PRIVACY CONSTRAINED ENERGY MANAGEMENT FOR SELF-INTERESTED MICROGRIDS

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ABSTRACT

This paper studies the energy management problem for two self-interested microgrids with integrated renewable energy and energy storage systems, which can exchange energy with each other through the transmission line connecting them. Microgrids are willing to cooperate if and only if both can benefit from the energy cooperation, e.g. achieve lower energy costs as compared to the without energy cooperation case, while sharing limited information due to privacy considerations. We thus propose an iterative algorithm for the *partially cooperative* energy management problem, which aims to reduce energy costs of both microgrids simultaneously, while sharing limited information. To provide performance benchmark, we also consider the *fully cooperative* energy management problem, for which we ideally assume that microgrids share all their information to minimize their *total* energy cost. Last, we evaluate our proposed algorithms for the partially and fully cooperative energy management via simulations based on the Tucson power system data.

Index Terms— Microgrids, energy cooperation, smart grid.

1. INTRODUCTION

The increasing trend in the electrical energy consumption has increased the need for conventional fossil fuel based energy generations, which are costly and also damaging to the environment. Renewable energy has emerged as an alternative solution to address the growing energy consumption. As a result, microgrids that integrate a networked group of renewable energy generators and distributed loads have become essential components of smart grids.

Unlike the conventional energy, renewable energy is intermittent in nature; thus, it does not ensure the reliable operation of microgrids at all time. The traditional approach to mitigate renewable energy fluctuations is deploying energy storage systems; however, relying solely on energy storage systems may not be a viable solution since they incur high installment and maintenance costs and also have practically limited capacities. Another approach is enabling energy cooperation among geographically distributed microgrids, where microgrids with energy surplus compensate those with energy deficit. The energy cooperation among microgrids can be performed under the coordination of a central controller, which has access to all or part of the information of cooperating microgrids. If the microgrids belong to the same entity or different entities with common interests, they share all their information with the central controller. The central controller then minimizes the *total* energy cost of all microgrids given their provided information. Otherwise, if the microgrids belong to different self-interested entities, they only share limited information with the central controller due to privacy considerations. In order for self-interested microgrids to have energy cooperation with each other, we need to motivate them by offering some benefits in return, e.g., reductions in their energy costs.

In this paper, we study the energy management problem for two self-interested but cooperative microgrids that are connected to each other via a dedicated power transmission line and also to the main grid. Each microgrid consists of renewable energy generators, an energy storage system, and an aggregate load. We assume that renewable energy generations in microgrids can be perfectly predicted without any error. In this case, we propose a *partially cooperative* energy management paradigm, under which the central controller coordinates the energy exchanged between microgrids based on the limited information received from them. Given the exchanged energy, each microgrid independently optimizes the energy charged/discharged to/from its energy storage system and that drawn form the main grid so as to minimize its energy cost. To motivate the energy cooperation between the two microgrids, we devise an iterative algorithm for the central controller to gradually update the energy exchanged between microgrids such that their energy costs reduce simultaneously as compared to the without energy cooperation case, i.e., they operate independently without energy exchange. To provide performance benchmark, we further consider the ideal case that microgrids have common interests and thus share all their information with the central controller. We then formulate the *fully cooperative* energy management problem, under which the central controller jointly optimizes the energy exchanged between microgrids, that charged/discharged to/from their energy storage systems, and that drawn from the main grid by each microgrid to minimize the total energy cost of both microgrids. Last, we present simulation results based on the real data of Tucson power system [1] to compare the total energy cost of microgrids resulting from the partially cooperative energy management versus that of the fully cooperative counterpart.

There have been a handful of prior studies on the energy management for a single microgrid [2] as well as multiple microgrids [3–9]. Particularly, [3–6] studied the fully cooperative energy management, for microgrids with common interests, to minimize their total energy cost by assuming full information sharing between microgrids and the central controller [3, 4] or limited information sharing [5, 6]. However, microgrids may not have common interests; as a result, the fully cooperative energy management is not always valid in practice. On the other hand, [7–9] studied the partially cooperative energy management for self-interested microgrids using game-theoretical approaches [7, 8] or heuristically designed algorithms based on multi-agent systems [9]. Although [7–9] have shown interesting results on the energy management problem for self-interested microgrids, they did not provide a complete view of the problem. For instance, it is not clear under which circumstances microgrids should exchange energy with each other. The energy trading (selling/buying) among microgrids was also not modeled in [7–9].

In contrast to the aforementioned works, in this paper we propose an algorithm for the partially cooperative energy management of microgrids under a practical setup with two self-interested microgrids that can exchange energy given known prices. In particular, our algorithm aims to reduce energy costs of both microgrids simultaneously, while limited information is exchanged with the central controller. The obtained results show that our proposed algorithm is helpful to motivate self-interested microgrids to cooperate with each other, since both can benefit from the energy cooperation while preserving their privacy.

2. SYSTEM MODEL

We consider a power system consisting of two microgrids that are connected to each other and also to the main grid via separate transmission lines. Each microgrid, denoted by index j, $j \in \mathcal{J} = \{1, 2\}$, consists of renewable energy generators, an energy storage system, and an aggregate load. The two microgrids exchange energy given known prices that are specified based on a certain agreement of both microgrids. The energy cooperation is coordinated by a central controller that microgrids are trusting of and has access to all or part of the information of microgrids. Our goal is to devise an algorithm to optimize the energy exchanged between microgrids such that their energy costs decrease simultaneously as compared to the without energy cooperation case, while sharing only limited information with the central controller due to privacy considerations.

For the convenience of analysis, we assume a time-slotted system with slot index i, $i \in \mathcal{N} = \{1, \ldots, N\}$, where N denotes the total number of time slots for scheduling. We also assume a quasi-static time-varying energy model, in which the rate of the renewable energy generation at each microgrid is constant within each time slot, while may change from one time slot to another. Furthermore, we assume that the duration of each time slot is normalized to a unit time; hence, we use power and energy interchangeably in this paper. In the following, we define our system model in detail.

• *Microgrids' Energy Costs:* We consider a linear time-varying cost model for the conventional energy drawn from the main grid by each microgrid [10]. Denote $G_{j,i} \geq 0$ as the energy drawn from the main grid by microgrid j at time slot i. The energy cost for microgrid j at time slot i is expressed as $\lambda_{j,i} G_{j,i}$, where $\lambda_{j,i} > 0$ is the price of a unit of energy offered by the main grid. We assume that prices $\lambda_{j,i}$, $\forall j \in \mathcal{J}$, $\forall i \in \mathcal{N}$, are known to microgrids.

• *Energy Storage:* We denote the energy charged (discharged) to (from) the energy storage system of microgrid j at time slot i as $C_{j,i} \geq 0$ ($D_{j,i} \geq 0$). The energy losses during charging and discharging processes are specified by the charging and discharging efficiency parameters, denoted by $0 < \alpha_j^c < 1$ and $0 < \alpha_j^d < 1$, respectively. Denote the state (stored energy) of the energy storage system of microgrid j at the beginning of time slot i as $S_{j,i} \geq 0$. Then, the energy storage dynamics is obtained as $S_{j,i+1} = S_{j,i} + \alpha_j^c C_{j,i} - D_{j,i}/\alpha_j^d$, $\forall i \in \mathcal{N}$. We also denote $S_j^{\max} \geq 0$ and $S_j^{\min} \geq 0$ as the storage capacity and the minimum energy required in storage of microgrid j, respectively. We thus have the following constraints for the energy storage system of microgrid j

$$S_j^{\min} \leq S_{1,j} + \alpha_j^c \sum_{k=1}^{i} C_{j,k} - 1/\alpha_j^d \sum_{k=1}^{i} D_{j,k} \leq S_j^{\max}, \forall i \in \mathcal{N} \quad (1)$$

where $S_j^{\min} \leq S_{j,1} \leq S_j^{\max}$, $\forall j \in \mathcal{J}$, are assumed by default.

• *Microgrids' Net Energy Profiles:* We consider microgrids with renewable energy integration. We define the total generated renewable energy offset by the aggregate load in microgrid j at time slot i as the net energy profile, denoted by $\Delta_{j,i}$. In this paper, we assume that $\Delta_{j,i}$'s can be perfectly predicted and thus are known to microgrids (e.g., in day-ahead energy management).

• *Microgrids' Energy Exchange:* Let $E_{j,i} \geq 0$ denote the power transferred from microgrid j to microgrid $\bar{j}$, $\bar{j} \in \mathcal{J} \backslash \{j\}$, at time slot i. In practice, some power will be lost while flowing over transmission line due to the ohmic resistance of the line. Denote $R > 0$ and $V > 0$ as the ohmic resistance of the transmission line connecting the two microgrids per length unit and its operating voltage, respectively. The transmission loss resulted from flowing $E_{j,i}$ amount of energy over the transmission line is modeled as $\beta E_{j,i}^2$, where $\beta = (R \cdot d)/V^2$ [10]. As a result, the net power received in microgrid $\bar{j}$ from microgrid j at time slot i can be expressed as $E_{j,i} - \beta E_{j,i}^2$.[1] Moreover, the power transferred over the line connecting the two microgrids is constrained by the transmission line capacity, denoted by $0 \leq \overline{E} < 1/(2\beta)$, due to, e.g., thermal limitations of its conductors. We thus have the following constraints for the power transferred from microgrid j to $\bar{j}$ as

$$0 \leq E_{j,i} \leq \overline{E}, \ \forall i \in \mathcal{N}. \quad (2)$$

Intuitively, it is not optimal for microgrids to exchange energy at the same time given the energy loss in the transmission lines; hence, we only consider $\{E_{j,i}\}$ satisfying

$$E_{j,i} \cdot E_{\bar{j},i} = 0, \ \forall i \in \mathcal{N}. \quad (3)$$

Last, we denote $\omega_{j,i} \geq 0$ as the price that microgrid j sells a unit of energy to microgrid $\bar{j}$ at time slot i. We assume that microgrids always exchange energy with each other in lower prices compared to those offered by the main grid, i.e., $\omega_{j,i} < \lambda_{j,i}$. The monetary profit for microgrid j at time slot i obtained from selling $E_{j,i}$ amount of energy to microgrid $\bar{j}$ is $\omega_{j,i} E_{j,i}$, while the monetary profit for microgrid $\bar{j}$ is $-\omega_{j,i} E_{j,i}$.[2]

• *Microgrids' Energy Neutralization Constraints:* We assume that microgrid j meets its load by 1) using its renewable energy generation and/or 2) discharging its energy storage system and/or 3) purchasing energy from microgrid $\bar{j}$ and/or 4) purchasing conventional energy from the main grid. The energy neutralization constraints in microgrid j is thus expressed as

$$G_{j,i} + \Delta_{j,i} + D_{j,i} - E_{j,i} + E_{\bar{j},i} - \beta E_{\bar{j},i}^2 \geq C_{j,i}, \ \forall i \in \mathcal{N}. \quad (4)$$

Note that in case of renewable energy surplus $\Delta_i > 0$, part of the energy may be curtailed due to the limited capacity of the energy storage system. In this case, (4) needs to hold with a strict inequality.

3. PARTIALLY COOPERATIVE ENERGY MANAGEMENT

We define $F_j(\boldsymbol{e})$ as the minimum energy cost of microgrid j, given any energy exchange vector $\boldsymbol{e} = [E_{1,1} \ldots E_{1,N} \ E_{2,1} \ldots E_{2,N}]^T$, with $E_{j,i}$, $\forall j \in \mathcal{J}$, $\forall i \in \mathcal{N}$, satisfying (2) and (3). Specifically, we formulate the following problem for achieving the minimum energy cost in microgrid j.

$$(\mathrm{P1-j}): \quad F_j(\boldsymbol{e}) = \min_{\{G_{j,i}\},\{C_{j,i}\},\{D_{j,i}\}} \sum_{i=1}^{N} \left(\lambda_{j,i} G_{j,i} - \omega_{j,i} E_{j,i} + \omega_{\bar{j},i} E_{\bar{j},i}\right)$$

$$\text{s.t. (1) and (4)}, \quad G_{j,i} \geq 0, \ C_{j,i} \geq 0, \ D_{j,i} \geq 0, \ \forall i \in \mathcal{N}.$$

It can be verified that $F_j(\boldsymbol{e})$ is a convex function of $\boldsymbol{e}$ [11]. Moreover, given any energy exchange vector $\boldsymbol{e}$, energy costs of both microgrids can be reduced simultaneously if and only if there exists sufficiently small $\Delta \boldsymbol{e} = [\Delta E_{1,1} \ldots \Delta E_{1,N} \ \Delta E_{2,1} \ldots \Delta E_{2,N}]^T$,

[1] Due to the fact that voltages of lines connecting the main grid to microgrids are high (over 220 KV), it follows that their β's are very small and thus we can ignore the resulting losses in these lines.

[2] Note that microgrid $\bar{j}$ pays $\omega_{j,i}$ to draw $E_{j,i}$ amount of energy from microgrid j, while it receives $E_{j,i} - \beta E_{j,i}^2$ due to the transmission loss.

with $\boldsymbol{e}+\Delta\boldsymbol{e}$ satisfying (2) and (3), such that $F_j(\boldsymbol{e}+\Delta\boldsymbol{e}) < F_j(\boldsymbol{e})$, $\forall j \in \mathcal{J}$. In the following, we first derive the dual problem of (P1-j). Next, we characterize the effect of changing the energy exchange vector $\boldsymbol{e}$ to $\boldsymbol{e}+\Delta\boldsymbol{e}$ on the minimum energy cost of microgrid j, i.e., we derive $F_j(\boldsymbol{e}+\Delta\boldsymbol{e}) - F_j(\boldsymbol{e})$. Last, we investigate whether such $\Delta\boldsymbol{e}$ exists or not.

Let $\gamma_{j,i} \geq 0$ be the Lagrange dual variables corresponding to constraint (4). The dual function of (P1-j) is given by

$$g(\{\gamma_{j,i}\}) = \min_{\{G_{j,i}\},\{C_{j,i}\},\{D_{j,i}\}} \Bigg(\sum_{i=1}^{N} (\lambda_{j,i}G_{j,i} - \omega_{j,i}E_{j,i} + \omega_{\bar{j},i}E_{\bar{j},i}) - \sum_{i=1}^{N} \gamma_{j,i}(G_{j,i}+\Delta_{j,i}+D_{j,i}-C_{j,i}-E_{j,i}+E_{\bar{j},i} - \beta E_{\bar{j},i}^2) \Bigg)$$
$$\texttt{s.t.}\ (1), \quad G_{j,i} \geq 0,\ C_{j,i} \geq 0,\ D_{j,i} \geq 0.$$

The dual problem of (P1-j) is thus expressed as

$$(\text{D1}): \max_{\{\gamma_{j,i}\geq 0\}} g(\{\gamma_{j,i}\})$$

Lemma 3.1. *In order for $g(\{\gamma_{j,i}\})$ to be bounded from below, it must hold that $\gamma_{j,i} \leq \lambda_{j,i}$, $\forall i \in \mathcal{N}$.*

Denote the optimal solution to (D1) as $0 \leq \gamma_{j,i}^* \leq \lambda_{j,i}$, $\gamma_{j,i}^* \in \mathcal{U}$, where $\mathcal{U}$ is the set of all optimal dual variables. We then have the following lemma.

Lemma 3.2. *Under any given $\Delta\boldsymbol{e}$, the change in the energy cost of microgrid j by adjusting energy cooperation decisions is given by*

$$F_j(\boldsymbol{e}+\Delta\boldsymbol{e}) - F_j(\boldsymbol{e}) = \sum_{i=1}^{N}\sum_{k=1}^{2} f_{j,E_{k,i}}^{+}[\Delta E_{k,i}]^+ - f_{j,E_{k,i}}^{-}[-\Delta E_{k,i}]^+, \quad (5)$$

where $[x]^+ \triangleq \max(0,x)$, $\Delta\boldsymbol{e}$ is sufficiently small, $\boldsymbol{e}+\Delta\boldsymbol{e} \geq \mathbf{0}$, $f_{j,E_{k,i}}^{+}$ and $f_{j,E_{k,i}}^{-}$, are right-partial and left-partial derivatives of $F_j(\boldsymbol{e})$ with respect to $E_{k,i}$, respectively, given by[3] *[11, 12]*

$$f_{j,E_{k,i}}^{+} = \begin{cases} \frac{\partial F_j(\mathbf{e})}{\partial E_{j,i}^{+}} = \max_{\mathcal{U}}\{\gamma_{j,i}^* - \omega_{j,i}\} & k=j \\ \frac{\partial F_j(\mathbf{e})}{\partial E_{\bar{j},i}^{+}} = \max_{\mathcal{U}}\{2\beta E_{\bar{j},i}\gamma_{j,i}^* - \gamma_{j,i}^* + \omega_{\bar{j},i}\} & k=\bar{j} \end{cases} \quad (6)$$

$$f_{j,E_{k,i}}^{-} = \begin{cases} \frac{\partial F_j(\mathbf{e})}{\partial E_{j,i}^{-}} = \min_{\mathcal{U}}\{\gamma_{j,i}^* - \omega_{j,i}\} & k=j \\ \frac{\partial F_j(\mathbf{e})}{\partial E_{\bar{j},i}^{-}} = \min_{\mathcal{U}}\{2\beta E_{\bar{j},i}\gamma_{j,i}^* - \gamma_{j,i}^* + \omega_{\bar{j},i}\} & k=\bar{j} \end{cases} \quad (7)$$

Given the partial derivatives in Lemma 3.2, we seek for sufficiently small $\Delta\boldsymbol{e}$ with $\boldsymbol{e}+\Delta\boldsymbol{e}$ satisfying (2) and (3), such that $F_j(\boldsymbol{e}+\Delta\boldsymbol{e}) < F_j(\boldsymbol{e})$, $\forall j \in \mathcal{J}$. We investigate the existence of such $\Delta\boldsymbol{e}$ by solving the following feasibility problem.

$$(\text{F1}): \texttt{find}\ \{\Delta E_{j,i}\}$$
$$\texttt{s.t.}\ |\Delta E_{j,i}| \leq \rho,\ \forall j \in \mathcal{J},\ \forall i \in \mathcal{N} \quad (8)$$
$$0 \leq E_{j,i} + \Delta E_{j,i} \leq \overline{E},\ \forall j \in \mathcal{J},\ \forall i \in \mathcal{N} \quad (9)$$
$$(E_{j,i}+\Delta E_{j,i}) \cdot (E_{\bar{j},i}+\Delta E_{\bar{j},i}) = 0,\ \forall i \in \mathcal{N} \quad (10)$$
$$\sum_{k=1}^{2}\sum_{i=1}^{N} f_{j,E_{k,i}}^{+}[\Delta E_{k,i}]^+ - f_{j,E_{k,i}}^{-}[-\Delta E_{k,i}]^+ < 0,\ \forall j \in \mathcal{J} \quad (11)$$

where $\rho > 0$ is a small constant. Constraint (8) restricts each $\Delta E_{j,i}$ to take small steps, since (5) is only valid nearby $\boldsymbol{e}$. Constraints (9) and (10) are due to (2) and (3), respectively. Last, constraint (11) ensures that energy costs of both microgrids decrease simultaneously after changing the energy exchange vector $\boldsymbol{e}$ to $\boldsymbol{e}+\Delta\boldsymbol{e}$. Note that (F1) is a non-convex optimization problem due to constraints (10) and (11). However, constraints (8) and (9) specify a convex set over $\{\Delta E_{j,i}\}$. In order to solve (F1), we can search over the set specified by constraints (8) and (9) to find $\{\Delta E_{j,i}\}$ that satisfy (10) and (11).

[3] In the case that $\mathcal{U}$ has only one element, the right-partial and the left-partial derivatives become equal and $F_j(\boldsymbol{e})$ is thus differentiable.

Table 1: Algorithm for the Partially Cooperative Energy Management

Algorithm 1

a) Initialize $\boldsymbol{e} \leftarrow \mathbf{0}$, $\epsilon^- < 0$, $\epsilon^+ > 0$, $\rho > 0$, and Flag$\leftarrow 0$.
b) **While** Flag $\neq 1$ **do**:
   1) Given the energy exchange vector $\boldsymbol{e}$, each microgrid j computes $f_{j,E_{k,i}}^{+}$ and $f_{j,E_{k,i}}^{-}$ using (6) and (7), respectively, and passes them to the central controller.
   2) Given the received partial derivatives, the central controller investigates the existence of $\Delta\boldsymbol{e}$ by solving the feasibility problem in (F1). If (F1) is infeasible, Flag$=1$ is set. Otherwise, the energy exchange vector $\boldsymbol{e}$ is updated as $\boldsymbol{e} = \boldsymbol{e}+\Delta\boldsymbol{e}$.
c) The central controller announces $\boldsymbol{e}$ to microgrids as the final decision for the energy exchange.

The algorithm for solving the partially cooperative energy management of microgrids is given in Table 1. The algorithm starts from the case of no energy cooperation between microgrids, i.e., $\boldsymbol{e} = \mathbf{0}$. The following procedures are implemented iteratively. In each iteration, given $\boldsymbol{e}$, each microgrid j computes $f_{j,E_{k,i}}^{+}$ and $f_{j,E_{k,i}}^{-}$ using (6) and (7), respectively, where partial derivatives are then passed to the central controller. The central controller then searches for $\Delta\boldsymbol{e}$ by solving the feasibility problem (F1). If (F1) is feasible, then the central controller updates the energy exchange vector $\boldsymbol{e}$ as $\boldsymbol{e} = \boldsymbol{e}+\Delta\boldsymbol{e}$ and returns the new energy exchange vector to microgrids for the next iteration. The procedure shall proceed until (F1) becomes infeasible, i.e., further update is impossible. Given the obtained energy exchange vector $\boldsymbol{e}$, each microgrid independently solves the linear programming in (P1-j) to derive $\{G_{j,i}, C_{j,i}, D_{j,i}\}$.

Remark 3.1. *The energy cost of microgrid j resulting from the partially cooperative energy management cannot be higher than that without energy cooperation, i.e., $F_j(\mathbf{0})$. Otherwise, microgrid j can simply operate independently without any energy exchange and information sharing with the other microgrid/central controller.*

It is worth noting that in Algorithm 1 in Table 1, each microgrid preserves its privacy, since it only needs to share the right-partial and left-partial derivatives of its minimum energy cost function $F_j(\boldsymbol{e})$ with the central controller; meanwhile it can achieve a lower energy cost as compared to the without energy cooperation case.

4. BENCHMARK CASE: FULLY COOPERATIVE ENERGY MANAGEMENT

In this section, we ideally assume that the two microgrids have common interests and cooperate with each other in order to minimize their *total* energy cost. We formulate the fully cooperative energy management for the two microgrids as follows.

$$(\text{P2}): \min_{\{G_{j,i}\geq 0\},\{C_{j,i}\geq 0\},\{D_{j,i}\geq 0\},\{E_{j,i}\geq 0\}} \sum_{j=1}^{2}\sum_{i=1}^{N} \lambda_{j,i}G_{j,i}$$
$$\texttt{s.t.}\ (1), (2),\ \text{and}\ (4),\ \forall j \in \mathcal{J}.$$

It can be verified that (P2) is a convex optimization problem. Note that in (P2), we have not explicitly included (3) in the constraints. However, it will be shown that the optimal solution to (P2) always satisfies (3). Denote the optimal solution to (P2) as

$\{G^\star_{j,i}, C^\star_{j,i}, D^\star_{j,i}, E^\star_{j,i}\}$. The optimal solution to (P2) is given in the following proposition.

Proposition 4.1. *The optimal solution to (P2) is given by*

$$E^\star_{j,i} = \begin{cases} 0 & \gamma^\star_{\bar{j},i} = 0 \\ \min\left(\left[\frac{\gamma^\star_{\bar{j},i} - \gamma^\star_{j,i}}{2\gamma^\star_{\bar{j},i}\beta}\right]^+, \bar{E}\right) & \textit{otherwise} \end{cases}, \ \forall j \in \mathcal{J},\ \forall i \in \mathcal{N} \quad (12)$$

where $0 \le \gamma^\star_{j,i} \le \lambda_{j,i}$, $\forall j \in \mathcal{J}$, $\forall i \in \mathcal{N}$, are the optimal Lagrange dual variables corresponding to constraints in (4). Given $\{E^\star_{j,i}\}$ in (12), $\{G^\star_{j,i}, C^\star_{j,i}, D^\star_{j,i}\}$ are solutions to the following linear programming problem that can be solved by existing softwares such as CVX [13].

$$\min_{\{G_{j,i}\ge 0\},\{C_{j,i}\ge 0\},\{D_{j,i}\ge 0\}} \sum_{j=1}^{2}\sum_{i=1}^{N} \lambda_{j,i} G_{j,i}$$

$$\text{s.t. } (1),\ \forall j \in \mathcal{J}$$

$$G_{j,i} + \Delta_{j,i} + D_{j,i} - C_{j,i} - t_{j,i} \ge 0,\ \forall j \in \mathcal{J},\ \forall i \in \mathcal{N} \quad (13)$$

where $t_{j,i} = E^\star_{j,i} - E^\star_{\bar{j},i} + \beta E^{\star\,2}_{\bar{j},i}$.

From (12), it follows that given any $(\gamma^\star_{j,i}, \gamma^\star_{\bar{j},i})$, $E^\star_{j,i}$ and $E^\star_{\bar{j},i}$ cannot be non-zero simultaneously and thus (3) always holds.

Main differences between the partially cooperative and fully cooperative energy management schemes are highlighted as follows:

• The optimal solution in Proposition 4.1 resulted from the fully cooperative energy management can be only achieved when the central controller has access to all the required information from both microgrids. In this case, each microgrid feeds back its information (including its net energy profile, the available energy in its energy storage system, etc.) to the central controller. This is in contrast to Algorithm 1, proposed for the partially cooperative energy management, which only requires to exchange $2N$ scalars (i.e., the partial-left and partial-right derivatives of $F_j(\boldsymbol{e})$ with respect to $E_{j,i}$, $\forall j \in \mathcal{J}$, $\forall i \in \mathcal{N}$) between microgrids and the central controller. Therefore, Algorithm 1 preserves the privacy of microgrids.

• Algorithm 1 minimizes energy costs of the two microgrids simultaneously based on the gradients of two convex cost functions (see (11) in (F1)), which differs from the conventional gradient descent method in convex optimization which minimizes a single convex objective [11]. In contrast, in (P2), one microgrid may incur a higher energy cost compared to the case of no energy cooperation, although the total energy cost of the two microgrids is reduced.

5. SIMULATION RESULTS

In this section, we provide simulation results to evaluate the performance of the proposed algorithms for microgrids' partially versus fully cooperative energy management. We consider two microgrids located in Tucson, Arizona, United States [1].[4] Microgrid 1 and microgrid 2 own 70 and 80 Vestas V90 wind turbines, respectively, where each turbine has the rated output of 3 MW. We model $\{\Delta_{j,i}\}$ as the aggregate hourly predicted wind energy generations of all wind turbines in microgrid j over 12 hours (from 12 PM to 11 PM, 5 August 2006) offset by its load that is set as 25 MW and 7 MW for microgrid 1 and microgrid 2, respectively. Parameters of the energy storage systems in microgrids are set as $\alpha^c_j = 0.7$, $\alpha^d_j = 0.8$, $S_{j,1} = 0$, $S^{\min}_j = 0$, and $S^{\max}_j = 10$ MW, $\forall j \in \mathcal{J}$. We consider the type of transmission line connecting the two microgrids as Peacock [14] with $R = 0.0945$ Ω/MW. Given $d = 45$ Km and $V = 33$ KV, we have $\beta = 0.0039$ (MW)$^{-1}$. Last, we set $\lambda_{j,i} = 89.85$ \$/MW, $\forall j \in \mathcal{J}, \forall i \in \mathcal{N}$ [15].

[4] We assume that microgrid 1 comprises of wind generators with site IDs: 151, 161, 162, 163, 170, 171, 189, and microgrid 2 with site IDs: 152, 172, 181, 190, 200, 216, 219, 220 [1].

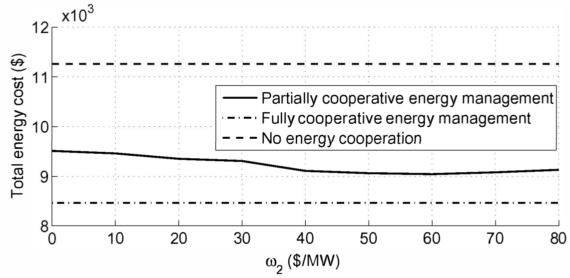

Fig. 1: Total energy cost of the two microgrids versus ω_2.

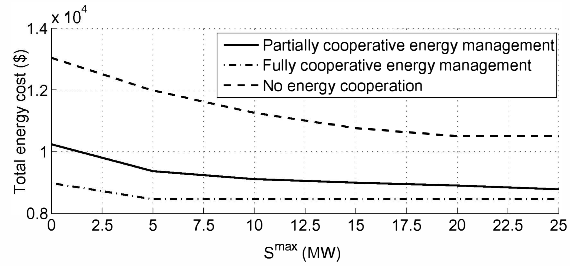

Fig. 2: Total energy cost of the two microgrids versus $S^{\max}$.

By setting $\omega_{1,i} = 40$ \$/MW and $\omega_{2,i} = \omega_2$, $\forall i \in \mathcal{N}$, we plot the total energy cost of the two microgrids over ω_2 in Fig. 1. It is observed that the total energy cost of microgrids resulting from the fully cooperative energy management is the lowest, since both share all their information with the central controller and the total energy cost is minimized. The obtained results also show that with only limited information sharing, the total energy cost of the two self-interested microgrids can be remarkably reduced as compared to the case of no energy cooperation, while it also performs close to the lower bound derived from the fully cooperative energy management.

Next, we set $\omega_2 = 40$ \$/MW and $S^{\max}_j = S^{\max}$, $\forall j \in \mathcal{J}$. Fig. 2 shows the total energy cost of microgrids over $S^{\max}$. For small values of $S^{\max}$, the difference among the total energy cost of microgrids resulting from partially/fully energy management and the case of no energy cooperation is large, while the difference decreases with increasing $S^{\max}$. This is because when $S^{\max}$ is small, any energy deficit is mainly satisfied by drawing energy from the other microgrid and/or the main grid. Therefore, energy cooperation saves the total energy cost significantly as it reduces the purchase of more expensive energy from the main grid. However, as $S^{\max}$ becomes large, each microgrid can rely more on its own energy storage system to deal with energy deficit and thus the energy exchange between microgrids becomes less effective. It is also observed that the difference in total energy costs between the partially and fully energy management is small and does not vary much with $S^{\max}$. This shows that energy cooperation can greatly reduce the need for large energy storage systems.

6. CONCLUSION

In this paper, we study the energy management problem for two self-interested microgrids with energy cooperation. We devise an iterative algorithm by which energy costs of both microgrids can reduce simultaneously while they share only limited information. We then evaluate the performance of the proposed algorithm by simulations based on real system data. Our results show that using the proposed partially cooperative energy management algorithm, both microgrids achieve lower energy costs as compared to the case without energy cooperation and the total energy cost in this case performs close to the lower bound derived from the fully cooperative energy management benchmark.

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