Privacy-Preserving Energy Scheduling in Microgrid Systems

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***Abstract*—We propose privacy-preserving energy management strategies for a microgrid system that consists of several cells and a central control center, with each cell composed of a local controller, a distributed renewable energy generator, and some energy consuming customers. It is assumed that the cells can cooperate by exchanging their locally generated energy and they can obtain external energy, both through the control center. The goal of energy management is to distribute the energy flow within the microgrid system to meet the energy demands of the customers and to minimize the cost of the external energy imported to the system. The problem is formulated as a linear optimization problem with privacy constraints. However, the privacy constraint, i.e., the constraint that the information related to the customers' behaviors in a cell cannot be disclosed to other cells and/or the control center, makes the standard linear programming tools not directly applicable. This motivates us to develop privacy-preserving schemes for effective energy management in such systems. To this end, we develop a dual decomposition-based algorithm and a fast suboptimal algorithm to solve the energy management problem with privacy constraints in a distributed fashion. Simulation results are provided to demonstrate the superior performance of the proposed techniques over the traditional methods.**

***Index Terms*—Distributed algorithms, dual decomposition, energy scheduling, information privacy, microgrid system, smart grid.**

I. Introduction

ONE OF THE notable characteristics of modern smart grid systems is the employment of environment-friendly distributed energy generators [1]. The so-called microgrid systems that employ such generators can be deployed to provide quality and economic energy supplies, while reducing the carbon footprints. The reliable and efficient operation of a microgrid system relies highly on the effective and efficient energy management, which may be facilitated by balancing the electricity supply and demand [2], [3]. The challenges associated with such systems are discussed in [1], [4], [5], including energy management.

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One typical domestic grid system that employs the distributed generators is the smart house (self-fed customers), which consists of the renewable energy source, traditional energy source, and controllable loads [6], [7]. This is a basic local energy management structure to reduce the carbon emission and utility bills. Extending such "smart house" model, based on the microgrid structure, the energy management issues for a general microgrid system are discussed in [8], [9]. To further enhance the benefits of smart grid systems, in addition to local energy management, the cooperation between different domestic grid systems, such as the smart houses, should be considered in the microgrid system. A general structure of smart grid systems that features the cooperation between different distributed generators as well as advanced smart meters is discussed in [10]. Supply management and demand management are treated in [11] and [12] respectively. Moreover, for a specific distributed generator, an energy management scheme that minimizes the total system cost is proposed in [13]

The issue of privacy is another important consideration for smart grid systems, especially when there are cooperations among subsystems. In particular, it is argued in [14] that the customers' energy demand patterns may expose their habits and behaviors. To prevent those who would exploit such information from mining behavioral data, the customers' personally identifiable information should be kept confidential from the electricity suppliers except for what is absolutely needed for billing [15]. Hence devising effective cooperation schemes among customers within a microgrid while meeting the privacy constraints is yet another challenge for smart grid systems. To resolve the privacy issue, the energy management strategy may need to be obtained and performed in a distributed fashion. In [16], [17], the distributed optimization method is applied to solve the energy management problem for energy hubs in a decentralized way, but without considering privacy constraints.

Based on the typical domestic smart grid model in [6], [7], in this paper, we consider customer cooperation mechanisms in a system that consists of a group of self-fed customers (also called cells) and a control center, under the general smart grid system structure described in [9], [10], taking into consideration the privacy constraints. Comparing to the existing major works, e.g., [11], [13], and [16], our objective is to integrate the supply- and demand-side management to globally optimize the grid operations, with the restricted information exchanges imposed by the privacy constraints. Specifically, we consider a microgrid system that is composed of renewable energy sources, e.g., solar panels and wind turbines, local controller, and consumers. To cope with the limitation of unstable availability and capacity of the renewable energy resources, a complementary traditional energy source, e.g., utility grid, is also employed together with the buffer batteries. Such a microgrid system can offer not only reliable electricity supply but also efficient utilization of the renewable energy, leading to reduced carbon emissions as well as utility bills. An optimized energy management schedule consisting of the *transmission schedule* and *demand schedule* enforces the grid operational reliability and environment protection.

An important goal of the energy scheduling policy in the microgrid system is to balance the energy supply and demand at every time instant. The optimal energy management requires striking a balance between the inter-cell cooperation and unnecessary energy loss (non-ideal battery loss and potential battery overflow for energy deposition). Maintaining such a balance becomes more complicated due to the fact that the privacy constraints, which are related to the consumers' behaviors, are involved in the demand-side energy management. Therefore, designing an optimal energy scheduling policy that takes into account the privacy constraints poses significant challenges for the power grid operator.

We consider a scheduling strategy for a microgrid system to minimize the cost of the non-green energy consumption. Such a scheduling problem is formulated as a privacy constrained linear programming problem. We then propose two energy scheduling methods that take into account the privacy constraints and can be implemented in a distributed fashion.

The remainder of the paper is organized as follows. In Section II, we describe the practical smart grid model under the privacy consideration. In Section III, we provide the mathematical model of the microgrid system and formulate the energy scheduling problem as a linear programming problem with privacy constraints. In Section IV, we provide an iterative distributed algorithm to optimally solve the energy scheduling problem with privacy constraints. In Section V, a fast but suboptimal energy scheduling method is proposed. Simulation results are provided in Section VI. Finally, Section VII concludes the paper.

II. The Microgrid System

We consider a microgrid system consisting of a central control center, local controllers, distributed generators, and consumers, connected to the utility grid, as shown in Fig. 1.

In this model, the control center is unique in the microgrid and directly connected to local controllers and the utility grid. It serves as a central controller that manages the energy imports from the utility grid and the communication with each local controller. In particular, the control center is equipped with computing power for implementing its part of the energy scheduling algorithm.

A local controller is connected to a group of consumers and a distributed generator (DG), forming a *cell*. In each cell, the local controller acts as the domestic control center, by not only managing the energy distributions to the battery for storage, to the consumers for in-cell consumption, or/and to the microgrid for out-cell consumption, but also controlling the users' loads. Similar to the microgrid control center, the local controllers are also equipped with computing power and implement their shares of

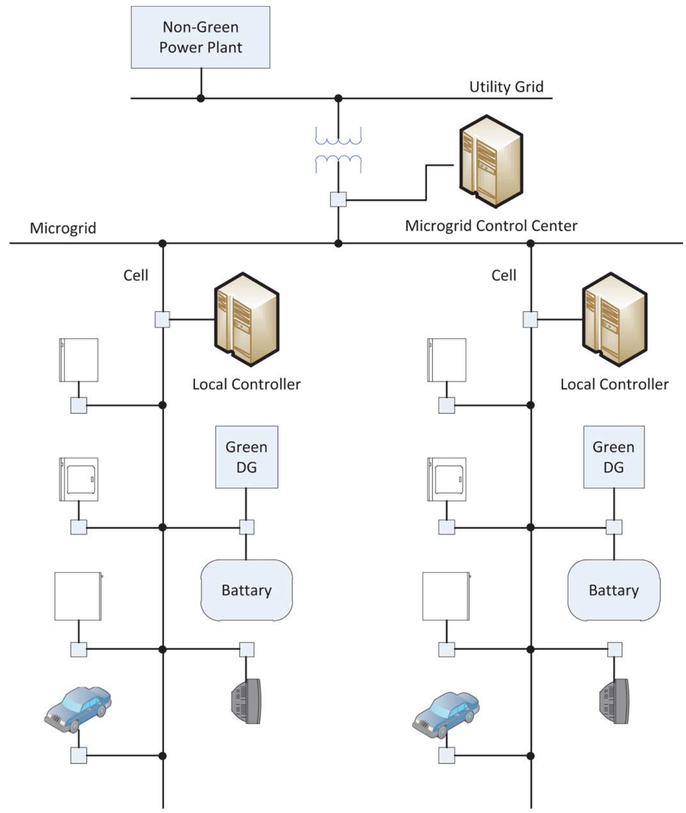

Fig. 1. Structure of the microgrid system.

the energy scheduling algorithm. Note that except for the microgrid control center, each component in the microgrid system belongs to a particular cell.

There are a number of consumers and one distributed generator in each cell. The consumers may be the household facilities, e.g., washing machine, dryer, refrigerator, air conditioner, electric car, etc., and can be controlled or partially controlled by the local controller, e.g., switched on/off or turned up/down. The distributed generator in each cell is assumed to be a renewable energy source, e.g., solar panel, wind turbine, and is equipped with a buffer battery to mitigate the fluctuation of the energy supply. The consumers in each cell are powered by the buffer battery rather than generator directly and the generated energy can only be deposited to the corresponding buffer battery.

The energy scheduling for the microgrid involves two aspects, cooperative energy supply and elastic demand dispatch. For cooperative energy supply, each local controller either imports the energy from the outside of its cell or exports the surplus energy to other cells, while fulfilling the consumers' demands. Moreover, to resolve the possible shortage in energy generation by the renewable source, the microgrid control center can import energy from the utility grid system, where we consider such imported energy non-green. We assume that the green energy generated within the microgrid is free while the customers need to pay for the imported non-green energy with the known *Time of Use* (TOU) price. On the other hand, we assume that portions of the consumer energy demands are elastic, that is, they are allowed to be met within a certain time window. For elastic demand dispatch, the local controller manages energy assignment

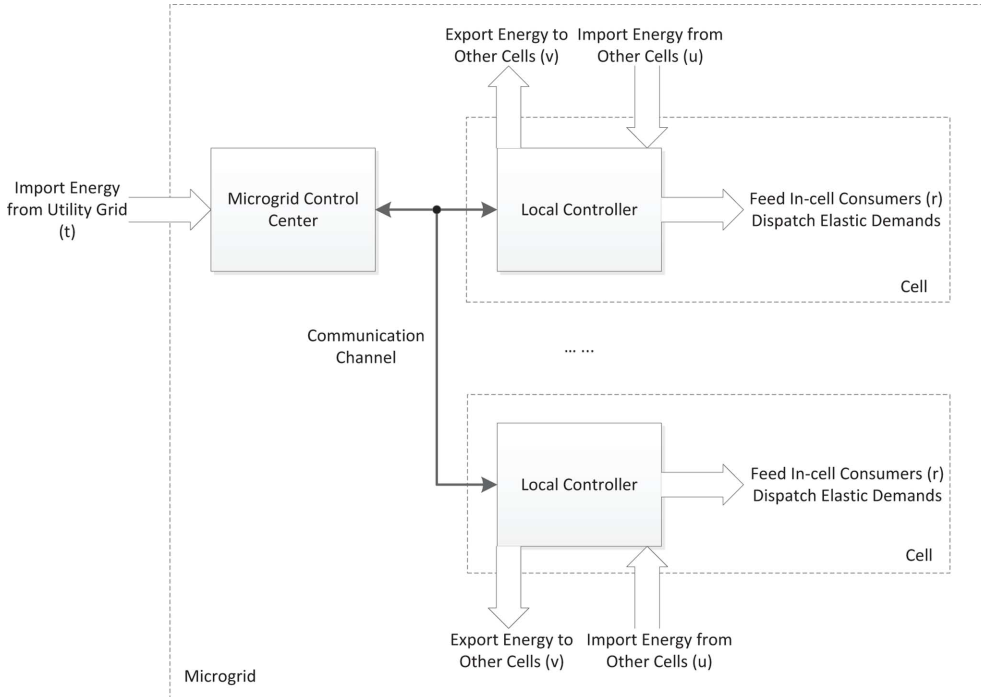

Fig. 2. Block diagram of energy management.

in such window and controls the consumers to operate in the assigned time window according to the energy schedule.

The energy management is implemented distributively by the microgrid control center and the local controllers, necessitating information exchange. Such information exchange can be facilitated by the communication links between the microgrid control center and local controllers. However, such information exchange may involve certain private information of the customers that should be kept confidential. Hence it is important to consider the design of distributed energy scheduling algorithms with privacy constraints.

III. System Model and Problem Formulation

A. Energy Management

Based on the above system structure, the overall system energy management is composed of supply-side and demand-side energy management, as shown in Fig. 2. The supply-side energy management involves importing/exporting energy from/to other cells and feeding the in-cell consumers, which is performed by the local controller, and importing energy from the utility grid, which is performed by the microgrid control center. The demand-side energy management dispatches the elastic demands which performed by the local controllers. Assume that the energy management occurs in a time-slotted fashion. The beginning of a time slot is reserved for information collection, exchange, and schedule calculation. Then the schedule is applied for energy management. Throughout the paper, the set of cells is denoted as $\mathcal{N} \triangleq \{1, 2, \ldots, N\}$, and the set of time slots is $\mathcal{K} \triangleq \{1, 2, \ldots, K\}$. In addition, the utility grid is viewed as a special cell seen from the microgrid system and labeled as cell 0.

The supply-side energy management regulates the energy flows in the microgrid, including collecting energy from each cell and the utility grid, and distributing energy to each cell. The distribution of energy among in-cell consumers is regulated by the supply-side energy management as well. Specifically, we may use the controllable devices at the controllers to dictate such energy import/export. We denote u_n^k and v_n^k as the total incoming and outgoing green energy to/from cell n in the k-th time slot, respectively. Moreover, t_n^k denotes the conventional energy imported to cell n and r_n^k denotes the reserved energy for in-cell consumers. Also, since the major energy source is the in-cell distributed generator and the geographic scale of the microgrid is relatively small, we assume that the transmission loss is negligible. Since the incoming energy and the outgoing energy are balanced in the control center, we have

$$\sum_{n=1}^{N} v_n^k = \sum_{n=1}^{N} u_n^k,\ k \in \mathcal{K}. \tag{1}$$

Then, the consumers' demand in cell n in the k-th time slot, denoted by d_n^k, is given by

$$d_n^k = r_n^k + t_n^k + u_n^k,\ n \in \mathcal{N},\ k \in \mathcal{K}. \tag{2}$$

We assume that the generated energy in each cell $n \in \mathcal{N}$ is predictable for the subsequent K time slots and denote the predicted value as E_n^k; we also assume that the battery may not be ideal and denote $\gamma_n \in [0, 1]$ as the charge/discharge loss factor, i.e., the ratio of the energy deposing to the battery and that discharging from the battery. Assuming that the energy generating is a steady process in each time slot, we then have the following relationship between the battery levels at the beginning of two consecutive time slots:

$$B_n^{k+1} = \min\left\{B_n^k + \gamma_n x_n^k - y_n^k, B_n^{\max}\right\}, \tag{3}$$

where $B_n^{\max}$ is the capacity of the battery, x_n^k is the energy deposited to the battery, and y_n^k is the energy discharge from the battery. Also, B_n^k is nonnegative, i.e.,

$$B_n^k \geq 0, \ n \in \mathcal{N}, \ k \in \mathcal{K}. \tag{4}$$

In order to ensure the energy is balanced in each cell, we also have

$$r_n^k + v_n^k = E_n^k - x_n^k + y_n^k, \ n \in \mathcal{N}, \ k \in \mathcal{K}, \tag{5}$$

where $x_n^k \geq 0$ and $y_n^k \geq 0$.

The demand-side energy management partially controls the energy consumptions of the consumers in the same cell, e.g., switches on or off the consumers. In view of the controllability of the demands, we classify the consumers' demand into the following two categories: *schedulable demand*, which is mentioned as elastic demand in the previous section, denoted by $\hat{c}_n^k$; and *un-schedulable demand*, which is not allowed to be scheduled by the local controller, denoted by c_n^k. Therefore, the total demands can be written as

$$d_n^k \triangleq c_n^k + \hat{c}_n^k, \ n \in \mathcal{N}, \ k \in \mathcal{K}. \tag{6}$$

The schedulable demands are constrained by certain conditions, namely *schedulable demand constraints*. For example, one typical mapping from the consumer's preference to the constraint is that a specific task is required to be completed within a designated time window, e.g., charging the electric vehicle between 12 P.M. and 5 A.M. Such constraint can be formulated as

$$\sum_{k=K_1}^{K_2} \hat{c}_n^k = C_n, \tag{7}$$

where $[K_1, K_2]$ defines the time window that is available for energy scheduling and C_n is the total required energy.

B. Privacy Control

Privacy is an important issue in smart grid systems. In this paper, following [14], [15], we treat the consumers' behaviors and preferences as the privacy information, which are reflected in terms of the consumers' energy demands d_n^k and $\hat{c}_n^k$, as well as the related constraints. Such privacy information can be further categorized by their sensitivities, i.e, information with different sensitivities may be concealed to different persons [18]. In particular, we assume that consumers' total energy demands d_n^k, which are needed for billing and energy delivery, can be revealed to the microgrid control center. On the other hand, the consumers' schedulable demands $\hat{c}_n^k$ and the related constraints, which contain more details of their behaviors and are only related to energy scheduling, should be kept confidential from both the control center and other cells. We summarize the different types of the privacy information in the microgrid system in Table I.

As seen in Table I, the Type-I privacy information is related to the consumer's schedulable demand $\hat{c}_n^k$, e.g., the constraint (7) which is mapped from the consumer's behavior. Such information is considered strictly private and cannot be shared outside the cell, including the control center.

TABLE I
PROPERTIES OF PRIVATE INFORMATION

Type	Information Related to	Cell n	Control Center	Cells Other Than n
I	$\hat{c}_n^k$	Non-private	Private	Private
II	$d_n^k, u_n^k, v_n^k, x_n^k$	Non-private	Non-private	Private

The Type-II privacy information includes all other information related to the energy schedule d_n^k, u_n^k and v_n^k. Such information can only be released to the control center for energy scheduling, delivery, and billing.

In addition, we assume that the information related to the working status of the distributed generator is non-private and accessible to every cell as well as the control center.

C. Problem Formulation

It is well known that man-made CO_2 emission causes negative environmental effects, e.g., global warming [3]. From the microgrid's perspective, importing less energy from the utility grid leads to lower CO_2 emission and economic cost, which is the main goal of the energy scheduling policy.

We denote $T_n^k \triangleq \left(t_n^k, r_n^k, u_n^k, v_n^k, x_n^k\right)$ and $\boldsymbol{T}_n$ and $\hat{\boldsymbol{c}}_n$ as vectors formed by stacking up T_n^k and $\hat{c}_n^k$, respectively. By defining

$$\mathcal{S} \triangleq \left\{S_n | S_n = \left(\boldsymbol{T}_n, \hat{\boldsymbol{c}}_n\right), n \in \mathcal{N}\right\} \tag{8}$$

as the energy schedule that directs the microgrid control center to import, collect, and distribute energy, our objective is to minimize the cost of the imported energy to the microgrid within K time slots, i.e.,

$$\mathcal{S}^* = \arg\min_{\mathcal{S} \geq 0} I(\mathcal{S}), \tag{9}$$

where

$$I(\mathcal{S}) = \sum_{k=1}^{K} \alpha(k) \sum_{n=1}^{N} t_n^k, \tag{10}$$

and $\alpha(k)$ is the time of use (TOU) price over different time slot k. A feasible schedule $\mathcal{S}$ must meet various constraints, i.e., the *battery capacity constraints* in (3) and (4) to ensure the physical realizability of the battery, the *demand fulfilment constraints* in (2) to ensure the ensure demand-supply balance, the *schedule window constraints* in (7) to ensure the consumers' satisfaction, and the *privacy constraints* in Table I to protect the consumers' privacy.

Note that in contrast to the other constraints listed above that can be written in terms of (in)equalities, the privacy constraints given in Table I cannot be expressed by equations but still need to be taken into consideration when calculating and implementing the energy schedule.

Remark 1: In the above formulation, we assumed that the distributed generators in the microgrid are renewable energy sources. On the other hand, even if some generators correspond to non-renewable sources, they can be easily incorporated to our model by considering the non-renewable sources as a new virtual utility grid that supplies the traditional energy for the microgrid system with possibly different utility costs. The proposed energy scheduling algorithms are also applicable to this case.

IV. Computing the Optimal Energy Schedule

A. Problem Reformulation

We first convert the problem in (9) into a linear programming problem with privacy constraints. By introducing the auxiliary variables $\hat{t}_n^k,\ n \in \mathcal{N},\ k \in \mathcal{K}$, which denote the virtual energy consumptions to prevent the battery from overflowing, (3) can be equivalently written as

$$\begin{cases} B_n^{k+1} = B_n^k + \gamma_n x_n^k - y_n^k - \hat{t}_n^k \\ B_n^{k+1} \le B_n^{\max} \end{cases}. \tag{11}$$

Substituting (5) and (11) into (4), we obtain the following inequalities:

$$\sum_{k=1}^{\kappa}((1-\gamma_n)x_n^k + r_n^k + v_n^k + \hat{t}_n^k) \ge B_n^0 + \sum_{k=1}^{\kappa} E_n^k - B_n^{\max}, \quad \kappa \in \mathcal{K}, \tag{12}$$

$$\sum_{k=1}^{\kappa}((1-\gamma_n)x_n^k + r_n^k + v_n^k + \hat{t}_n^k) \le B_n^0 + \sum_{k=1}^{\kappa} E_n^k,\ \kappa \in \mathcal{K}, \tag{13}$$

and

$$r_n^k + v_n^k + x_n^k - E_n^k \ge 0,\ k \in \mathcal{K}. \tag{14}$$

With the new set of constraints, we obtain the optimization problem in (15) at the bottom of the page.

The optimization problem (15) can be viewed as a standard LP problem with additional privacy constraints. However, due to the privacy constraints, it is not feasible to solve (15) directly. For example, if we solve this problem in the microgrid control center, the Type-I privacy constraints will hide the schedule window constraints in (7), i.e., the solver do not have these hidden constraints while they still need to be met. Similarly, if we solve this problem in any cell $n \in \mathcal{N}$, the Type-II privacy constraints will hide all constraints that are not related to cell n.

To resolve the problem of "hidden constraints," we convert the problem in (15) into a partial *Lagrange dual problem* by moving the constraints in (1) into the objective function using a set of *Lagrangian multipliers* [20]:

$$L(\mathcal{S}, \boldsymbol{\lambda}) = I(\mathcal{S}) + \sum_{k=1}^{K} \lambda_k \Big(\sum_{n=1}^{N} v_n^k - \sum_{n=1}^{N} u_n^k \Big), \tag{16}$$

where $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \ldots, \lambda_K] \in \mathbb{R}^K$ are the *dual variables*.

Instead of solving the original problem, we can solve the dual problem:

$$\max_{\boldsymbol{\lambda}} g(\boldsymbol{\lambda}), \tag{17}$$

where

$$g(\boldsymbol{\lambda}) = \inf_{\mathcal{S}\ge 0, \mathcal{A} \ge 0} L(\mathcal{S}, \boldsymbol{\lambda}), \tag{18}$$

with the battery capacity constraints in (12) and (13), demand fulfillment constraints in (2), schedule window constraints in (7), and privacy constraints in Table I.

Based on the partial dual decomposition technique, we can develop an iterative algorithm to solve the optimization problem in (15) in a distributed fashion [21], [24]: as shown in Fig. 3, at each iteration, the local controllers solve the dual problem in (18) to obtain the optimal S_n; and the microgrid control center solves the master problem in (17) to obtain the dual variables $\boldsymbol{\lambda}$.

B. Solving the Master Problem at Control Center

The Lagrangian dual problem in (17) can be decomposed into two levels of optimization. At the higher level, we have the master problem:

$$\mathcal{P} = \begin{cases} \max_{\boldsymbol{\lambda}} & L(\mathcal{S}, \boldsymbol{\lambda}) \\ \text{s.t.} & \text{Privacy constraints} \end{cases}, \tag{19}$$

where the energy schedule $\mathcal{S}$ is given.

This problem can be solved by employing the sub-gradient method [22]. Specifically, the dual variables can be recursively updated as follows [20]:

$$\lambda_k^{(q)} = \lambda_k^{(q-1)} - \beta(q-1) \cdot h_k(\mathcal{S}^{(q-1)}), \tag{20}$$

where q is the iteration number, $\beta(q)$ is the step size, and $h_k(\mathcal{S})$ corresponds to the constraint that is moved to the objective function, i.e.,

$$h_k(\mathcal{S}) = \sum_{n=1}^{N} v_n^k - \sum_{n=1}^{N} u_n^k. \tag{21}$$

$$\mathcal{P} = \begin{cases} \min_{\mathcal{S}\ge 0, \mathcal{A}\ge 0} & I(\mathcal{S}) \\ \text{s.t.} & \text{Battery capacity constraints in (12), (13), (14) } (n \in \mathcal{N}) \\ & \text{Demand fulfillment constraints in (2) } (n \in \mathcal{N}) \\ & \text{Energy flow equilibrium constraints in (1)} \\ & \text{Schedule window constraints in (7) } (n \in \mathcal{N}) \\ & \text{Privacy constraints in Table I} \end{cases}, \tag{15}$$

where $\mathcal{A} \triangleq \{\hat{\boldsymbol{t}}_n \mid n \in \mathcal{N}\}$ and $\hat{\boldsymbol{t}}_n$ is a vector formed by stacking up $\hat{t}_n^k,\ k \in \mathcal{K}$.

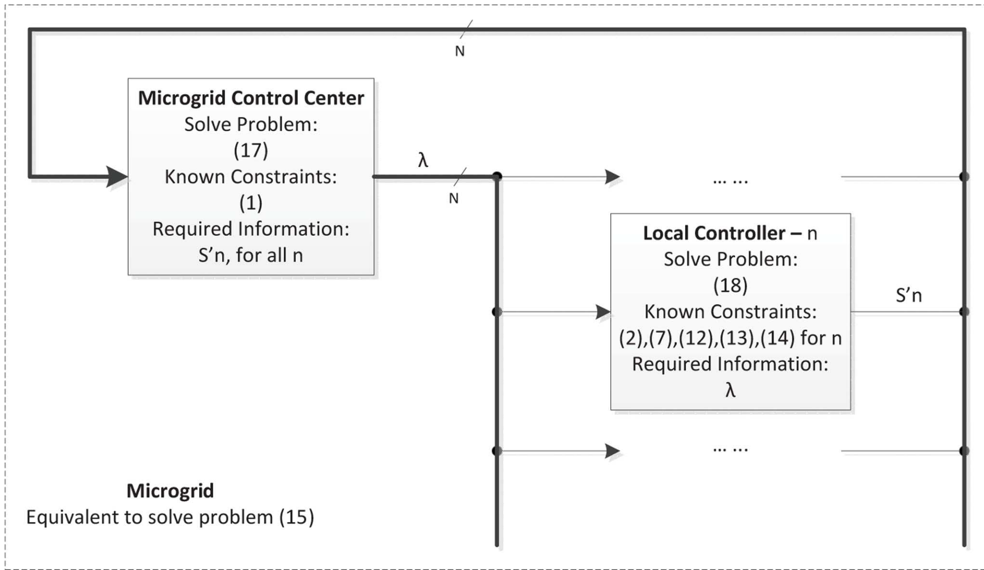

Fig. 3. The operations at the control center and the cells, and the information exchange in the dual decomposition method.

With a diminishing step size, e.g., $\beta(q) = 1/q$, we have $L(\mathcal{S}, \boldsymbol{\lambda}^{(q+1)}) \geq L(\mathcal{S}, \boldsymbol{\lambda}^{(q)})$, with equality if all constraints are met, and finally $g(\boldsymbol{\lambda}^{(q)})$ achieves its maximum [20], [21].

Observing the definition of the energy schedule in (8), the schedulable demand $\hat{\boldsymbol{c}}_n$, which is concealed to outside cell n, may need to be exchanged between the microgrid control center and the local controller. We use the total schedule demand $\boldsymbol{d}_n$ to replace $\hat{\boldsymbol{c}}_n$ and define the equivalent form of the energy schedule $S'_n = (\boldsymbol{T}_n, \boldsymbol{d}_n)$, where $\boldsymbol{T}_n$ is used to update the dual variable and $\boldsymbol{d}_n$ is used to calculate the objective value. The master problem, therefore, is solvable in the microgrid control center without privacy violations.

With the energy schedule $\mathcal{S} \triangleq \{S'_n \,|\, n \in \mathcal{N}\}$ which is collected from each cell, the microgrid control center uses (20) to update the dual variables $\boldsymbol{\lambda}$ and calculate the objective value $L(\mathcal{S}, \boldsymbol{\lambda})$, until the dual solution converges. Specifically, at the m-th iteration, the control center collects ${S'}_n^{(m)}$ from every cell first. Then, it updates the dual variables $\boldsymbol{\lambda}$ according to (20) and calculates the objective value $L^{(m)} \triangleq L(\mathcal{S}^{(m)}, \boldsymbol{\lambda})$. Given a pre-specified threshold ϵ and an integer M, if

$$\max_{i=m-M,m-M+1,\ldots,m-1} |L^{(i)} - L^{(m)}| < \epsilon, \tag{22}$$

then the algorithm stops.

C. Solving the Dual Problem at Local Controllers

At the lower level of the Lagrangian dual problem in (17), we have the dual problem in (23) at the bottom of the page.

By decomposing the objective function in (23), we have:

$$L(\mathcal{S}, \boldsymbol{\lambda}) = \sum_{n=1}^{N} L_n(S'_n, \boldsymbol{\lambda}), \tag{25}$$

where

$$L_n(S'_n, \boldsymbol{\lambda}) = \sum_{k=1}^{K} \Big(\alpha(k) t_n^k + \lambda_k (v_n^k - u_n^k)\Big). \tag{26}$$

Thus we obtain N homogeneous sub-problems in (24).

For any cell n, the problem in (24) is only related to the privacy information of the consumers in cell n. No constraints are

$$\mathcal{P} = \begin{cases} \min_{\mathcal{S}\geq 0, \mathcal{A}\geq 0} & L(\mathcal{S}, \boldsymbol{\lambda}) \\ \text{s.t.} & \text{Battery capacity constraints in (12), (13), (14) } (n \in \mathcal{N}) \\ & \text{Demand fulfillment constraints in (2) } (n \in \mathcal{N}) \\ & \text{Schedule window constraints in (7) } (n \in \mathcal{N}) \\ & \text{Privacy constraints} \end{cases}, \tag{23}$$

where the dual variable $\boldsymbol{\lambda}$ is given.

$$\mathcal{P}_n = \begin{cases} \min_{S'_n \geq 0, \hat{\boldsymbol{t}}_n \geq 0} & L_n(S'_n, \boldsymbol{\lambda}_n) \\ \text{s.t.} & \text{Battery capacity constraints in (12), (13), (14) related to } n \\ & \text{Demand fulfillment constraints in (2) related to } n \\ & \text{Schedule window constraints in (7) related to } n \\ & \text{Privacy constraints} \end{cases}. \tag{24}$$

hidden if this sub-problem is solved in the corresponding cell n. Moreover, the standard LP tools can be employed to solve (24)[19].

The sub-problems in (24) can be solved at the local controllers in the corresponding cells simultaneously with a given dual variable $\boldsymbol{\lambda}$. Specifically, at the m-th iteration, cell n retrieves $\boldsymbol{\lambda}^{(m)}$ from the control center first; then it solves the LP problem (24) and obtains the dual solution ${S'_n}^{(m)}$ which is then sent to the microgrid control center.

D. Recovery of Feasible Primary Solution

In the previous subsections, we solved the original energy scheduling problem in (15) by solving its dual problem in (17) using the sub-gradient method. Since the original problem is solved in the dual domain, the feasibility of the obtained solution for the original problem needs to be checked. Specifically, employing the sub-gradient optimization approach, an optimal solution $(\mathcal{S}, \boldsymbol{\lambda})$ that maximizes (17) can be obtained. If $\mathcal{S}$ is feasible for the original problem in (15), then it is also the optimal solution to the original problem. However, this feasibility does not always hold [23].

An infeasible schedule leads to energy surplus or shortage at the microgrid control center. In case of energy surplus, the energy collected from the cells exceeds the energy required to be distributed to the cells, resulting in energy waste; in case of energy shortage, extra energy needs to be imported from the utility grid.

To ensure the feasibility of the obtained schedule, a step that maps the infeasible solution to a feasible one can be implemented at the microgrid control center at the end of each outer primal-dual iteration. Specifically, we denote $\tilde{\mathcal{S}}^{(m)}$ as the mapped primal feasible solution obtained at the end of the m-th outer primal-dual iteration. Then the mapping is given by [23]

$$\tilde{\mathcal{S}}^{(m+1)} = \frac{m}{m+1} \cdot \tilde{\mathcal{S}}^{(m)} + \frac{1}{m+1} \cdot \mathcal{S}^{(m)}. \tag{27}$$

We define $I^{(m)} = I(\tilde{\mathcal{S}}^{(m)})$ and set the optimal solution $\mathcal{S} = \tilde{\mathcal{S}}^{(m^*)}$ where m^* is the iteration index corresponding to the smallest $I^{(m)}$ among the last M iterations. Finally we summarize the distributed algorithm for solving the energy scheduling problem (15) as follows.

Algorithm 1 Partial Dual Decomposition Algorithm

1: Initialization (implemented by the control center)
  $\boldsymbol{\lambda}^{(0)} = \mathbf{0}, I^{(0)} = 0, m = 1$
  Specify ϵ and M
2: Local optimization (implemented at each cell)
  FOR $n \in \mathcal{N}$
    Retrieve $\boldsymbol{\lambda}^{(m-1)}$
    Solve **(24)** using an LP solver to obtain $S_n^{(m)}$
    Submit $S_n^{(m)}$
  ENDFOR
3: Global optimization (implemented at the control center)
  Using **(20)** to update $\boldsymbol{\lambda}^{(m)}$
  Using **(16)** to update calculate $L^{(m)}$
  Map the dual solution $S_n^{(m)}$ to primal solution $\tilde{S}^{(m)}$ by **(27)**
  IF $\max_{i=m-M,\ldots,m-1} |L^{(i)} - L^{(m)}| < \epsilon$, **GOTO STEP 4**
  ELSE
    Activate cells
    $m \leftarrow m + 1$
    GOTO STEP 2
  ENDIF
4: Schedule generation
  Deactivate cells
  $\mathcal{S}^* = \tilde{\mathcal{S}}^{(m^*)}$

The problem in (15) is a linear programming problem without the privacy constraints. Then, the strong duality holds and there exists a saddle point for the Lagrangian dual problem in (17). If the step size $\beta(q)$ in (20) is properly chosen and the optimal solution to (25) is unique in $\mathcal{S}$, then the above Algorithm 1 can obtain the primal optimal and feasible solution to (15)[21]; if the solution to (25) is not unique in $\mathcal{S}$, one primal feasible and optimal solution can be obtained after the mapping step (27) with a properly chosen step size $\beta(q)$[23]. Therefore, Algorithm 1 can provide the globally optimal primal solution to (15). Moreover, as shown in Fig. 3, there is no privacy violation during the process of information exchange and schedule calculation.

V. A Fast Suboptimal Energy Scheduling Algorithm

A. Problem Decomposition

In the previous section, by solving the Lagrangian dual problem we obtain the optimal solution to (15). However, the dual decomposition algorithm with the sub-gradient method typically has a slow convergence rate. In this section, we propose a simple suboptimal algorithm with much faster convergence rate to solve the problem directly in the primal domain.

Based on the energy schedule defined in (8), we divide it into the transmission schedule $\boldsymbol{T}_n,\ n \in \mathcal{N}$ that is only related to the Type-I privacy and the demand schedule $\hat{\boldsymbol{c}}_n,\ n \in \mathcal{N}$ that is only related to the Type-II privacy. By alternatively optimizing $\boldsymbol{T}_n, n \in \mathcal{N}$ and $\hat{\boldsymbol{c}}_n,\ n \in \mathcal{N}$, both privacy constraints will be met. In particular, based on (15), we define the sub-problems $\mathcal{P}_n,\ n = 0, 1, \ldots, N$ in (28) and (29) at the bottom of the next page.

Since the problem $\mathcal{P}_0$ does not involve any schedule window constraint for $\hat{\boldsymbol{c}}_n$, no constraint is hidden due to privacy if we solve it in the microgrid control center. Similarly, the problem $\mathcal{P}_n$ involves constraints only related to cell n. Then, solving $\mathcal{P}_n$ in the corresponding cell n does not result in the "hidden constraint" problem either.

Based on the above problem decomposition, we propose a distributed algorithm for suboptimally solving (15). It is an iterative algorithm with each iteration consisting of two stages, *global adjustment* and *local optimization*, corresponding to problem $\mathcal{P}_0$ and $\mathcal{P}_1$ to $\mathcal{P}_n$, respectively.

Fig. 4 shows the operations at the cells and the control center for implementing the fast algorithm. This figure also illustrates

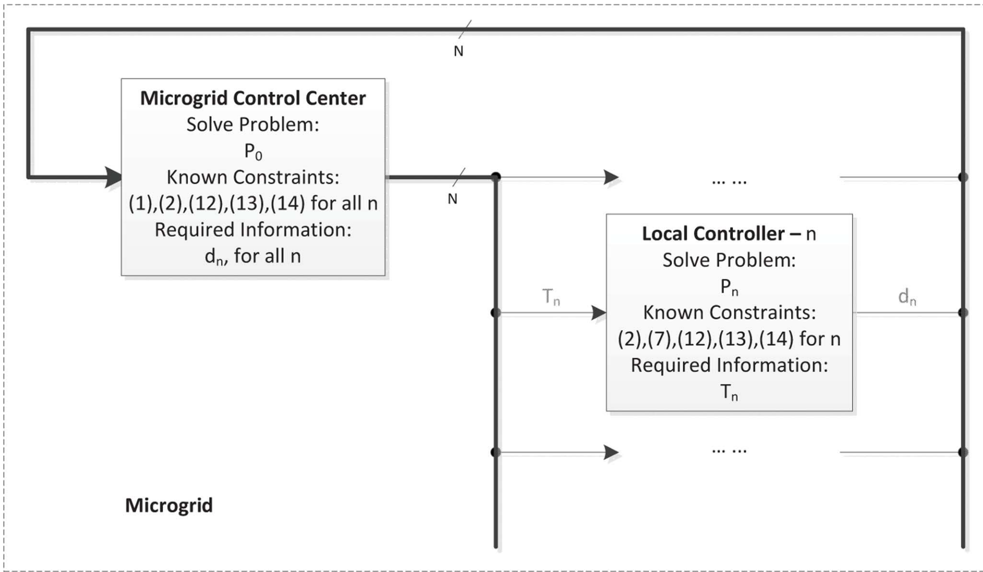

Fig. 4. The operations at the control center and the cells, and information exchange in the fast algorithm.

that there is no privacy violation during the process of information exchange and schedule calculation. The detailed steps of the fast algorithm are provided in the following subsections.

B. Global Adjustment At Control Center

In the global adjustment stage, based on the given demand schedule $\boldsymbol{d}_n,\ n \in \mathcal{N}$, the microgrid control center solves the LP problem $\mathcal{P}_0$ in (28). This problem is a standard LP problem and can be solved by using standard LP optimizations tools [25].

Specifically, at the m-th iteration, the microgrid control center solves the LP problem $\mathcal{P}_0$ based on the demand schedule $\boldsymbol{d}_n^{(m)},\ n \in \mathcal{N}$ obtained from each cell. Then, the microgrid control center updates the energy transmission schedule $\boldsymbol{T}_n^{(m)},\ n \in \mathcal{N}$ and the corresponding optimal objective value $I^{(m)} = I(\mathcal{S}^{(m)})$. Given a pre-specified threshold number ϵ and an integer M, if

$$|I^{(m)} - I^{(m-1)}| < \epsilon \text{ or } m = M, \tag{31}$$

set the optimal solution $\mathcal{S}^* = \mathcal{S}^{(m)}$. Otherwise, activate each cell for the next local optimization.

C. Local Optimization at Local Controllers

In the local optimization stage, the local controller in each cell n solves the corresponding LP problem $\mathcal{P}_n$ defined in (29) simultaneously, based on the given transmission schedule T_n.

Specifically, at the m-th iteration, cell n retrieves its energy transmission schedule $T_n^{(m-1)}$ from the control center, which was calculated in the previous global adjustment stage. Then, cell n solves the LP problem $\mathcal{P}_n$, to obtain the demand schedule $\hat{\boldsymbol{c}}_n^{(m)}$. Finally, cell n submits the demand schedule $\boldsymbol{d}_n^{(m)}$ (calculated based on $\hat{\boldsymbol{c}}_n^{(m)}$) to the microgrid control center.

The fast algorithm is summarized as Algorithm 2. As opposed to the optimal Algorithm 1 which has a slow convergence rate, this algorithm can obtain a suboptimal solution within only a few iterations while meeting the privacy constraints.

$$\mathcal{P}_0 = \begin{cases} \min_{\boldsymbol{T}_n \geq 0, \hat{\boldsymbol{t}}_n \geq 0\ (n \in \mathcal{N})} & I(\mathcal{S}),\ (\text{for given } \boldsymbol{d}_n) \\ \text{s.t.} & \text{Battery capacity constraints in } (12),\ (13),\ (14)\ (n \in \mathcal{N}) \\ & \text{Demand fulfillment constraints in } (2)\ (n \in \mathcal{N}) \\ & \text{Energy flow equilibrium constraints in } (1) \\ & \text{Type-I privacy constraints in Table I} \end{cases} \tag{28}$$

$$\mathcal{P}_n = \begin{cases} \min_{\hat{\boldsymbol{c}}_n \geq 0, \hat{\boldsymbol{t}}_n \geq 0} & I_n(S_n),\ (\text{for given } \boldsymbol{T}_n) \\ \text{s.t.} & \text{Battery capacity constraints in } (12),\ (13),\ (14) \text{ related to } n \\ & \text{Demand fulfillment constraints in } (2) \text{ related to } n \\ & \text{Schedule window constraints in } (7) \text{ related to } n \\ & \text{Type-I privacy constraints in Table I} \end{cases}, \tag{29}$$

where

$$I_n(S_n) = \sum_{k=1}^{K} \alpha(k) t_n^k. \tag{30}$$

Algorithm 2 Fast Algorithm

1: Initialization (implement by the control center)
$\{T_n^{(0)} \mid n \in \mathcal{N}\} = \{\mathbf{0}\}, I^{(0)} = 0, m = 1$
Specify ϵ and M
2: Local optimization (implemented at each cell)
FOR $n \in \mathcal{N}$
Retrieve $T_n^{(m-1)}$
Solve $\mathcal{P}_n$ to obtain $\hat{\boldsymbol{c}}_n^{(m)}$
Submit $\boldsymbol{d}_n^{(m)}$
ENDFOR
3: Global adjustment (implement at the control center)
Solve $\mathcal{P}_0$ to obtain $\{\boldsymbol{T}_n^{(m)},\ n \in \mathcal{N}\}$ and $I^{(m)}$
IF $|I^{(m)} - I^{(m-1)}| < \epsilon$ or $m = M$, **GOTO STEP 4**
ELSE
Activate cells
$m \leftarrow m + 1$
GOTO STEP 2
ENDIF
4: Schedule generation
Deactivate cells
$\mathcal{S}^* = \mathcal{S}^{(m)}$

It is easy to see that in the above algorithm the objective value of $\mathcal{P}_0$ is monotonically non-increasing with the iteration number. Although theoretically the fast algorithm may not yield the optimal solution to (15) [22], [25], simulation results in the next section show that it achieves the comparable performance to the dual decomposition algorithm with a much faster convergence rate.

Remark 2: Although the control center may store the intermediate results submitted by the each cell, e.g., u_n^k, v_n^k in the dual decomposition algorithm and T_n in the fast algorithm, it is also very difficult for the control center to mine the user's protected privacy.

Specifically, from the prospective of the local controller, the user's behavior and preference may vary day by day, highly relying on the custom's personal time schedule, e.g., dine outside, work late, visit a friend, etc.; also, from the prospective of the control center, the received schedule data is not only determined by the user's behavior and preference but also affected by some external environment, e.g., weather, TOU price, local power system operation status, and etc. With the variations and the external "interference" factors, capturing the user's intermediate results cannot provide enough information for privacy mining, even for a couple of days.

VI. Simulation Results

We assume that there are $N = 4$ cells in the microgrid system. We set the scheduling period as 6 hours and divide it into $K = 6$ time slots of equal durations and express the energy in terms of per unit (p.u.). For each cell $n \in \mathcal{N}$ we set the battery capacity $B_n^{\max} = 8$ p.u. and the initial energy level $B_n^0 = 5$ p.u.. Assume that the un-schedulable energy c_n^k follows a uniform distribution and we use the real measured data found in [26] to characterize the generated renewable energy E_n^k. Also, we assume that in (7) the total schedulable demand is $C_n = 12$ p.u. and $K_1 = 1$, $K_2 = 6$. In addition, we set the TOU price factors as $\alpha(1) = 0.6$, $\alpha(2) = 0.9$, $\alpha(3) = 0.8$, $\alpha(4) = 0.9$, $\alpha(5) = 1.2$, and $\alpha(6) = 0.6$, the step size as $\beta(q) = 1/q$.

For comparison, we consider two simplified scheduling strategies, namely, the *energy transmission scheduling only* (ETS-only) strategy and the *demand scheduling only* (DS-only) strategy. The ETS-only strategy assumes that all demands are un-schedulable and only the energy transmission schedule is performed. To obtain the ETS-only schedule, we distribute the schedulable demands to each available time slot evenly and solve (28) in the central control center only. On the other hand, the DS-only strategy assumes that each cell cannot receive energy from outside and only optimizes its own schedulable demands. To obtain the DS-only schedule, we apply the fixed non-cooperative transmission schedule ($v_n^k = 0,\ k \in \mathcal{K},\ n \in \mathcal{N}$) and solve (29) in each local controller. Moreover, we also consider a "no schedule" strategy where we distribute the schedulable demands to each available time slots evenly and no intercell-cooperation is allowed. The convergence threshold is set as $\epsilon = 10^{-3}$.

Based on the measured wind pattern, we first consider a typical scenario where the energy demand c_n^k follow a uniform distribution over the interval $[3 - a/2, 3 + a/2]$, with the value of a varies from 1 to 6, i.e., the variance varies from $1/12$ to 3 and the generated energy E_n^k are normalized to the mean of 5 for the winter data. In this scenario, we further consider two typical batteries: low efficient (LE) battery with as low as 70% efficiency (LE), e.g., the Lead-acid battery, and high efficient (HE) with as high as 98% efficiency, e.g., the Lithium-ion battery. We set $\gamma_1 = 0.97, \gamma_2 = 0.98, \gamma_3 = 0.96, \gamma_4 = 0.99$ for the HE case and $\gamma_1 = 0.70, \gamma_2 = 0.71, \gamma_3 = 0.69, \gamma_4 = 0.66$ for the LE case. Also, since the energy generation and consumption are balanced in the long term but they fluctuate at different time slots in this scenario, the required external energy is mainly caused by the fluctuations of the energy supply and demand. To evaluate the scheduling performance, we simulate under 2000 users' demand profiles with winter and summer wind pattern, respectively. The total amount of energy importing cost given by various scheduling strategies, as well as by the optimal schedule without the privacy constraints, is shown in Fig. 5 for winter month data (February) and in Fig. 6 for summer month data (July). In both Figs. 5 and 6, the solid lines represent battery HE case and the dashed lines represent battery LE case.

We continue to consider a more general case that both of the harvested energy E_n^k and the energy demand c_n^k follow the non-negative truncated Gaussian progress with the mean $m = 5$ and the variance $v = 1, 1.5, 2, 2.5, 3, 3.5$, which contributes the "most" randomness, evaluating the generality of the proposed energy scheduling strategy. Also, we consider two battery conditions as above, HE battery and LE battery, and simulate for 2000 profiles. The cost of the imported energy is shown in Fig. 7.

It is seen from Figs. 5–7 that, for both HE and LE cases, the proposed dual decomposition method, fast method, and the optimal schedule without the privacy constraints give the best performance. As expected, the dual decomposition method achieves the same performance as the optimal schedule without

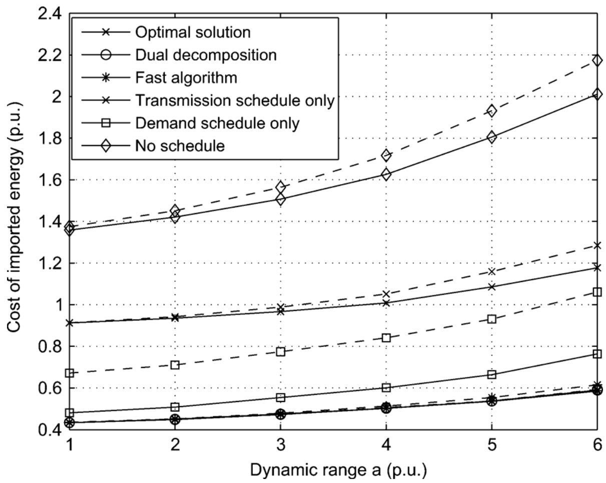

Fig. 5. Performance comparisons among different energy schedules for measured winter data (Solid line—battery HE case; dashed line—battery LE case).

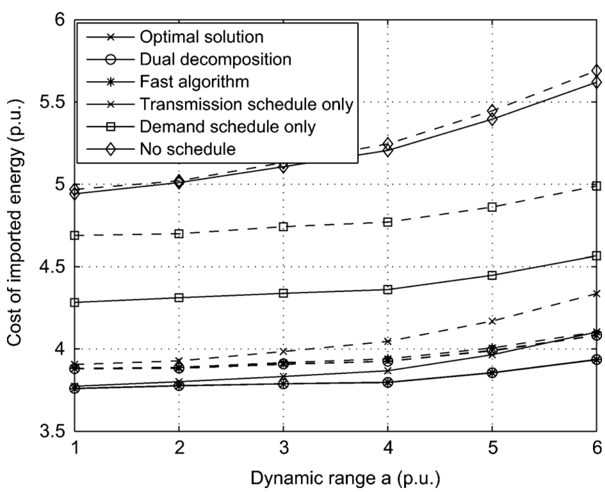

Fig. 6. Performance comparisons among different energy schedules for measured summer data (Solid line—battery HE case; dashed line—battery LE case).

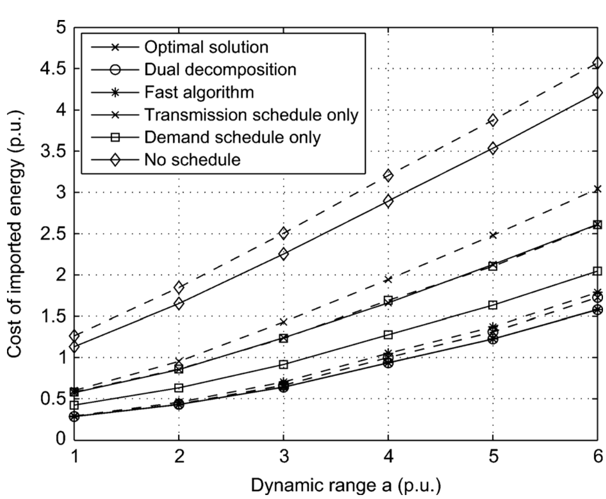

Fig. 7. Performance comparisons among different energy schedules for Gaussian random data (Solid line—battery HE case; dashed line—battery LE case).

privacy constraints. Moreover, although the fast method is a suboptimal algorithm, it achieves the comparable performance to the dual decomposition method in this simulation. The ETS-only and the DS-only strategies perform worse than the optimal schedule because they do not fully exploit inter-cell cooperation in the microgrid system and significant amount of energy is overflowed due to the battery capacity limit. Also, as the range (and therefore the variance) of the generated energy and the energy demand increases, the performances of all methods degrade due to the fluctuations of the energy supplies and demands.

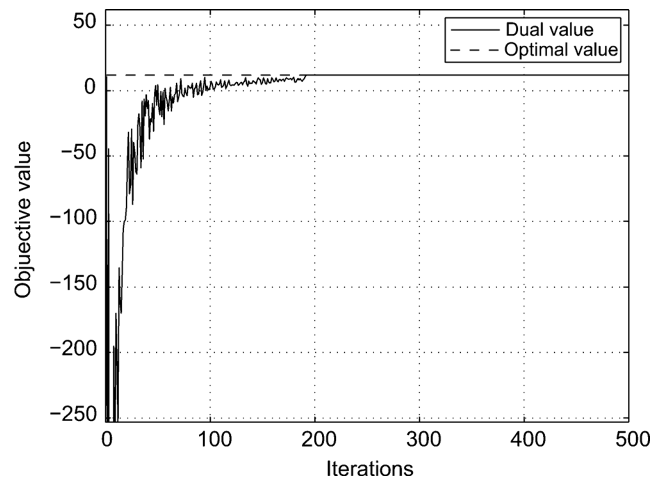

Fig. 8. Convergence of the dual decomposition method.

TABLE II
AVERAGE NUMBER OF ITERATIONS TO REACH CONVERGENCE BY THE FAST ALGORITHM

Variance v	1	1.5	2	2.5	3	3.5
Average iterations (HE)	3.9010	3.7940	3.9710	4.6920	5.3810	6.0565
Average iterations (LE)	4.4115	5.3850	6.0115	7.0310	7.5150	8.5850

On the other hand, for the optimal solution, it is also seen from Figs. 5–7 that the battery efficiency influences more for summer case than winter case. It is mainly because that, in the winter case, the wind provides more energy and the microgrid generally operates in the energy balanced situation and the optimal energy scheduling makes effect on suppressing the frequent energy deposit and discharge and enhancing the energy exchange among different cells, eliminating the affect of demand-supply fluctuation; however, in summer case, the microgrid generally operates in the energy deficit situation and the optimal energy scheduling makes effects on utilizing the battery by frequently charging and discharging to cope with the TOU fluctuation.

We next compare the convergence rates of the dual decomposition method and the fast method. In this simulation, we assume that the generated energy E_n^k and energy demand c_n^k follow a Gaussian distribution with $m = 5$ and $v = 1, 1.5, 2, 2.4, 3, 3.5$. We record the objective value of the dual problem in (17) at each iteration, and plot them in Fig. 8, comparing to the optimal value. It is seen that the dual decomposition method converges after around the 200-th iteration. Moreover, upon the convergence, zero dual gap should be exhibited and the optimality can be achieved. For the fast algorithm, the convergence rate statistics are listed in Table II, showing the outstanding convergence rate.

VII. Conclusions

We have considered the privacy-preserving energy scheduling problem for a microgrid system equipped with the renewable energy sources and local controllers. This energy scheduling problem is formulated as a linear programming problem with privacy constraints. We have developed the dual decomposition method to optimally solve this problem. The proposed algorithm takes into account the privacy constraint and can be implemented in a distributed fashion. Another distributed suboptimal algorithm is also developed that converges much faster than the dual decomposition method. Simulation results based on real renewable energy source data have demonstrated that the proposed energy scheduling methods can provide substantial reduction in the non-renewable energy consumption, while meeting the energy demands of the consumers as well as their privacy constraints.

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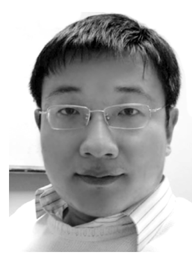

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