since $Z_i(t)$ has the same service process as $Q_i(t)$, but has an arrival process that adds ϵ_i whenever the actual backlog is nonempty, this ensures that $Z_i(t)$ grows if there are energy loads in the queue $Q_i(t)$ that have not been serviced for a long time. The following lemma shows that if we can control the system to ensure that the queues $Q_i(t)$ and $Z_i(t)$ have finite upper bounds, then any buffered energy load is served within a worst-case delay as follows:

Lemma 1: Suppose we can control the system to ensure that $Z_i(t) \le Z_i^{max}$ and $Q_i(t) \le Q_i^{max}$ for all slots t, where Z_i^{max} and Q_i^{max} are some positive constants. Then, the worst-case delay for all buffered energy loads in household i is upper bounded by δ_i^{max} slots where

$$\delta_i^{max} \triangleq \left\lceil \frac{(Q_i^{max} + Z_i^{max})}{\epsilon_i} \right\rceil. \tag{11}$$

Proof: See Appendix A. ■

We will show that there indeed exist such constants Z_i^{max} and Q_i^{max} for all households i later.

B. The Lyapunov-Based Approach

The idea of our algorithm is to construct a Lyapunov-based scheduling algorithm with perturbed weights for determining the optimal power usage. By carefully perturbing the weights, we can ensure that whenever we charge or discharge the battery, the energy level in the battery always lies in the feasible region.

First, we choose a perturbation vector $\theta = (\theta_i, \forall i)$ (to be specified later). We define a perturbed Lyapunov function as follows:

$$L(t) \doteq \frac{1}{2}\sum_{i=1}^{N}\left[\left(E_i(t) - \theta_i\right)^2 + Q_i^2(t) + Z_i^2(t)\right]. \tag{12}$$

Now define $\mathbf{K}(t) = (\mathbf{Q}(t), \mathbf{Z}(t), \mathbf{E}(t))$, and define a one-slot conditional Lyapunov drift as follows:

$$\triangle(t) = \mathbb{E}\left\{L(t+1) - L(t)|\mathbf{K}(t)\right\}. \tag{13}$$

Here the expectation is taken over the randomness of load arrivals, cost function, and renewable generation, as well as the randomness in choosing the control actions. Then, following the Lyapunov optimization framework, we add a function of the expected cost over one slot (i.e., the penalty function) to (13) to obtain the following *drift-plus-penalty* term:

$$\triangle_V(t) \doteq \triangle(t) + V\mathbb{E}\left\{C\left(\sum_{i=1}^{N} g_i(t)\right) + \sum_{i=1}^{N} F_i\left(r_i(t)\right)|\mathbf{K}(t)\right\}, \tag{14}$$

where V is a positive control parameter to be specified later. Then, we have the following lemma regarding the *drift-plus-penalty* term:

Lemma 2: For any feasible action under constraints (2), (5), and (6) that can be implemented at slot t, we have

$$\begin{aligned}\triangle_V(t) \leq B &+ \sum_{i=1}^{N} \mathbb{E}\left\{(E_i(t)-\theta_i)\, r_i(t)|\mathbf{K}(t)\right\} \\ &+ \sum_{i=1}^{N} \mathbb{E}\left\{Q_i(t)\left(d_{i,2}(t)-y_i(t)\right)|\mathbf{K}(t)\right\} \\ &+ \sum_{i=1}^{N} \mathbb{E}\left\{Z_i(t)\left(\epsilon_i-y_i(t)\right)|\mathbf{K}(t)\right\} \\ &+ V\mathbb{E}\left\{C\left(\sum_{i=1}^{N} g_i(t)\right)+\sum_{i=1}^{N} F_i\left(r_i(t)\right)|\mathbf{K}(t)\right\}, \quad (15)\end{aligned}$$

where B is a constant given by

$$B \doteq \sum_{i=1}^{N}\left\{\frac{\max\left\{\left(r_i^{min}\right)^2,\left(r_i^{max}\right)^2\right\}}{2}+\frac{\max\left\{\left(y_i^{max}\right)^2,\epsilon_i^2\right\}}{2} + \frac{\left(y_i^{max}\right)^2+\left(d_{i,2}^{max}\right)^2}{2}\right\}. \quad (16)$$

Proof: See Appendix B. ■

We now present the LCMA algorithm. The main design principle of our algorithm is to choose control actions that approximately minimize the R.H.S. of (15).

Lyapunov-Based Cost Minimization Algorithm (LCMA): Initialize (θ_i, ϵ_i), $\forall i$ and V. At each slot t, observe $(d_{i,1}(t), d_{i,2}(t), s_i(t))$, $\forall i$, and $\mathbf{K}(t)$, and do:

- Choose control decisions $\mathbf{y}^*$ and $\mathbf{r}^*$ as the optimal solution to the following optimization, called $\mathbf{P3}$:

$$\begin{aligned}\underset{\substack{0\leq y_i(t)\leq y_i^{max},\forall i;\\ r_i^{min}\leq r_i(t)\leq r_i^{max},\forall i}}{\text{Minimize}} : &\sum_{i=1}^{N}\left\{(E_i(t)-\theta_i)\, r_i(t)+VF_i\left(r_i(t)\right)\right. \\ &\left.-\left(Q_i(t)+Z_i(t)\right)y_i(t)\right\}+VC\left(\sum_{i=1}^{N} g_i(t)\right), \quad (17)\end{aligned}$$

- Update $\mathbf{K}(t)$ according to the dynamics (1), (4), and (10), respectively.

The intuition behind our algorithm is trying to store excess renewable energy for later use, recharge the battery during the period of low electricity price while discharging it during the period of high electricity price, and delay elastic energy loads to later slots with lower electricity price. Note that we do not need to consider the time-coupling constraints (6) of the battery energy level in the algorithm, since they can be automatically satisfied during our operation of the queues, as proven in Theorem 1 below. Moreover, the algorithm only requires the knowledge of the instantaneous values of system dynamics and does not require any knowledge of the statistics of these stochastic processes. However, the algorithm above should be able to run in a decentralized manner in order to be implemented in practice. In the ensuing subsection, we design a decentralized algorithm to solve the optimization problem $\mathbf{P3}$.

C. Decentralized Algorithm to $\mathbf{P3}$

First, we introduce the following slack variables: $h_i(t)$, $\forall i$ to upper bound individual grid power demand and $D(t)$ to upper bound the total grid power demand. Then, we can transform $\mathbf{P3}$ into the following formulation, called $\mathbf{P4}$:

$$\begin{aligned}\underset{\substack{0\leq y_i(t)\leq y_i^{max},\forall i;\\ r_i^{min}\leq r_i(t)\leq r_i^{max},\forall i}}{\text{Minimize}} : &\sum_{i=1}^{N}\left\{(E_i(t)-\theta_i)\, r_i(t)+VF_i\left(r_i(t)\right)\right. \\ &\left.-\left(Q_i(t)+Z_i(t)\right)y_i(t)\right\}+VC\left(D(t)\right), \quad (18a)\end{aligned}$$

s.t.

$$h_i(t) \geq d_{i,1}(t)+y_i(t)+r_i(t)-s_i(t), \quad \forall i \quad (18b)$$

$$0 \leq h_i(t) \leq h_i^{max}, \quad \forall i \quad (18c)$$

$$\sum_{i=1}^{N} h_i(t) \leq D(t) \leq D^{max}, \quad (18d)$$

where the maximum grid power consumption h_i^{max} is imposed because of security and reliability considerations for household i, and D^{max} is the transformer capacity. Since $C(\cdot)$ is a strictly increasing function, we can easily prove by contradiction that the formulation above and $\mathbf{P3}$ are equivalent and have exactly the same optimal solutions in terms of $\mathbf{r}^*$ and $\mathbf{y}^*$. Since $\mathbf{P4}$ is a convex optimization problem and has decomposability structures, it motivates us to design the following distributed subgradient-based algorithm to iteratively solve it based on the idea of consistency price in network utility maximization [17], [18]. In each time slot t, the algorithm implements the steps as indicated in Algorithm 1. The flow chart for Algorithm 1 is shown in Fig. 2. When the constant step-size γ is small enough, the algorithm above converges to the optimal solution [19]. Note that other types of step-size can also be used with different convergence properties [20]. A desirable feature of our decentralized algorithm is that the LSE does not need to know the detailed information about the energy usage in each individual household and only requires the total grid energy usage for all N households. By operating in this manner, our algorithm can help preserve the privacy of homeowners, who are shown to be concerned with some privacy issues associated with the the smart grid [21].

Algorithm 1: Decentralized Algorithm to $\mathbf{P3}$

1 **Initialization**: *Set* $\lambda^{(0)}(t)$ *equal to some nonnegative value*, $k = 0$

2 **foreach** *Iteration* k

3 **while** *Not satisfying convergence criterion* **do**

4 The home energy management system (HEMS) in household i's smart meter updates $r_i^{(k)}(t)$, $y_i^{(k)}(t)$, and $h_i^{(k)}(t)$ after receiving the Lagrangian multiplier $\lambda^{(k)}(t)$ according to the solution to the following optimization problem:

$$\begin{aligned}\min : &(E_i(t)-\theta_i)\, r_i(t)+VF_i\left(r_i(t)\right)+\lambda^{(k)}(t)h_i(t) \\ &-\left(Q_i(t)+Z_i(t)\right)y_i(t), \quad (19a)\end{aligned}$$

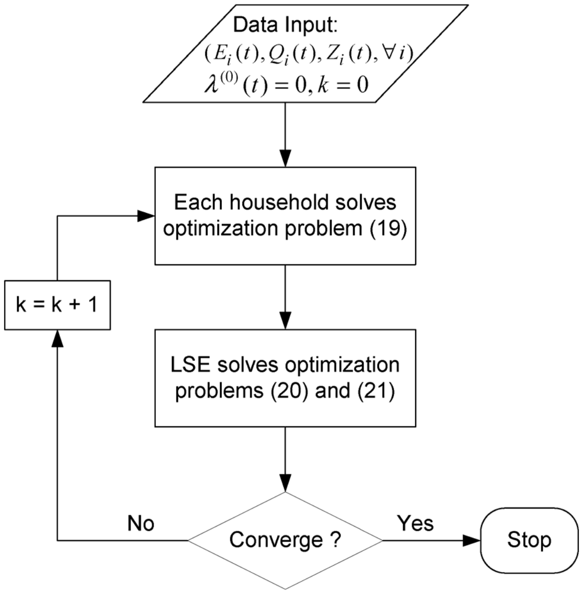

Fig. 2. Flow chart for the Algorithm 1.

s.t.

$$h_i(t) - y_i(t) - r_i(t) \geq d_{i,1}(t) - s_i(t), \tag{19b}$$

$$0 \leq h_i(t) \leq h_i^{max}, \tag{19c}$$

$$r_i^{min} \leq r_i(t) \leq r_i^{max}, \tag{19d}$$

$$0 \leq y_i(t) \leq y_i^{max}. \tag{19e}$$

The LSE collects the predications of total utility power demands $\sum_{i=1}^N h_i^k(t)$ from all households i over the FAN. Then, its neighborhood energy management system (NEMS) obtains the optimal generation power and updates the Lagrange multiplier as follows:

$$D^{(k)}(t) = \underset{0 \leq D(t) \leq D^{max}}{\arg\min} \; VC(D(t)) - \lambda^{(k)}(t)D(t), \tag{20}$$

$$\lambda^{(k+1)}(t) = \left[\lambda^{(k)}(t) - \gamma\left(D^{(k)}(t) - \sum_{i=1}^N h_i^{(k)}(t)\right)\right]^+, \tag{21}$$

where $\gamma > 0$ is a constant step-size, and then, broadcasts $\lambda^{(k+1)}(t)$ to all households over the FAN

Set $k \leftarrow k+1$

Note that the optimal Lagrangian multiplier $\lambda^*(t)$ is similar to the dynamic electricity retail price charged by the LSE to each household at time t.

IV. Performance Analysis

In this section, we analyze the performance of LCMA under the case that the renewable energy generation $s_i(t)$, $\forall i$, energy load arrival processes $d_{i,1}(t)$, $\forall i$ and $d_{i,2}(t)$, $\forall i$ are all i.i.d. Note that our results can also be extended to the more general setting where $s_i(t)$, $\forall i$, $d_{i,1}(t)$, $\forall i$, and $d_{i,2}(t)$, $\forall i$ all evolve according to some finite state irreducible and aperiodic Markov chains according to the Lyapunov optimization framework [16].

Theorem 1: If $Q_i(0) = Z_i(0) = 0$ and $\theta_i = V(\alpha^{max} + \beta_i^{max}) - r_i^{min}$ for all households i, then under the LCMA algorithm for any fixed parameters $0 \leq \epsilon_i \leq \mathbb{E}\{d_{i,2}(t)\}$, and $0 < V \leq V^{max}$, where

$$V^{max} \doteq \min_i \frac{E_i^{max} - r_i^{max} + r_i^{min}}{\alpha^{max} + \beta_i^{max} - \alpha^{min} - \beta_i^{min}}, \tag{22}$$

we have the following properties:

1) The queues $Q_i(t)$ and $Z_i(t)$ are deterministically upper bounded by Q_i^{max} and Z_i^{max} at every slot, where

$$Q_i^{max} \doteq V\alpha^{max} + d_{i,2}^{max}, \tag{23}$$

$$Z_i^{max} \doteq V\alpha^{max} + \epsilon_i. \tag{24}$$

Further, $Q_i(t) + Z_i(t)$ are upper bounded by Θ_i^{max} where

$$\Theta_i^{max} \doteq V\alpha^{max} + d_{i,2}^{max} + \epsilon_i. \tag{25}$$

2) The worst-case delay of any buffered elastic energy load is given by:

$$\delta_i^{max} = \left\lceil \frac{2V\alpha^{max} + d_{i,2}^{max} + \epsilon_i}{\epsilon_i} \right\rceil. \tag{26}$$

3) The energy queue $E_i(t)$ satisfies the following for all time slots t:

$$0 \leq E_i(t) \leq E_i^{max}. \tag{27}$$

4) All control decisions are feasible.

5) If $s_i(t)$, $\forall i$, $d_{i,1}(t)$, $\forall i$, and $d_{i,2}(t)$, $\forall i$ are i.i.d. over slots, then the time-average expected operating cost under our algorithm is within bound B/V of the optimal value, i.e.,

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\left\{C\left(\sum_{i=1}^N g_i(t)\right) + \sum_{i=1}^N F_i(r_i(t))\right\} \leq \mathbf{P1}^* + B/V, \tag{28}$$

where B is the constant specified in (16).

Proof: The proof is also a straightforward extension of the results in our previous work [14] into the case of multiple households. We provide the sketch of our proof as follows. Details can be found in our technical report [22].

1) We prove the results by induction. First, if $Q_i(t) \leq V\alpha^{max}$, the maximum increase during one slot is $d_{i,2}^{max}$. Therefore, we obtain the upper bound in this case. Second, if $V\alpha^{max} < Q_i(t) \leq V\alpha^{max} + d_{i,2}^{max}$, LCMA will choose the maximum possible value for $y_i(t)$ since the partial derivative of the objective function in $\mathbf{P3}$ w.r.t. $y_i(t)$ is negative. The arrival amount can not be larger than the served amount by our assumption. Therefore, the queue length cannot increase. This completes the proof. The upper bound of $Z_i(t)$ and $Q_i(t) + Z_i(t)$ can be proved similarly.

2) This follows directly from Lemma 1.

3) Once again, we prove the result by induction. If $0 \leq E_i(t) < \theta_i - V(\alpha^{max} + \beta_i^{max})$, then LCMA will choose the maximum value for $r_i(t)$. Therefore the battery would charge as much as possible, i.e., $0 \leq E_i(t) \leq$

$E_i(t+1) < E_i(t)+r_i^{max} \leq E_i^{max}$. Second, assuming that $\theta_i - V(\alpha^{max}+\beta_i^{max}) \leq E_i(t) \leq \theta_i - V(\alpha^{min}+\beta_i^{min})$, then $\leq E_i(t) + r_i^{min} \leq E_i(t+1) \leq E_i(t) + r_i^{max} \leq E_i^{max}$, where we have used the upper bound V_{max} of V. Third, suppose $\theta_i - V(\alpha^{min} + \beta_i^{min}) \leq E_i(t) \leq E_i^{max}$, then LCMA will choose the minimum value for $r_i(t)$. Therefore, the battery would discharge as much as possible, i.e., $0 \leq E_i(t)+r_i^{min} \leq E_i(t+1) \leq E_i(t) \leq E_i^{max}$. This completes the proof.

4) Since we choose our decisions to satisfy all constraints in $\mathbf{P3}$, combining it with the results above together, all constraints of $\mathbf{P1}$ are satisfied. Therefore, our control decisions are feasible to $\mathbf{P1}$.
5) As we have mentioned before, the LCMA is always trying to greedily minimize the R.H.S. of the upper bound (15) of the *drift-plus-penalty* term at every slot t over all possible feasible control policies. Therefore, by plugging this policy into the R.H.S. of the inequality (15), and comparing it with a stationary, randomized control policy to the problem without the time coupling constraint (6), we can obtain the performance result following the performance result derivation in Lyapunov optimization framework.

■

V. Numerical Experiments

In this section, we provide numerical results based on real-world data sets to complement the analysis in the previous sections.

A. Experiment Setup

We consider a simple power system consisting of eight households in one neighborhood that share the same load serving entity and have on-site renewable generation, energy storage, and elastic and inelastic energy loads. The households are divided into two categories. For the first type of households (indexed by $i = 1, 2, 3, 4$), both the elastic and inelastic energy load arrivals during one slot are i.i.d. and take value from [1, 5] kWh uniformly at random. For the second type of households (indexed by $i = 5, 6, 7, 8$), both the elastic and inelastic energy load arrivals during one slot are also i.i.d. and take value from [1.5, 7.5] kWh uniformly at random. For the renewable generation, we use the hourly average solar irradiance data for Los Angeles area from the Measurement and Instrumentation Data Center (MIDC) [23] at the National Renewable Energy Laboratory. The period we consider in this paper is half a year from January 1, 2011 to June 30, 2011. In total, this duration includes 181 days or 4344 1-hour slots. The control interval is chosen to be one hour. We use different scaling factors to characterize the heterogeneity of households. Specifically, we choose the scaling factors such that the average solar energy production during one slot is about 3 kWh for the first type of households and 4.5 kWh for the second type of households. We fix the maximum charge and discharge rates of batteries in households as follows: for $i \in \{1,2,3,4\}$, $r_i^{max} = 1$ kWh, $r_i^{min} = -1$ kWh, and for $i \in \{5,6,7,8\}$, $r_i^{max} = 1.5$ kWh, $r_i^{min} = -1.5$ kWh. Also, we choose $y_i^{max} = d_{i,2}^{max}$ for all i. As [12], the battery cost is assumed to be a simple quadratic function as follows:

$$F_i(r_i) = b_1 r_i^2, \tag{29}$$

where b_1 is a constant coefficient. For the purpose of simple illustration, we choose the same battery cost function for all households i in the evaluations.

For the LSE, we assume that the energy cost function is a smooth quadratic function as follows:

$$C(D) = c_1 D^2 + c_2 D + c_3, \tag{30}$$

where c_1, c_2, and c_3 are constant coefficients. We choose $c_1 = 0.1$, $c_2 = 0.1$, and $c_3 = 0.2$ in our evaluations.

B. Results and Analysis

In order to analyze the performance improvement due to our LCMA, we compare it with the following two approaches: i) No storage, no demand response (B1): The household tries to use the renewable energy as much as possible. When the renewable energy is not sufficient, the household draws energy from the utility grid. Unused renewable energy is wasted; ii) Storage, no demand response (B2): The household uses renewable energy only as a supplement to the grid by consuming it whenever it is available. The household stores any extra renewable energy in its battery, but never charges the battery from the grid. The stored energy would be used to serve the future demands. Note that LCMA differs from the approaches above in the sense that LCMA would actively charge the battery when the grid power is cheap while discharging it when the grid power is expensive. Moreover, LCMA differentiates between inelastic and elastic energy loads and delays the elastic energy loads to later time when the grid power cost is low.

First, we start by considering the convergence of the distribution algorithm. Fig. 3(a) illustrates the convergence of Algorithm 1. We use a step size $\gamma = 0.1$ and the algorithm shows no sign of lack of convergence.

Then, we compare our algorithm with the two approaches above using the real-world solar power generation. Note that the performance of LCMA depends on the battery capacity, the battery cost, and the control parameters V and ϵ_i. We choose $b_1 = 0.5$, $E_i^{max} = 20$ kWh, $i \in \{1,2,3,4\}$, and $E_i^{max} = 30$ kWh, $i \in \{5,6,7,8\}$. The initial battery energy level at each household is chosen to be zero. Let $V = V^{max}$ and $\epsilon_i = \mathbb{E}\{d_{i,2}\}$, $\forall i$. As can be seen in Fig. 3(b), our proposed LCMA can reduce the total energy cost by approximately 20% compared with B1 and 13% compared with B2 in the six-month period. Also, the slopes of the lines are different, meaning that the savings are unbounded as the time increases. Meanwhile, the LCMA has on average a much smaller delay than the worst-case guarantee (11), as shown in Fig. 3(c).

In the following, we consider the impact of varying control parameters on the performance of LCMA.

- **Impact of Battery Capacity**: In this evaluation, we vary the battery capacities of households with other parameters fixed. We set $E_i^{max} = \{20, 30, 40\}$ kWh for $i \in \{1,2,3,4\}$, $E_i^{max} = \{30, 40, 50\}$ kWh for $i \in \{5,6,7,8\}$, and $V = V^{max}$. The result is illustrated in Fig. 4(a). From the figure, it is clear that the larger the capacity is, the more cost saving LCMA can obtain, which coincides with the algorithmic performance results of our algorithm in Theorem 1. As we have mentioned before,

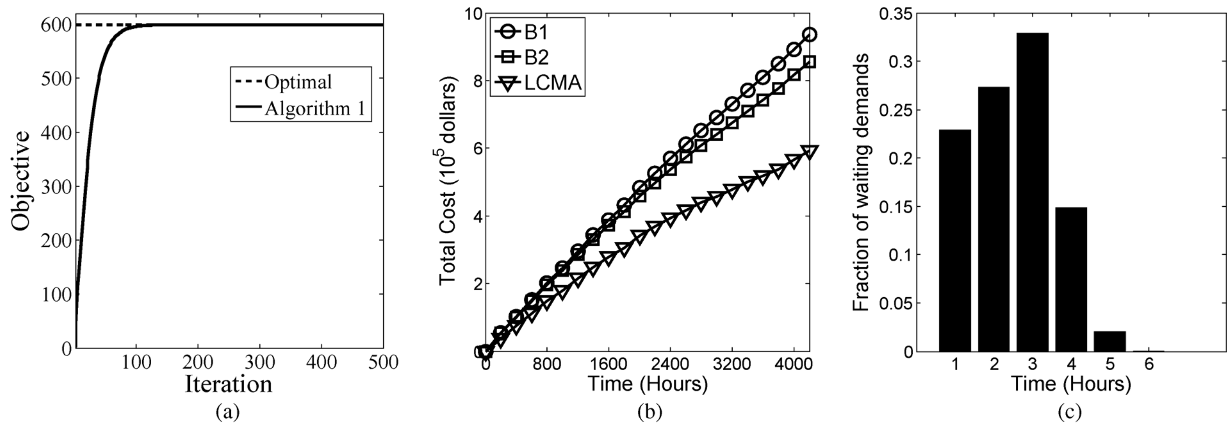

Fig. 3. (a) Convergence of Algorithm 1; (b) comparison of the total energy cost in three approaches; (c) histogram of delay for the elastic demands in the service queue for one household.

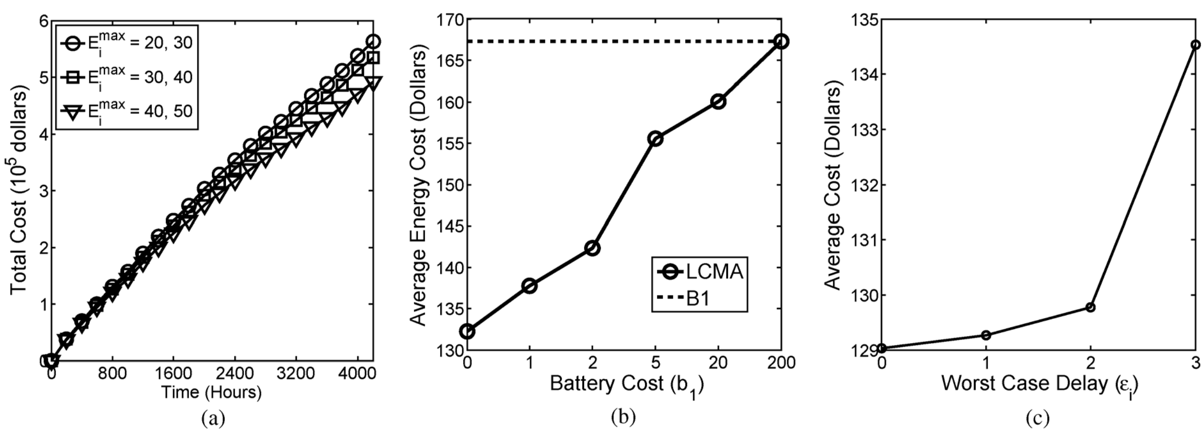

Fig. 4. (a) The impact of battery capacity on the cost saving; (b) the impact of battery cost b_1 on the cost saving; (c) the impact of ϵ_i on the cost saving.

the saving comes from the fact that our algorithm charges the battery when the marginal energy cost is low, while discharging it when the marginal energy cost is high.

- **Impact of Battery Cost**: Currently, batteries are still expensive. The charging or discharging operation would reduce the lifetime of the battery. However, it is expected that the cost of the battery would decrease greatly in the next decade. In this evaluation, we estimate the impact of battery cost on the cost saving of our algorithm. We set $b_1 = \{0, 1, 2, 5, 20, 200\}$ and keep $E_i^{max} = 20, i \in \{1, 2, 3, 4\}$, and $E_i^{max} = 30, i \in \{5, 6, 7, 8\}$ fixed. The result is shown in Fig. 4(b). Note that when the battery cost per usage during one period b_1 is very large (e.g., 200 $), our algorithm would not charge or discharge the battery at all, so it is the same as the approach B1. As the battery cost increases, the total cost saving of LCMA compared with B1 would decrease until they are the same since the opportunity to utilize the temporal variation of electricity prices is smaller.
- **Impact of Worst-case Delay Requirement**: In this setting, we adjust the parameters ϵ_i while fixing other parameters to see the impact of the worst-case delay guarantee for elastic energy loads on the performance of LCMA. We choose $\epsilon_i = \{0, 1, 2, 3\}, \forall i$, respectively. As observed in Fig. 4(c), the increase of ϵ_i (i.e., the worst-case delay) gives more opportunity to optimize the energy cost, since the elastic energy loads are more likely to be served in the low energy cost period.

VI. Conclusions

In this paper, we present an algorithm (LCMA) for the decentralized and coordinated stochastic optimization of flexible energy resources in a smart grid setting. The total system cost can be reduced if more energy loads are elastic and can tolerate being served with some delay. Our algorithm is simple and was shown to be able to operate without knowing the statistical properties of the underlying dynamics in the system. With the increase of energy storage capacities, the performance of our algorithm is proved to be arbitrarily close to the optimal value. Moreover, our algorithm provides an explicit relationship between energy storage capacity, worst-case delay, and cost saving. Extensive numerical evaluations based on real-world data sets show the effectiveness of our approach.

Appendix A
Proof of Lemma 1

Here we prove Lemma 1.

Proof: For all households i, consider any slot t for which $d_{i,2}(t) > 0$. We will show that this energy load $d_{i,2}(t)$ is served on or before time slot $t + \delta_i^{max}$ by contradiction. Suppose not, then during slots $\tau \in \{t+1, \ldots, t+\delta_i^{max}\}$, it must be that

$Q_i(\tau) > 0$. Otherwise, the energy load $d_{i,2}(t)$ would have been served before τ. Therefore, $1_{Q(\tau)>0} = 1$, and from the update (10) of $Z_i(t)$, we have for all $\tau = \{t+1, \ldots, t+\delta_{max}\}$:

$$Z_i(\tau+1) \geq Z_i(\tau) - y_i(\tau) + \epsilon_i. \tag{31}$$

Summing the above over $\tau = \{t+1, \ldots, t+\delta_i^{max}\}$ yields:

$$Z_i\left(t+\delta_i^{max}+1\right) - Z_i(t+1) \geq -\sum_{\tau=t+1}^{t+\delta_i^{max}} y_i(\tau) + \delta_i^{max}\epsilon_i. \tag{32}$$

Rearranging the terms and using the facts that $Z_i(t+1) \geq 0$ and $Z_i(t+\delta_i^{max}+1) \leq Z_i^{max}$ yields:

$$\sum_{\tau=t+1}^{t+\delta_i^{max}} y_i(\tau) \geq \delta_i^{max}\epsilon_i - Z_i^{max}. \tag{33}$$

Since the energy loads $d_{i,2}(t)$ are queued in a FIFO manner and $Q_i(t+1) \leq Q_i^{max}$, they would be served on or before time $t+\delta_i^{max}$ whenever there are at least Q_i^{max} units of energy served during $\tau \in \{t+1, \ldots, t+\delta_i^{max}\}$. Since we have assumed that the energy loads $d_{i,2}(t)$ are not served by time $t+\delta_i^{max}$, it must be that $\sum_{\tau=t+1}^{t+\delta_i^{max}} y_i(\tau) < Q_i^{max}$. Comparing this inequality with (33) yields:

$$Q_i^{max} > \delta_i^{max}\epsilon_i - Z_i^{max}, \tag{34}$$

which implies that $\delta_i^{max} < (Q_i^{max} + Z_i^{max})/\epsilon_i$, contradicting the definition of δ_i^{max} in (11). ∎

APPENDIX B
PROOF OF LEMMA 2

Proof: From (4), subtracting both sides by θ_i, and squaring both sides, we have for each household i,

$$\frac{\left(E_i(t+1)-\theta_i\right)^2-\left(E_i(t)-\theta_i\right)^2}{2} = \frac{r_i^2(t)}{2} + r_i(t)\left(E_i(t)-\theta_i\right). \tag{35}$$

Moreover, we have the following inequality:

$$\frac{r_i^2(t)}{2} \leq \frac{\max\left\{\left(r_i^{max}\right)^2, \left(r_i^{min}\right)^2\right\}}{2}. \tag{36}$$

Taking expectations of both sides of (4) given $\mathbf{K}(t)$, and summing over all households i, we can get the following upper bound for the Lyapunov drift for $E_i(t) - \theta_i$:

$$\frac{\left(E_i(t+1)-\theta_i\right)^2-\left(E_i(t)-\theta_i\right)^2}{2} \leq \frac{\max\left\{\left(r_i^{max}\right)^2, \left(r_i^{min}\right)^2\right\}}{2} + r_i(t)\left(E_i(t)-\theta_i\right). \tag{37}$$

Also, from (1), squaring both sides, and using the following inequality:

$$\left(\max\left\{Q_i(t)-y_i(t), 0\right\} + d_{i,2}(t)\right)^2 \leq d_{i,2}^2(t) + Q_i^2(t) + y_i^2(t) + 2Q(t)\left(d_{i,2}(t) - y_i(t)\right), \tag{38}$$

we obtain

$$\frac{Q_i^2(t+1) - Q_i^2(t)}{2} \leq \frac{\left(y_i^{max}\right)^2 + \left(d_{i,2}^{max}\right)^2}{2} + Q_i(t)\left(d_{i,2}(t) - y_i(t)\right). \tag{39}$$

Similarly, from (10), we have

$$Z_i^2(t+1) \leq \left(Z_i(t) - y_i(t) + \epsilon_i\right)^2. \tag{40}$$

Then, we obtain the following inequality:

$$\begin{aligned}\frac{Z_i^2(t+1) - Z_i^2(t)}{2} &\leq \frac{\left(\epsilon_i - y_i(t)\right)^2}{2} + Z_i(t)\left(\epsilon_i - y_i(t)\right) \\ &\leq \frac{\max\left\{\left(y_i^{max}\right)^2, \epsilon_i^2\right\}}{2} + Z_i(t)\left(\epsilon_i - y_i(t)\right).\end{aligned} \tag{41}$$

Combining these three bounds together, summing over all households, taking the expectation w.r.t. $\mathbf{K}(t)$ on both sides, and adding penalty term $V\mathbb{E}\{C(\sum_{i=1}^N g_i(t)) + \sum_{i=1}^N F_i(r_i(t))|\mathbf{K}(t)\}$ to both sides of the above inequality, we arrive at the conclusion in the Lemma. ∎

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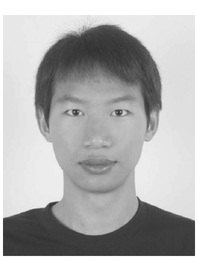

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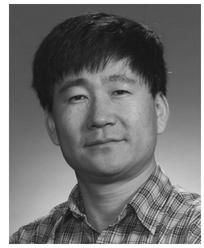

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