Renewable Energy Pricing Driven Scheduling in Distributed Smart Community Systems

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Abstract—A smart community is a distributed system consisting of a set of smart homes which utilize the smart home scheduling techniques to enable customers to automatically schedule their energy loads targeting various purposes such as electricity bill reduction. Smart home scheduling is usually implemented in a decentralized fashion inside a smart community, where customers compete for the community level renewable energy due to their relatively low prices. Typically there exists an aggregator as a community wide electricity policy maker aiming to minimize the total electricity bill among all customers. This paper develops a new renewable energy aware pricing scheme to achieve this target. We establish the proof that under certain assumptions the optimal solution of decentralized smart home scheduling is equivalent to that of the centralized technique, reaching the theoretical lower bound of the community wide total electricity bill. In addition, an advanced cross entropy optimization technique is proposed to compute the pricing scheme of renewable energy, which is then integrated in smart home scheduling. The simulation results demonstrate that our pricing scheme facilitates the reduction of both the community wide electricity bill and individual electricity bills compared to the uniform pricing. In particular, the community wide electricity bill can be reduced to only 0.06 percent above the theoretic lower bound.

Index Terms—Smart home, smart community, pricing scheme, cross entropy optimization, renewable energy

1 Introduction

The smart community features the automatical control of household activities for each home. It improves reliability, quality and efficiency of power supply and influences the usage of electricity energy with smart home scheduling and renewable energy integration [1], [2], [3], [4]. In smart home scheduling, home appliances are scheduled in order to reduce the electricity bill given the dynamic electricity prices provided from utility companies, in which the electricity price at each time slot is computed based on the historical energy usage. Renewable energy resources are commonly available at the community level which are typically inexpensive [5], [6]. The community level renewable energy can be a wind turbine or a large photovoltaic (PV) panel, which is accessible to all the customers in the community. Customers can be supplied directly with community level renewable energy which mitigates the burden of power plants and power transmission networks [7]. However, customers in a community need to compete with each other for the limited resources of renewable energy.

A smart community is usually implemented in a distributed fashion due to the independent customer energy usage behavior. Thus, a decentralized approach is widely adopted to implement smart home scheduling [8], [9]. The electricity bill of the community is computed based on the total energy load shared by customers [8]. In such a context, the electricity bill of a customer actually depends on the energy usage of him/her and others. Thus, a common idea of decentralized smart home scheduling techniques is to iteratively schedule the energy usage of each customer to minimize the electricity bill [8]. This idea fails to address the competition on community level renewable energy. Note that since each customer is selfish and renewable energy is much cheaper than grid energy, he/she intends to use it as much as possible. However, the renewable energy generation cannot supply the demand of the whole community.

This work aims to handle the competitions on community level renewable energy usage. Assuming the existence of a community level electricity pricing policy aiming to minimize the total electricity bill, our philosophy is to design a new pricing scheme for the renewable energy usage such that each customer can only be assigned with a reasonable amount of renewable energy. However, there is a major difficulty in implementing this idea. As shown in Fig. 1, the utility energy and community level renewable energy usually merge at the substation of the community. Thus, it is impossible to distinguish the renewable energy usage from the total energy usage for each customer. To tackle this challenge, our proposed pricing scheme works as follows. At each time slot, each customer receives a discount factor, assigned by the community level policy maker, accounting for the electricity bill reduction due to using renewable energy. A larger discount factor is of course preferred by each customer, but total renewable energy resource is limited. Thus, the policy maker needs to determine a set of "optimal" discount factors which lead to the minimum total electricity bill from the community's perspective. Compared to a standard smart home scheduling, discount factor triggers the rescheduling of energy usage such that each customer launches smart home scheduling accordingly to reduce the electricity bill. Before discussing how to compute those optimal discount factors, *this paper demonstrates that a*

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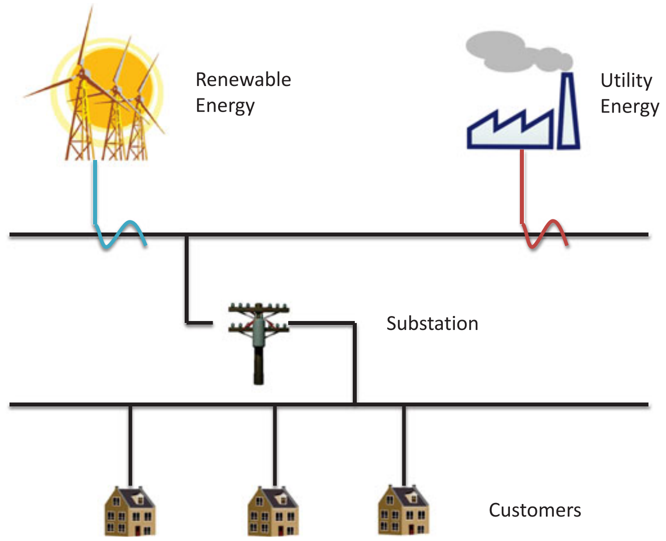

Fig. 1. Utility energy and community level renewable energy merge at the substation. Thus, the energy supplied to the customers is indistinguishable.

set of appropriately designed discount factors can achieve the target that while each individual customer minimizes his/her own bill, the community wide total electricity bill can be simultaneously minimized. Let us first take a look at a motivational example.

Consider a mini community consisting of two customers. They will schedule household appliances during a time horizon of two hours, when customer 1 has a task of 3 kWh to schedule and customer 2 has a task of 4 kWh to schedule. Denote by $x_{n,h}$ the energy usage of customer n at time slot h. Denote by R_h the renewable energy generation, and suppose that $R_1 = 1$ kWh and $R_2 = 2$ kWh. Typically, the quadratic model is used to bill the customers [8]. Thus, the total electricity bill of the community is computed by $\sum_h a_h\,(x_{1,h} + x_{2,h} - R_h)^2$ for some a_h. Customer 1 and 2 share the bill proportionally based on their energy usages. Thus, the bill of customer 1 is $\sum_h a_h \frac{x_{1,h}}{x_{1,h}+x_{2,h}}(x_{1,h} + x_{2,h} - R_h)^2$ and the bill of customer 2 is $\sum_h a_h \frac{x_{2,h}}{x_{1,h}+x_{2,h}}(x_{1,h} + x_{2,h} - R_h)^2$. Assuming that $a_h = 1$ for $h = 1$ and $h = 2$, one solves the smart home scheduling problem in the fashion that each customer aims to minimize the individual electricity bill. Using the scheduling algorithm in [8], the solution is $x_{1,1} = 1$ kWh, $x_{1,2} = 2$ kWh, $x_{2,1} = 1.5$ kWh and $x_{2,2} = 2.5$ kWh. The corresponding total electricity bill is 8.5. Refer to Fig. 2.

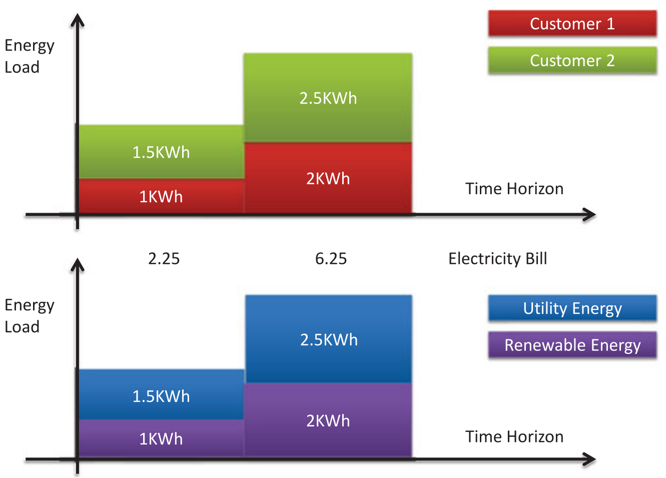

Fig. 2. The first smart home scheduling solution with the total electricity bill of 8.5.

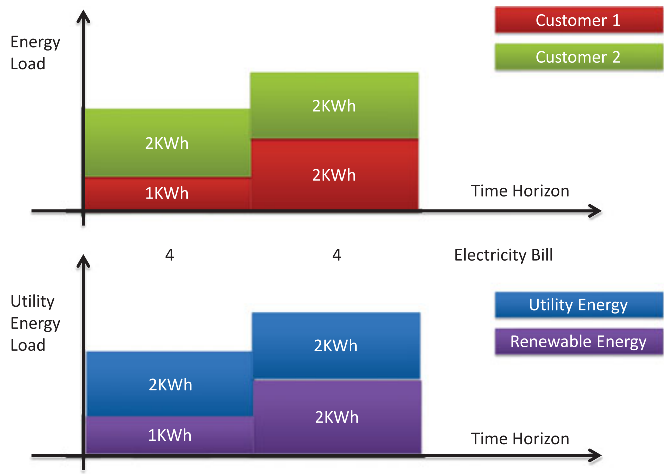

Fig. 3. The optimal smart home scheduling solution with the total electricity bill of 8.

In contrast, our newly designed pricing scheme which discounts the bill due to using renewable energy can trigger the rescheduling of energy usage to further reduce the community-wide electricity bill. Denote by $\beta_{n,h}$ the discount factor for customer n at time h. Thus, the electricity bill of the customer n is $\sum_h a_h \beta_{n,h} \frac{x_{n,h}}{x_{1,h}+x_{2,h}}(x_{1,h} + x_{2,h})^2$. The optimal discount factors can be computed as $\beta_{1,1} = 1$, $\beta_{1,2} = \frac{4}{9}$, $\beta_{2,1} = \frac{24}{25}$ and $\beta_{2,2} = \frac{2}{3}$, respectively. Using these discount factors, one solves the smart home scheduling problem again using [8]. The scheduling solution is $x_{1,1} = 1$ kWh, $x_{1,2} = 2$ kWh, $x_{2,1} = 2$ kWh and $x_{2,2} = 2$ kWh. The corresponding total electricity bill is 8, which is smaller than the previous case and it actually minimizes the total electricity bill of the community. Refer to Fig. 3. Comparing the smart home scheduling solutions with and without our renewable energy pricing scheme, even though renewable energy is used up in both cases the community wide electricity bills are significantly different. Our renewable energy discount factor facilitates the further reduction of total electricity bill due to the rescheduling triggered by our discount factors.

The next question is obviously how to systematically find such a set of "optimal" discount factors which leads to the minimum total electricity bill. In this paper, we first establish the proof that using the proposed renewable energy pricing scheme, under certain assumptions the solution of decentralized smart home scheduling is equivalent to that of the centralized method, reaching the theoretical lower bound of the community wide total electricity bill. In addition, an advanced cross entropy optimization technique is proposed to compute such a pricing scheme to be integrated with smart home scheduling. Our algorithm generates a set of discount factors, which are gradually updated to approach the optimal discount factors according to the energy consumption scheduling solutions of the customers.

In fact, there are some existing works addressing the competitions on various resources. In [10], Zhang et al. investigate the time dependant and usage based pricing for congestion control in wireless data networks. In [11], Markov decision

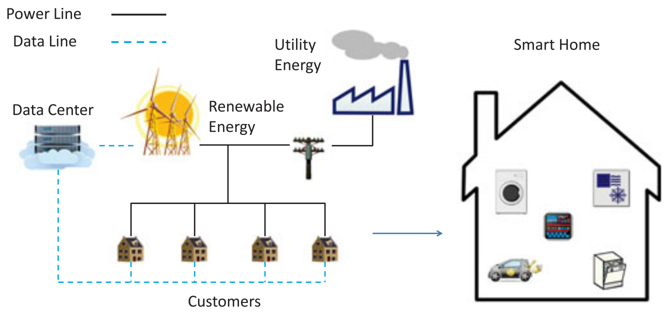

Fig. 4. The model of smart community considered in this paper.

process is deployed to compute the optimal pricing to regulate the user requests in scalable video coding system. In [12], two different pricing schemes are studied in terms of total revenue maximization and social welfare maximization, respectively, to control spectrum access in cognitive radio networks. In [13], the reputation based pricing mechanism is proposed to encourage the cooperation on job allocation in social cloud system. However, none of the above works consider the competitions on renewable energy usage among customers for electricity bill reduction.

Comparing to the centralized smart home scheduling scheme, a major deficiency of the decentralized scheme is lack of capability to achieve the theoretical minimum community-wide electricity bill. However, this paper demonstrates that under certain assumptions it is actually achievable with a nicely designed pricing scheme. The contributions of this paper are summarized as follows.

- The problem of competitions among customers on renewable energy usage for minimizing the community wide total electricity bill is considered in this paper. A proof is established that there exists a renewable energy pricing scheme such that the solution of decentralized smart home scheduling is equivalent to that of the centralized method, reaching the theoretical lower bound of the community wide total electricity bill.
- An advanced cross entropy optimization technique is proposed to compute such a pricing scheme, which empirically validates the above proof. The basic idea is to generate a set of discount factors, which are gradually updated to approach the optimal discount factors according to the energy consumption scheduling solutions of the customers.
- The performance of the proposed algorithm is evaluated using simulations. With the generated benchmark containing 500 customers and the penetration of real wind farm generation data, the electricity bill for the community is reduced by 32.73 percent compared to a state-of-the-art scheduling technique. This bill is only 0.06 percent above the theoretical lower bound.

The rest of this paper is organized as follows. Section 2 presents a specific system model of the smart community. Section 3 formulates the game model where the customers compete for electricity bill reduction as well as renewable energy usage. Section 4 proposes the cross entropy based pricing scheme optimization algorithm. Simulations are conducted in Section 5 to validate the proposed algorithm, where the analysis of the simulation results are provided. A summary of paper is given in Section 6.

2 System Model

Consider a smart community depicted in Fig. 4 in which a set of customers $\mathcal{N} = \{1, \ldots, N\}$ share the energy from two resources: utilities and a renewable energy generation resource (e.g., a wind turbine). The customers are scheduling the energy consumption in next 24 hours from present, which is divided into H time slots, i.e., $\mathcal{H} = \{1, \ldots, H\}$. Besides the customers, an aggregator plays an important role in the community. It has the electricity pricing, energy load and renewable generation information in the data center and shares it to the customers. It is also the policy maker in the community. Note that this model is a typical one adopted in many works such as [4], [8].

Denote by Θ_h the renewable energy generation at each time slot $h \in \mathcal{H}$. In this paper, the standard day ahead forecast model for renewable energy generation is used. Conventional utility energy need to be purchased from the utilities since renewable energy only cannot satisfy the demand from customers.

2.1 Energy Consumption

In the community, each customer schedules the energy consumption of the home appliances using the smart home controller. This work adopts the model commonly used in the literature [8], [14], which can be described as follows. For each customer $n \in \mathcal{N}$, denote by $l_{n,h}$ the energy consumption at time slot h, and denote by $\mathcal{A}_n$ the set of home appliances. For home appliance $m \in \mathcal{A}_n$, denote by $\mathcal{X}_m$ the set of available power levels, where a power level denotes the energy consumption of the home appliance per time slot. The home appliances can generally be divided into two categories: manually controlled home appliances and automatically controlled ones. The power level of a manually controlled home appliance is fixed at all time slots. In contrast, for an automatically controlled home appliance m, the smart home scheduler chooses a power level $x_{m,h} \in \mathcal{X}_m$ at each time slot subject to the constraints as follows.

- For a specific task, the total energy consumption of home appliance m is denoted by E_m, which is fixed and can be pre-computed. It is equal to the summation of energy consumptions over the time horizon such that

$$\sum_{h=1}^{H} x_{m,h} t_{m,h} = E_m, \tag{1}$$

  where $t_{m,h}$ is the actual execution time period of home appliance m at time slot h.
- The home appliance m should be started no earlier than a required starting time α_m and complete the task no later than the deadline β_m, that is

$$x_{m,h} = 0, \ \forall h < \alpha_m || h > \beta_m. \tag{2}$$

- At time slot h, the energy consumption of customer n is equal to the total energy consumption of all the home appliances such that

$$\sum_{m \in \mathcal{A}_n} x_{m,h} = l_{n,h}. \tag{3}$$

- The real time energy load of the system is defined by L_h, which is computed by

$$L_h = \sum_{n \in \mathcal{N}} l_{n,h}. \tag{4}$$

2.2 Electricity Bill Computation

The customers are supplied by both utility energy and renewable energy. Without loss of generality, the renewable energy is modeled as a free public resource in this paper. Thus, the community need to pay for using the conventional utility energy. At each time slot h, the total conventional utility energy demand is the difference between total energy consumption and renewable energy generation, which is $L_h - \Theta_h$. Following literatures such as [8], [14], the electricity bill at each time slot h is typically modelled as a quadratic function of the total energy purchase from the utility, that is

$$C_h = a_h (L_h - \Theta_h)^2, \tag{5}$$

where a_h is a parameter.

2.3 Centralized Smart Home Scheduling

In the community, the aggregator aims to minimize the total electricity bill for conventional utility energy consumption. If centralized control is feasible, the aggregator can directly select $(x_{m,h}, \forall m \in \mathcal{A}_n, \forall h \in \mathcal{H})$ to schedule the automatically controlled home appliances for all customers. In that case, the community wide total electricity bill minimization problem is formulated as follows:

$$\begin{aligned} \mathbf{P1}: \quad & \underset{x_{m,h},\ \forall m \in \mathcal{A}_n, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}}{\textbf{minimize}} \sum_{h=1}^{H} \Big[a_h (L_h - \Theta_h)^2 \Big] \\ & \textbf{subject to} \quad x_{m,h} \in \mathcal{X}_m \\ & \qquad L_h = \sum_n \sum_m x_{m,h} t_{m,h} \\ & \qquad \sum_{h=\alpha_m}^{\beta_m} x_{m,h} t_{m,h} = E_m. \end{aligned} \tag{6}$$

P1 can be solved using various optimization methods. The corresponding optimal solution leads to the minimum community-wide electricity bill. However, in practice customers are independent decision makers and their behaviors cannot be directly controlled by a centralized aggregator.

3 Decentralized Smart Home Scheduling Considering Renewable Energy

Since each customer is an independent decision maker, the centralized smart home scheduling is not feasible in many cases. Thus, a *decentralized* game theoretic mechanism is a common solution for multi-customer smart home scheduling [8], [14]. In that approach, each customer individually decides the energy consumption scheduling to minimize his/her own electricity bill over the entire time horizon based on the renewable energy generation prediction and other customers' decisions. At each time slot h, each customer n is billed proportionally to the individual energy consumption. Suppose that $\theta_{n,h}$ is the amount of renewable energy consumed by customer n at time slot h such that $\sum_{n \in \mathcal{N}} \theta_{n,h} = \Theta_h$. The electricity bill of customer n is computed as follows:

$$\begin{aligned} C_{n,h} &= \frac{l_{n,h} - \theta_{n,h}}{L_h - \Theta_h} a_h (L_h - \Theta_h)^2 \\ &= a_h (l_{n,h} - \theta_{n,h})(L_h - \Theta_h) \\ &= a_h (l_{n,h} - \theta_{n,h})(l_{n,h} + l_{-n,h} - \Theta_h), \end{aligned} \tag{7}$$

where $l_{-n,h}$ is the summation of the energy load over all customers of the community except n, that is, $l_{-n,h} = \sum_{m \in \mathcal{N}, m \neq n} l_{m,h}$. However, the exact value of $\theta_{n,h}$ cannot be known due to the indistinguishable nature of electrical energy.

To tackle this problem, we use the ratio $p_{n,h}$ instead of the absolute amount such that $\theta_{n,h} = p_{n,h} \Theta_h$, where $\sum_{n \in \mathcal{N}} p_{n,h} = 1$. Thus, the electricity bill of customer n can be rewritten as

$$C_{n,h} = a_h (l_{n,h} - p_{n,h} \Theta_h)(l_{n,h} + l_{-n,h} - \Theta_h). \tag{8}$$

We define $p_{n,h}$ as the discount factor, which models the reduction of electricity bill of customer n at time slot h due to using renewable energy. $p_{n,h}$ is computed by the aggregator. Thus, in the decentralized smart home scheduling technique, each customer aims to minimize the electricity bill through solving the optimization problem as follows [14]:

$$\begin{aligned} \mathbf{P2}: \quad & \underset{x_{m,h},\ \forall m \in \mathcal{A}_n, \forall h \in \mathcal{H}}{\textbf{minimize}} \sum_{h=1}^{H} C_{n,h} \\ & \textbf{subject to} \quad x_{m,h} \in \mathcal{X}_m, \forall m \in \mathcal{A}_n \\ & \qquad \sum_{h=\alpha_m}^{\beta_m} x_{m,h} t_{m,h} = E_m. \end{aligned} \tag{9}$$

3.1 Game Model

For each customer, the electricity bill depends on the energy usage of other customers as well as that of his/her own. Refer to Eqn. (9). Thus, the impact of the other customers has to be considered when scheduling the energy consumption. This leads to the competition among the customers on reducing the electricity bill. Furthermore, the discount factors are computed based on the energy consumption of the customers, which leads to the competition among the customers on renewable energy usage. Those competitions are formulated in the game model. The payoff function for each customer n is defined as the negation of the electricity bill over the time horizon, given by

$$\begin{aligned} f_n(\boldsymbol{l}_n, \boldsymbol{l}_{-n}) &= -\sum_{h \in \mathcal{H}} C_{n,h} \\ &= -\sum_{h \in \mathcal{H}} \{ a_h l_{n,h} (l_{n,h} + l_{-n,h}) \\ &\quad - a_h \Theta_h [(p_{n,h} + 1) l_{n,h} - p_{n,h} l_{-n,h} - p_{n,h} \Theta_h] \}. \end{aligned} \tag{10}$$

In the formulated game, all customers are assumed to know, through the aggregator, the renewable power generation estimation Θ_h and the total energy consumption of other customers $l_{-n,h}$. Based on that, the customers seek to maximize their payoffs. The game model is formulated as follows:

- *Players*: Set $\mathcal{N}$ of all customers.
- *Information*: $l_{-n,h}$ and Θ_h at each time slot $h \in \mathcal{H}$.
- *Strategies*: At each time slot $h \in \mathcal{H}$, the customer n schedules the energy consumption $\{l_{n,t}\}_{t=h}^{H}$ and the aggregator computes $p_{n,h}$.
- *Payoffs*: For each customer n, at each time slot $h \in \mathcal{H}$,

$$\begin{aligned} f_n(\boldsymbol{l}_n, \boldsymbol{l}_{-n}) &= -\sum_{h\in\mathcal{H}} C_{n,h} \\ &= -\sum_{h\in\mathcal{H}} \{a_h l_{n,h}(l_{n,h} + l_{-n,h}) \\ &\quad - a_h\Theta_h[(p_{n,h}+1)l_{n,h} \\ &\quad - p_{n,h}l_{-n,h} - p_{n,h}\Theta_h]\}. \end{aligned}$$

- *Problem Formulation*:

$$\begin{aligned} \textbf{P2}: \quad & \underset{x_{m,h}}{\textbf{minimize}} \quad \sum_{h=1}^{H} C_{n,h} \\ & \textbf{subject to} \quad x_{m,h} \in \mathcal{X}_m, \forall m \in \mathcal{A}_n \\ & \qquad \sum_{h=\alpha_m}^{\beta_m} x_{m,h} t_{m,h} = E_m \\ & \qquad \forall m \in \mathcal{A}_n, \forall h \in \mathcal{H}. \end{aligned}$$

3.2 Analysis

The formulations of centralized and decentralized smart home scheduling problems are presented in Problems **P1** and **P2**. Comparing these two problems, we have the following observations.

- In the decentralized smart home scheduling formulated in Problem **P2**, the discount factor $\mathbf{p}_n = [p_{n,1}, p_{n,2}, \ldots, p_{n,H}]$ impacts the solution of each customer n.
- Compared to the decentralized smart home scheduling Problem **P2**, the solution of centralized smart home scheduling Problem **P1** only depends on the total amount of renewable energy Θ_h.
- The solution of the centralized smart home scheduling Problem **P1** leads to the minimum community-wide electricity bill, which is the theoretical lower bound.

Since the solution of decentralized smart home scheduling Problem **P2** depends on the discount factor $\mathbf{p}_n$, it is not guaranteed to achieve the theoretical lower bound of community-wide electricity bill. However, in the following we will prove that given a set of appropriately designed discount factors $\mathbf{p}_n$, with certain assumptions the solutions of decentralized smart home scheduling Problem **P2** and centralized smart home scheduling Problem **P1** are equivalent. This means that the theoretical lower bound of community-wide electricity bill can be achieved through solving the decentralized smart home scheduling Problem **P2** given the optimal discount factors.

Theorem 3.1. *There exist some scenarios such that the optimal solutions of Problems **P2** and **P1** are equivalent.*

Proof. The scenarios are designed with the following assumptions.

- a_h is flat in the time horizon such that:

$$a_h = a, \forall h \in \mathcal{H}. \tag{11}$$

- For each customer n, all home appliances are assumed to be fully schedulable and is only constrained by the total energy consumption D_n such that

$$\sum_{h\in\mathcal{H}} l_{n,h} = D_n. \tag{12}$$

The total energy consumption of the entire community is L, such that

$$\sum_{h\in\mathcal{H}} L_h = L. \tag{13}$$

□

For each home appliance, the starting time and deadline are $\alpha_m = 1$ and $\beta_m = H$. $x_{m,h}$ can be any positive number.

Thus, solving Problem **P1**, the corresponding energy load at each time slot L_h^1 is

$$L_h^1 = \frac{L - \sum_{h\in\mathcal{H}}\Theta_h}{H} + \Theta_h. \tag{14}$$

For Problem **P2**, we assume

$$p_{n,h} = \frac{1}{N}. \tag{15}$$

Hence, the energy cost for customer n can be derived as

$$\begin{aligned} C_n &= \sum_{h\in\mathcal{H}} C_{n,h} \\ &= \sum_{h\in\mathcal{H}} a\left(l_{n,h} - \frac{\Theta_h}{N}\right)(l_{n,h} + l_{-n,h} - \Theta_h) \\ &= a\sum_{h\in\mathcal{H}}\left[(l_{n,h})^2 + \left(l_{-n,h} - \frac{N+1}{N}\Theta_h\right)l_{n,h} \right. \\ &\quad \left. - \frac{\Theta_h}{N}(l_{-n,h} - \Theta_h)\right] \\ &= a\sum_{h\in\mathcal{H}}\left[\left(l_{n,h} + \frac{l_{-n,h} - \frac{N+1}{N}\Theta_h}{2}\right)^2 \right. \\ &\quad \left. - \frac{\Theta_h}{N}(l_{-n,h} - \Theta_h) - \left(\frac{l_{-n,h} - \frac{N+1}{N}\Theta_h}{2}\right)^2\right]. \end{aligned} \tag{16}$$

Since both Θ_h and $l_{-n,h}$ are treated as constant, the target of Problem **P2** can be rewritten as:

$$\begin{aligned} \textbf{P3} \quad & \textbf{minimize} \quad \sum_{h\in\mathcal{H}}\left(l_{n,h} + \frac{l_{-n,h} - \frac{n+1}{n}\theta_h}{2}\right)^2 \\ & \textbf{subject to} \quad \sum_{h\in\mathcal{H}} l_{n,h} = D_n. \end{aligned} \tag{17}$$

For each customer n, the solution of **P3** is

$$l_n^h = \frac{D_n - \sum_{h\in\mathcal{H}}(\frac{l_{-n,h} - \frac{N+1}{N}\Theta^h}{2})}{H} - \frac{l_{-n,h} - \frac{N+1}{N}\Theta^h}{2}. \tag{18}$$

This is computed in a fashion similar to Eqn. (14), where Θ_h is substituted by $\frac{l_{-n,h} - \frac{N+1}{N}\Theta_h}{2}$. Solving Problem **P2**, the corresponding community-wide energy load at each time slot h is denoted by L_h^2, which is derived as

$$L_h^2 = \frac{L - \sum_{h\in\mathcal{H}}(\frac{(N-1)L_h^2-(N+1)\Theta_h}{2})}{H} - (N-1)L_h^2 - (N+1)\Theta_h, \tag{19}$$

which is

$$L_h^2 = \frac{L - \sum_{h\in\mathcal{H}}\Theta_h}{H} + \Theta_h = L_h^1. \tag{20}$$

Thus, given this special case, the corresponding community-wide energy load computed by solving Problems **P1** and **P2** are identical. Furthermore, note that power levels of the home appliances at each time slot x_m^h subjects to the following constraints

$$L_h = \sum_n \sum_m x_{m,h} t_{m,h}, \tag{21}$$

and

$$E_m = \sum_{h=1}^{H} x_{m,h} t_{m,h}. \tag{22}$$

Extracting $x_{m,h}$ from the Eqns. (21) and (22), there are totally $N \times M \times H$ variables derived from $N \times M + H$ equations. Since $N \times M \times H > N \times M + H$, there exists a solution for $x_{m,h}$. Thus, given the energy load $L_h^1 = L_h^2$, we can always extract the identical corresponding combinations of power levels, which is the solution of Problems **P1** and **P2**. Hence, there exists a pricing scheme such that the optimal solutions of Problems **P1** and **P2** are equivalent.

Based on the above analysis, the decentralized smart home scheduling can be facilitated by designing pricing schemes for renewable energy usage. Thus, the renewable energy management and smart home scheduling problems in the distributed smart community can be decomposed into two steps. (1) Optimize the pricing scheme for renewable energy usage and compute the discount factors $p_{n,h}$. (2) Solve Problem **P2** given the optimized discount factors to compute the energy scheduling solution that leads to the minimum community-wide electricity bill.

In terms of optimizing the pricing scheme, we make the following observations. It is obvious that once the energy load of the community is fixed, the total electricity bill of the community would not change regardless of the discount factors $p_{n,h}$. However, with a different discount factor $p_{n,h}$, the customer n has a different solution of Problem **P2**. Thus, the impact of discount factors to the community-wide electricity bill is indirect, which imposes a significant challenge to the renewable energy pricing optimization. To tackle this difficulty, a cross entropy optimization based algorithm is proposed to compute the optimal discount factors.

4 Pricing Scheme

We are to compute discount factors for all customers for minimizing the community-wide electricity bill. The decentralized smart home scheduling has been studied in our previous works [14], [15]. For completeness, it is presented in Algorithm 1. The customer n deploys the dynamic programming based smart home scheduling technique proposed in [15] to solve Problem **P2** in line 4. If the electricity bill over the community does not change compared to the previous iteration, the algorithm terminates.

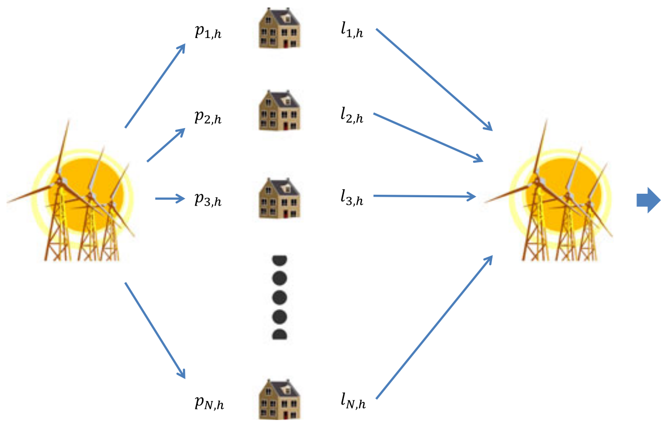

Fig. 5. Computing discount factors using cross entropy optimization method.

Algorithm 1. Decentralized Energy Consumption Scheduling Algorithm [14], [15], [16]

1: **loop**
2:   **for** Each customer $n \in \mathcal{N}$ **do**
3:     Receive $\boldsymbol{l}_{-n}$
4:     Solve Problem **P2**
5:     Update $\boldsymbol{l}_n$
6:   **end for**
7:   **if** Energy cost over the community converges **then**
8:     Break
9:   **else**
10:     Continue
11:   **end if**
12: **end loop**

Once the energy consumption scheduling is fixed, the community-wide electricity bill is also fixed regardless of the pricing scheme according to Eqn. (5) since it does not directly depend on the discount factors. Thus, one cannot compute the optimal discount factors analytically. To tackle this difficulty, an advanced cross entropy optimization technique is developed to optimize the pricing scheme for renewable energy usage.

4.1 Theoretical Foundation of Cross Entropy Method

Cross entropy optimization method is a stochastic optimization method based on importance sampling [17], [18], [19]. Given a optimization problem

$$\min f(x), \tag{23}$$

the cross entropy method aims to find the maximum value of ϵ such that

$$P[f(x) \le \epsilon] = 0, \tag{24}$$

Since $P[f(x) \le \epsilon]$ cannot be computed analytically, the cross entropy method employs a probability density function (PDF) and generate Monte Carlo samples of x to evaluate $P[f(x) \le \epsilon]$. Based on the evaluation, the PDF is updated to approach the optimal solution of Eqn. (23) iteratively. Let $\delta(\epsilon) = P[f(x) \le \epsilon]$. A brief overview of this technique is given as follows.

- Based on a family of pre-defined PDF $P(x, \rho)$ parameterizerd by ρ, a set of Monte-Carlo samples is

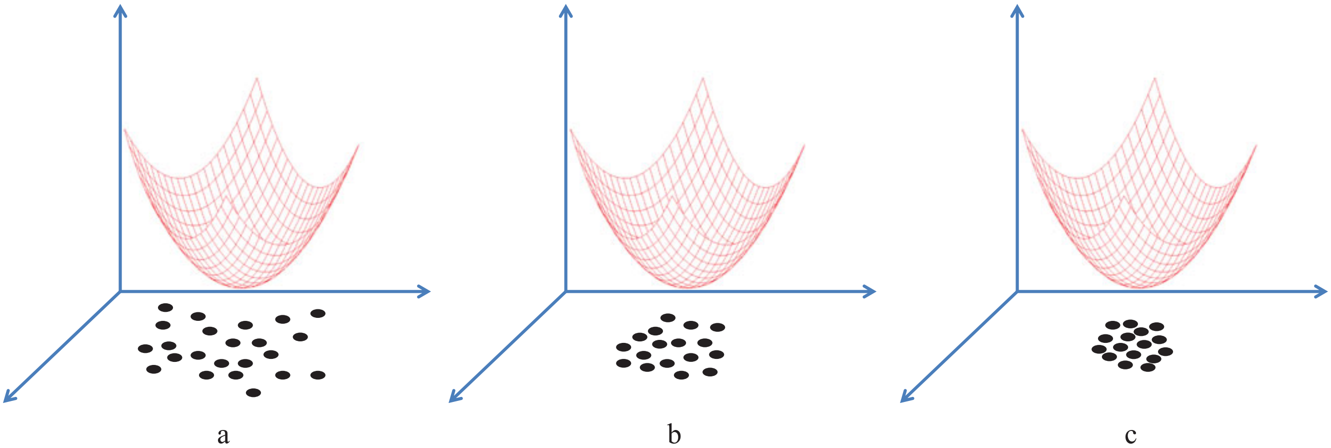

Fig. 6. In the cross entropy optimization technique, a set of samples are generated based on a pre-specified probability density function (PDF). Based on the values of these samples, the PDF is updated. This is repeated iteratively. While the PDF is updated, the generated samples are closer to the optimal solution of the optimization problem to solve.

generated, which is denote by $[X_1, X_2, \ldots, X_K]$. Given a set of Monte Carlo samples, the value of $\delta(\epsilon)$ can be estimated by

$$\hat{\delta}(\epsilon) = \frac{1}{K}\sum_{k=1}^{K} I(f(X_k) \leq \epsilon), \tag{25}$$

where $I(f(X_k) \leq \epsilon) = 1$ if $f(X_k) \leq \epsilon$.

- Note that $P[f(x) \leq \epsilon] = 0$ if ϵ is equal to the optimal value of $f(x)$. Thus, when ϵ is close to $\max f(x)$, $f(x) \leq \epsilon$ is a rare event. It means that a very large number of Monte Carlo samples need to be generated in order to find the one that satisfies $I(f(X_k) \leq \epsilon) = 1$. The cross entropy method tackles this difficulty through utilizing importance sampling. Suppose that there exists an optimal PDF $\psi(x)$ such that the sample X generated from $\psi(x)$ can always satisfy $f(X) \leq \epsilon$. In order to obtain $\psi(x)$, the cross entropy method iteratively updates $P(x, \rho)$.

  Denote by $\theta(x)$ the other PDF such that $\theta(x) = 0 \Rightarrow I(f(x) \leq \epsilon)P(x, \rho) = 0$. Thus, $\delta(\epsilon)$ can be estimated by [20]

$$\hat{\delta}(\epsilon) = \frac{1}{K}\sum_{k=1}^{K} I(f(X_k) \leq \epsilon)\frac{P(X_k, \rho)}{\theta(X_k)}. \tag{26}$$

  Based on Eqn. (26), the optimal distribution $\psi(x)$ is computed by [20]

$$\psi(x) = \frac{I(f(x) \leq \epsilon)P(x, \rho)}{\delta(\epsilon)}. \tag{27}$$

- The cross entropy method keeps updating $P(x, \rho)$ by computing the optimal parameter ρ such that it can approach the optimal distribution $\psi(x)$. This is solved through minimizing the Kullback-Leibler distance, which is equivalent to [20]

$$\max_{\rho} \int \psi(x) \ln P(x, \rho) dx. \tag{28}$$

  Solving the problem Eqn. (28), the parameter ρ can be estimated by [20]

$$\rho^* = \max_{\text{arg}} \frac{1}{K}\sum_{k=1}^{K} I(f(x) \leq \epsilon)\frac{P(X_k, w)}{P(X_k, u)} \ln P(X_k, \rho). \tag{29}$$

In summary, there are two important steps in cross entropy method. (1) Based on the PDF $P(X_k, \rho)$, the cross entropy method generates a set of Monte Carlo samples. (2) Based on the generated Monte Carlo samples, the cross entropy method updates the parameter ρ according to Eqn. (29). These steps are repeated until convergence. Refer to Fig. 6.

4.2 Cross Entropy Based Pricing Scheme Optimization Algorithm

Our proposed pricing scheme aims to compute the optimal discount factors using the cross entropy method to minimize the community-wide electricity bill. The complete algorithmic flow of our proposed technique is shown in Fig. 7. In the technique, we use Monte Carlo samples to estimate the optimal discount factors. A set of Monte Carlo samples are first generated based on a predefined PDF. Subsequently, those samples are evaluated by computing the total electricity bills, according to which the PDF is updated to generate new Monte Carlo samples. These steps are repeated until convergence. A pricing scheme is denoted by the global discount factor matrix $\mathbf{P}$ as follows.

$$\mathbf{P} = \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & \cdots & p_{1,H} \\ p_{2,1} & p_{2,2} & p_{2,3} & \cdots & p_{2,H} \\ p_{3,1} & p_{3,2} & p_{3,3} & \cdots & p_{3,H} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{N,1} & p_{N,2} & p_{N,3} & \cdots & p_{N,H} \end{bmatrix}, \tag{30}$$

where $p_{n,h}$ is the discount factor earned by customer n at time slot h. Thus,

$$\sum_{i=1}^{N} p_{i,h} = 1. \tag{31}$$

Following the general philosophy of cross entropy method [17], we iteratively generate the Monte Carlo samples of discount factors based on the predefined probability density function. In return, the samples are evaluated through solving the smart home scheduling problem and computing the corresponding community-wide electricity bill, based on which the PDF is updated. The sample set of discount factors is denoted by $\{\mathbf{P}^1, \mathbf{P}^2, \ldots, \mathbf{P}^S\}$, where S is the size of the sample set. Each generated sample $\mathbf{P}^s$ yields the Gaussian

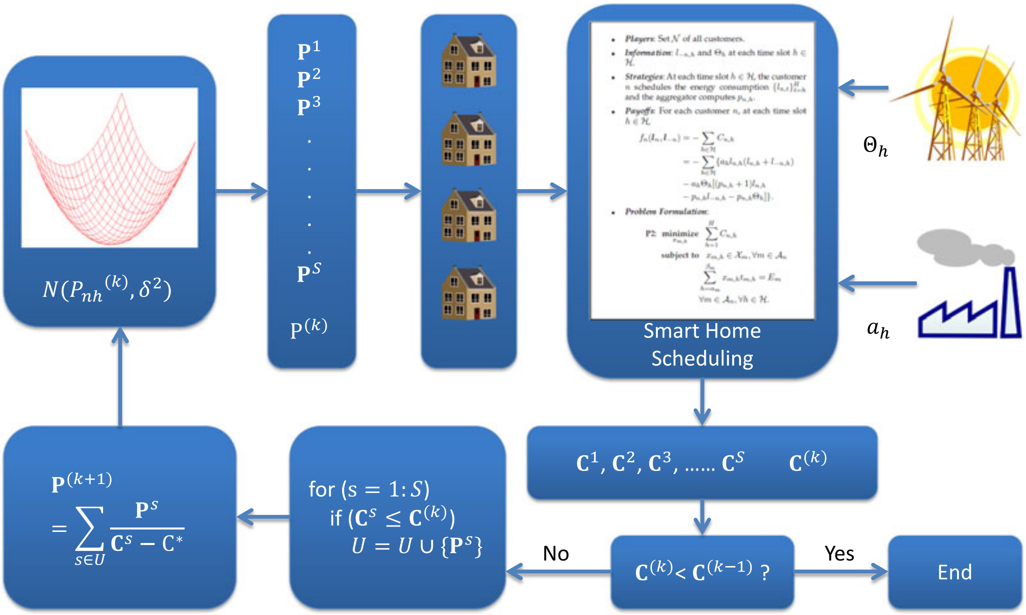

Fig. 7. In the technique, we use Monte Carlo samples to estimate the optimal discount factors. A set of Monte Carlo samples are first generated based on a predefined PDF. Subsequently, those samples are evaluated by computing the total electricity bills, according to which the PDF is updated to generate new Monte Carlo samples. These steps are repeated until convergence.

distribution with mean value $\mathbf{P}$ and variance σ^2. All the generated samples are evaluated based on their ability to reduce the community-wide electricity bill. Two values are computed for each sample $\mathbf{P}^s$ to facilitate the evaluation, which are the corresponding community-wide electricity bill $\mathbf{C}^s$ and the theoretical minimum community-wide electricity bill $\mathbf{C}^*$. $\mathbf{C}^s$ is computed by solving the decentralized smart home scheduling Problem **P2** and $\mathbf{C}^*$ is computed by solving the centralized smart home scheduling Problem **P1**. If $\mathbf{C}^s$ is closer to $\mathbf{C}^*$ than that of other samples, $\mathbf{P}^s$ is more important in updating the PDF. The principles of the proposed pricing scheme optimization algorithm are as follows.

Principles of Proposed Pricing Scheme Optimization Algorithm. The proposed pricing scheme optimization algorithm is an iterative algorithm with three steps in each iteration, which are *Sample Generation*, *Sample Evaluation* and *Pricing Scheme Updating*, respectively. In each iteration k, the sample set $\{\mathbf{P}^1, \mathbf{P}^2, \ldots, \mathbf{P}^S\}$ is generated based on the Gaussian distribution $N(\mathbf{P}^{(k)}, \sigma^2)$, where $\mathbf{P}^{(k)}$ is a $N \times H$ matrix, which is also the pricing scheme in iteration k. Subsequently, the samples are evaluated based on their abilities to reduce the community-wide electricity bill. Based on the evaluation, the mean value of percentage matrix is updated as $\mathbf{P}^{(k+1)}$, which is the mean value of the PDF in iteration $k+1$. If the community-wide electricity bill computed using $\mathbf{P}^{(k+1)}$ cannot be further reduced compared to that computed using $\mathbf{P}^{(k)}$, $\mathbf{P}^{(k)}$ is returned as the optimal discount factor matrix. The concrete procedure is described as follows.

- *Sample Generation:* The set of random samples $\{\mathbf{P}^1, \mathbf{P}^2, \ldots, \mathbf{P}^S\}$ are generated based on $N(\mathbf{P}^{(k)}, \sigma^2)$, where each entry of $\mathbf{P}^s$ satisfies $\mathbf{P}^s_{nh} \sim N(\mathbf{P}^{(k)}_{nh}, \sigma^2)$. However, when all the entries in the sample matrices are generated following this rule, the constraint (31) cannot be guaranteed. Therefore, the samples are normalized to satisfy (31) as follows:

$$\mathbf{P}^s_{nh} = \frac{\mathbf{P}^s_{nh}}{\sum_{i=1}^{N} \mathbf{P}^s_{ih}}. \tag{32}$$

- *Sample Evaluation:* Each sample $\mathbf{P}^s$ is evaluated based on the corresponding community-wide electricity bill $\mathbf{C}^s$, which can be computed by solving Problem **P2** using Algorithm 1. In each iteration k, we also compute the community-wide electricity bill corresponding to the current pricing scheme $\mathbf{P}^{(k)}$, denoted by $\mathbf{C}^{(k)}$. The sample $\mathbf{P}^s$ is used to update the pricing scheme and compute $\mathbf{P}^{(k+1)}$ only if $\mathbf{C}^s \le \mathbf{C}^{(k)}$. In that case, $\mathbf{P}^s$ is included in the set $\mathcal{U}$. Since we aim at reducing the community-wide electricity bill, the sample leading to an electricity bill $\mathbf{C}^s$, which is closer to the theoretical minimum community-wide electricity bill $\mathbf{C}^*$ should be encouraged. Thus, the evaluation of a sample $\mathbf{P}^s$ is defined as

$$\frac{1}{\mathbf{C}^s - \mathbf{C}^*}. \tag{33}$$

The philosophy is that a sample with an electricity bill closer to the theoretical lower bound should have a higher evaluation value.

- *Pricing Scheme Updating:* The renewable energy pricing scheme is updated after the samples are evaluated. Note that a sample results in a community-wide electricity bill closer to the theoretical lower bound should contribute more to the new pricing scheme. For this reason, the new discount factor matrix is a weighted sum of the samples, where a sample with a community-wide electricity bill closer to the theoretical lower bound has a higher weight. Thus, the weight of each sample $\mathbf{P}^s$ is the same with its evaluation $\frac{1}{\mathbf{C}_s - \mathbf{C}^*}$. The new discount factor matrix is updated as follows:

$$\mathbf{P}^{(k+1)} = \sum_{s \in \mathcal{U}} \frac{\mathbf{P}^s}{\mathbf{C}^s - \mathbf{C}^*}. \tag{34}$$

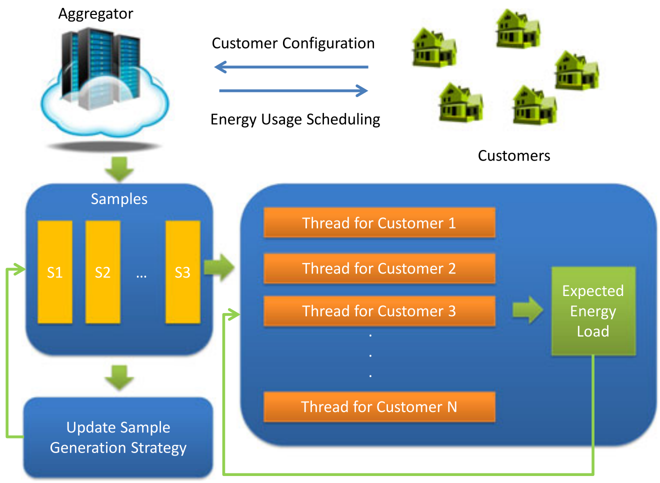

Fig. 8. The architecture of the smart community. The customers upload the configuration of the home appliances (e.g., required energy consumption, starting time and deadline) to the cloud server. Subsequently, the cloud server computes the energy usage scheduling for each customer.

The pseudocode of the algorithm is given in Algorithm 2. In practice, the percentage matrix is initialized such that $\mathbf{P}_{ih}^{(0)} = \frac{1}{N}$. In each iteration, the pricing scheme is updated only if the corresponding community-wide electricity bill is lower than that of the previous one.

Algorithm 2. Cross Entropy Optimization Based Renewable Energy Pricing Algorithm

$k = 0$, $p_{nh}^{(k)} = 1/N, \forall n \in \mathcal{N}, h \in \mathcal{H}$.
loop
  $\mathcal{U} = \emptyset$
  Generate the sample set of discount factor matrices $\{\mathbf{P}^1, \mathbf{P}^2, \ldots, \mathbf{P}^S\}$
  for $s = 1 : S$ **do**
    Call Algorithm 1 to solve Problem **P2** among all the customers
    if $\mathbf{C}_s \leq \mathbf{C}^{(k)}$ **then**
      Record the evaluate $\mathcal{U} = \mathcal{U} \bigcup \{\mathbf{P}_s\}$
    end if
  end for
  Update $\mathbf{P}^{(k+1)}$ according to Equation (34)
  $k = k + 1$
  if $\mathbf{C}^{(k)} \leq \mathbf{C}^{(k-1)}$ **then**
    Break and end algorithm
  else
    Continue
  end if
end loop
Return $\mathbf{P}^{(k)}$

This work employs the virtual distributed implementation, which has been discussed in our previous work [14]. Note that in the game theoretic smart home scheduling framework, each customer computes the individual energy scheduling while taking the expected energy usage of others as reference. This can induce a large amount of communication overhead. In this work, the customers employ the cloud server to compute the energy usage scheduling as shown in Fig. 8. Thus, no physical communications is needed between the customers. Each customer transmits the configurations of home appliances to the cloud server while receiving the energy usage scheduling. This saves the communication overhead significantly.

TABLE 1
Daily Energy Consumption and Run Time of Home Appliances Which Can be Automatically Scheduled [25]

Home Appliance	Daily Consumption	Execution Duration
Washing Machine	1.2 kWh-2 kWh	0.5 h-1.5 h
Dish Washer	1.2 kWh-2 kWh	0.5 h-1 h
Cloth Dryer	1.5 kWh-3 kWh	0.5 h-1.5 h
PHEV	9 kWh-12 kWh	4 h-8 h
Air Conditioner	2 kWh-3 kWh	1 h-3 h
Heater	2 kWh-3 kWh	1 h-3 h

5 Simulation Results and Analysis

Simulations are conducted to demonstrate the performance of the proposed algorithm. The simulation is conducted on a 64-bit machine with Intel(R) Core(TM)2 Quad CPU Q9550 2.83 GHz and 8 GB ram using C++. In the generated benchmark, we consider a community consisting of 500 customers, where each customer is equipped with both automatically and manually controlled home appliances. The energy load created by manually controlled home appliances is treated as the background energy load. The background energy usage of each customer is designed according to the previous works [21], [22], [23]. The daily energy consumption and run time of automatically controlled home appliances are shown in Table 1 according to previous works [14], [15], [21], [22], [24], [25]. Note that an automatically controlled home appliance can also be manually controlled by the customer, in which scenario its energy consumption is treated as a part of the background energy load. The pricing parameter a_h is set to be flat over the time horizon. The real wind energy generation of Belgian wind farm is scaled to model the renewable energy generation [26], which is available as a public community level renewable resource. The impact of renewable energy generation forecast accuracy is also considered in this work such that the simulations has been conducted using both

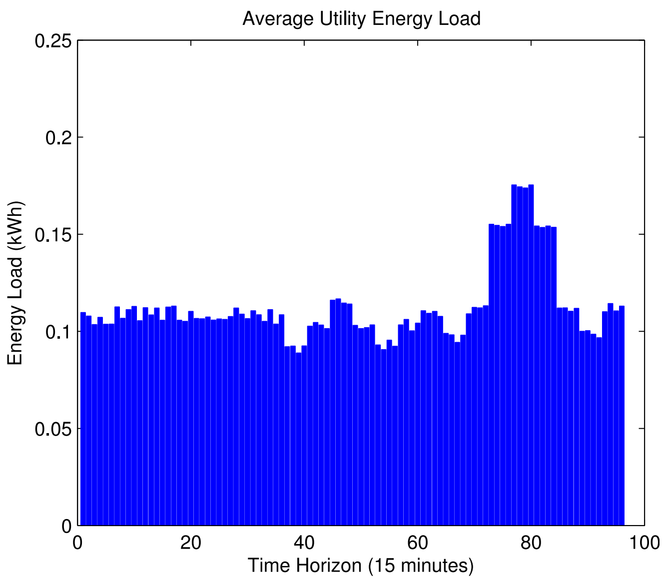

Fig. 9. Average energy load of each customer with smart home scheduling but without renewable energy, the average electricity bill of each customer is $4.020.

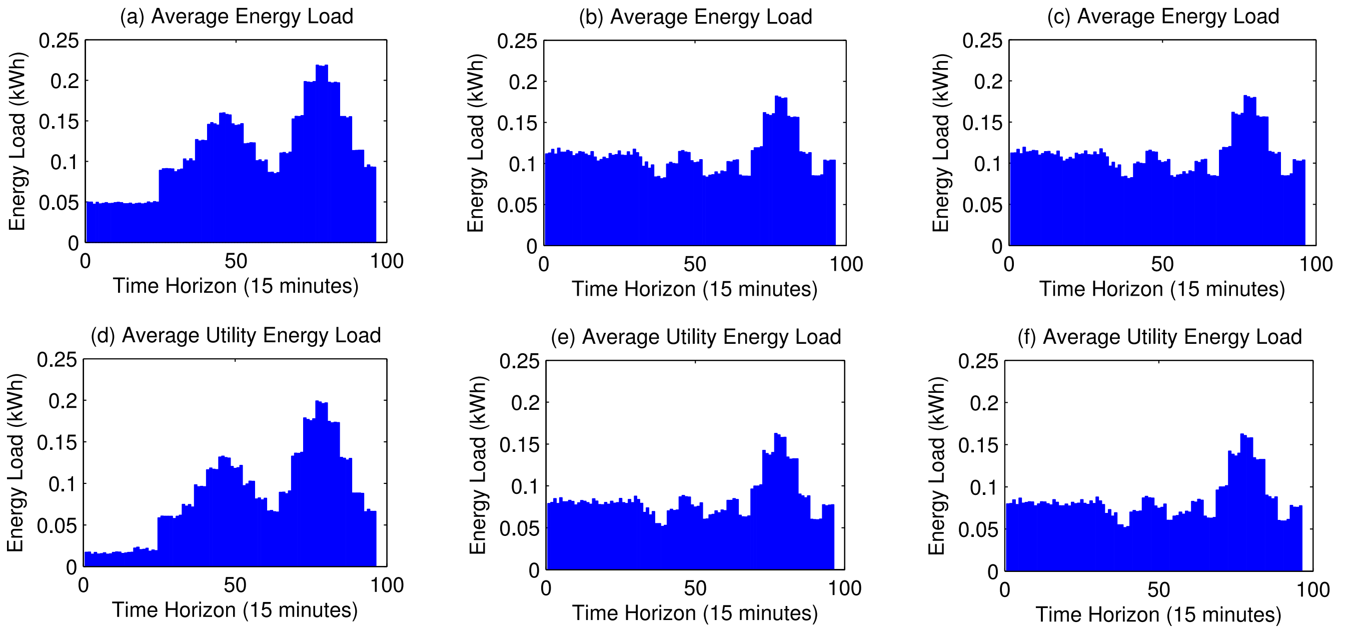

Fig. 10. (a) The average energy load of each customer without smart home scheduling and renewable energy, the average electricity bill of each customer is \$4.683. (b) Average energy load of each customer computed by solving the Problem **P1** using perfect forecast of renewable energy. (c) Average energy load of each customer computed through proposed pricing algorithm using perfect forecast of renewable energy. (d) The average conventional energy consumption of each customer without smart home scheduling but with renewable energy, the average electricity bill of each customer is \$3.591. (e) Average utility energy load of each customer computed by solving the Problem **P1** using perfect forecast of renewable energy. The average electricity bill of each customer is \$2.414. (f) Average utility energy load of each customer computed through proposed pricing algorithm using perfect forecast of renewable energy. The average electricity bill of each customer is \$2.415.

perfect forecast and real day-ahead forecast. The scheduling time horizon is the next 24 hours from present, which is divided into 96 time slots of 15 minutes each.

Our proposed scheduling technique is compared with different sets of other scheduling techniques. Shown in Fig. 10a is the average energy load profile of each customer without either smart home scheduling or renewable energy penetration. The average electricity bill of each customer is \$4.683. The average energy load of each customer with renewable energy and without smart home scheduling is shown in Fig. 10d. The average electricity bill of each customer is \$3.591. Compared to

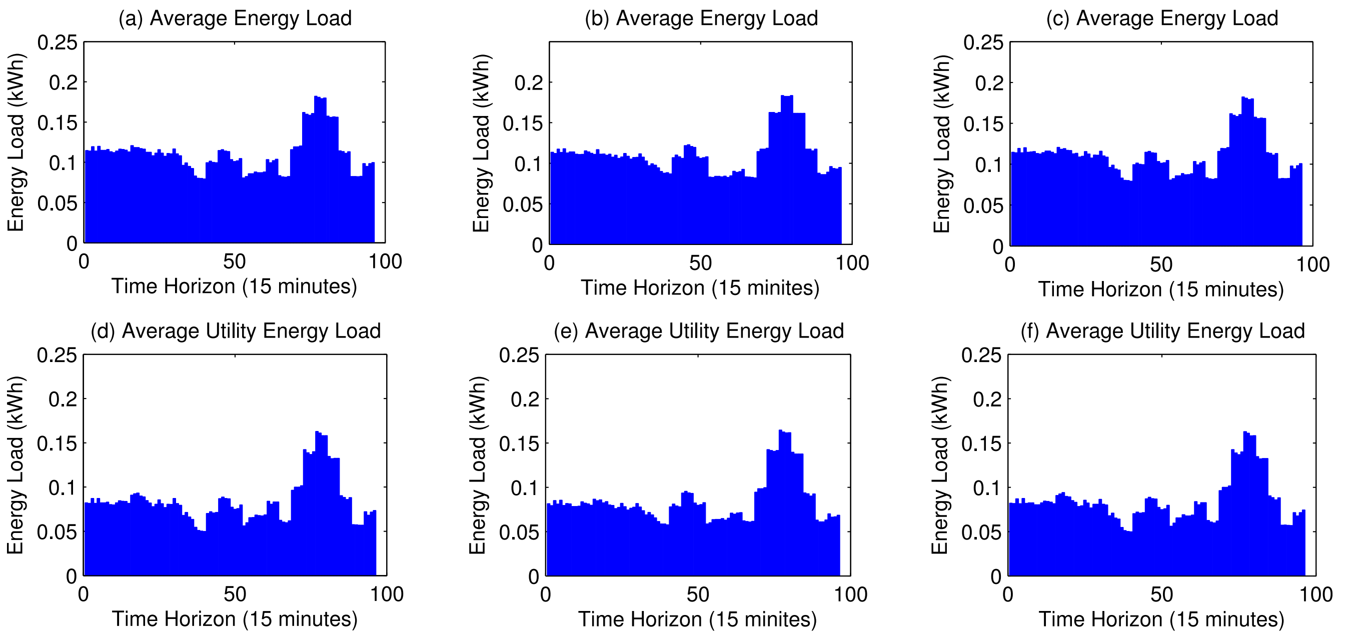

Fig. 11. (a) Average energy load of each customer computed by solving the Problem **P1** using real forecast of renewable energy. (b) Average energy load of each customer computed by uniformed distribution of renewable energy. (c) Average energy load of each customer computed by proposed pricing algorithm using real day-ahead forecast of renewable energy. (d) Average utility energy load of each customer computed by solving the Problem **P1** using real day-ahead forecast of renewable energy. The average electricity bill of each customer is \$2.424. (e) Average utility energy load of each customer computed by uniformed distribution of renewable energy. The average electricity bill of each customer is \$2.603. (f) Average utility energy load of each customer computed by proposed pricing algorithm using real day-ahead forecast of renewable energy. The average electricity bill of each customer is \$2.424.

TABLE 2
Simulation Setups and Corresponding Community-Wide Electricity Bill

	With Smart Home Scheduling	Without Smart Home Scheduling
With Renewable Renewable Energy	\$2.424 (Real Forecast) \$2.415 (Perfect Forecast) \$2.414 (Lower Bound)	\$3.591
Without Renewable Energy	\$4.020	\$4.683

Fig. 10a where neither smart home scheduling nor renewable energy is deployed, the average electricity bill is reduced by $\frac{4.683-3.591}{4.683} = 23.31\%$ due to the penetration of renewable energy.

Shown in Fig. 9 is the average energy load profile with smart home and without renewable energy. The energy load is balanced over the time horizon by smart home scheduling technique. The average electricity bill of each customer is \$4.020. Compared to Fig. 10a without either smart home scheduling or renewable energy, the bill is reduced by $\frac{4.683-4.020}{4.683} = 14.11\%$ due to smart home scheduling.

The average energy load of each customer computed using the proposed pricing algorithm with perfect forecast of renewable energy is shown in Figs. 10c and 10f. Shown in Fig. 10c is the total energy load and shown in Fig. 10f is the energy load of the conventional utility energy. The average electricity bill of each customer is \$2.415. Compared to Fig. 10a with renewable energy and without smart home scheduling, the bill is reduced by $\frac{3.591-2.415}{3.591} = 32.73\%$ due to smart home scheduling. Compared to Fig. 9, where only smart home scheduling is deployed, the electricity bill is reduced by $\frac{4.020-2.415}{4.020} = 40.03\%$ due to using renewable energy. Furthermore, for a community with 500 customers, it takes 2,187 s to compute the solution.

The theoretical minimum community-wide electricity bill is computed through solving Problem **P1**. The corresponding energy load of each customer on average is shown in Figs. 10b and 10e. The average electricity bill of each customer is \$2.414. It is demonstrated that the community wide electricity bill computed through proposed pricing algorithm is only $\frac{2.415-2.414}{2.414} = 0.06\%$ above the theoretical lower bound.

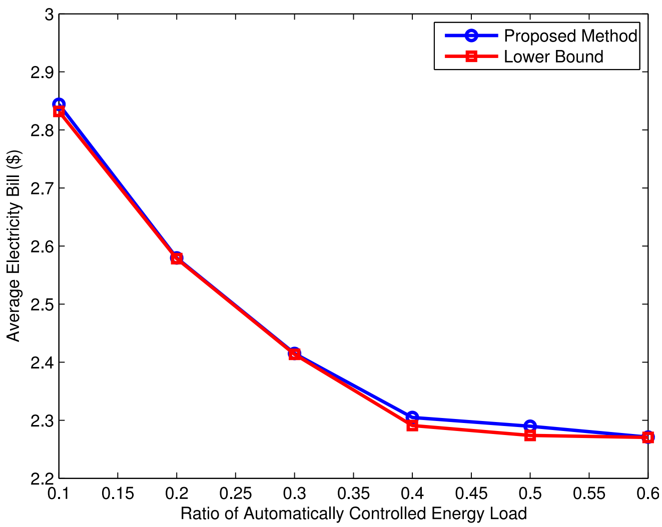

Fig. 12. Average electricity bill of each customer for different ratio of automatically scheduled energy load.

TABLE 3
Average Electricity Bills for Different Setups of Allowed Execution Lengthes of Home Appliances

Reduction of Power Level	25%	50%
Average Electricity Bill (Theoretic Lower Bound)	\$2.393	\$2.402
Average Electricity Bill (Proposed Method)	\$2.404	\$2.412

With real day-ahead forecast of renewable energy provided by [26], the average energy load of each customer computed using proposed pricing algorithm and that computed by solving Problem **P1** are shown in Figs. 11c, 11f, 11a, and 11d, respectively. For both of them, the average electricity bill for conventional utility energy is \$2.424, which is only $\frac{2.424-2.414}{2.414} = 0.37\%$ higher than the that computed using the perfect renewable energy forecast. For all these simulations presented above, the corresponding average electricity bills of each customer are summarized in Table 2.

In order to demonstrate the advantage of our technique, three sets of experiments are conducted for comparison. In the first set of experiment, uniformed distribution of renewable energy is deployed such that $p_{n,h} = \frac{1}{N}$. It means that each customer receives equal discount due to using renewable energy. Using this method, the are shown in Figs. 11b and 11e, respectively. The average electricity bill of each customer is \$2.603. Compared to this method, the proposed technique can further reduce the electricity bill by $\frac{\$2.603-\$2.415}{\$2.603} = 7.22\%$.

In the second set of experiment, we increase the ratio of schedulable energy load from 10 to 60 percent by making more home appliances automatically controlled. The average electricity bills of each customer are shown in Fig. 12. As shown in that figure, the average electricity bill decreases while the ratio of schedulable energy load increases. However, when the ratio of schedulable energy load is sufficiently large, the reduction of electricity bill is smaller since the schedulable energy load can already approach the ideal energy load distribution. The theoretic lower band is also shown in that figure, which is close to the result computed by the proposed method for each setup.

In the third set of experiment, we have compared different setups of execution periods of home appliances. We increase the allowed execution length of the home appliances by decreasing the power levels by 25 and 50 percent, respectively. The results are shown in Table 3.

6 Conclusion

This paper addresses competitions among the customers on renewable energy usage in a distributed smart community. We have proven that under certain assumptions the optimal solutions of decentralized and centralized smart home scheduling problems are equivalent. An advanced cross entropy optimization technique is then proposed to compute such a pricing scheme which is also integrated with smart home scheduling. As is demonstrated by the simulation results, the electricity bill is reduced by 32.73 percent using the proposed pricing scheme optimization algorithm compared to the state-of-the-art technique. More importantly, the achieved electricity bill is only 0.06 percent above the theoretical lower bound.

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Shiyan Hu is the corresponding author.

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