Bargaining-based Energy Trading Market for Interconnected Microgrids

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***Abstract*—This paper studies the energy trading among multiple connected microgrids, and analyzes the impacts of such trading on the microgrids' costs. In our model, microgrids with excessive power generations can trade with other microgrids in deficit of power supplies for mutual benefits. We design a bargaining-based energy trading market, where all the interconnected microgrids cooperatively decide the amount of energy trade and the associated payments. We propose a decentralized algorithm to solve the bargaining problem, with minimum information exchange overhead. Numerical studies based on realistic data demonstrate the effectiveness of the bargaining-based energy trading market design, and show that the reduction of total cost of the interconnected-microgrids system can be up to 22% comparing with the case of no trading.**

I. Introduction

Traditional power systems often generate power in large power stations using fossil fuel resources, and distribute it over long distances. This results in quick depletion of fossil fuel resources, increased environmental pollution, and potentially significant energy losses during distribution. This motivates the study and adoption of microgrids [1], which are small-scale power supply networks that are designed to supply electric power to small communities. A microgrid consists of an interconnected network of several energy sources (including both conventional and renewable ones), and serves the local electricity loads from households and industries. In comparison with the centralized and conventional models of power system, microgrids can enhance the power system reliability, reduce power transmission losses, and integrate distributed renewable sources.

The operation of the microgrid system has been extensively studied (*e.g.* [2]–[8]). One category of studies (*e.g.* [2]–[4]) focused on the power scheduling in a single microgrid to optimize the operational performance. Such studies often neglected the potential interactions between the microgrid and the main grid or other interconnected microgrids. The other category of studies (*e.g.* [5]–[8]) considered the joint operation for multiple microgrids. Fathi *et al.* [5] and Rahbar *et al.* [6] studied the cost minimization problems for networked microgrids under a centralized coordination. Asimakopoulou *et al.* [7] and Zhang *et al.* [8] studied the interactions between a distribution network operator and multiple microgrids under a hierarchical structure. However, the studies in [5]–[8] either assumed that the microgrids are coordinated by a common grid operator, or only focused on the interaction between networked microgrids and the main grid. Different from the traditional power grid operation, in reality autonomous microgrids are often operated by independent microgrid operators, instead of being controlled by a common coordinator [1]. Thus, we need to develop a new operation framework suitable for this decentralized paradigm.

In this paper, we consider an energy trading market among interconnected and autonomous microgrids. All the interconnected microgrids jointly optimize energy trading and power scheduling, by taking the advantages of diverse supply and demand profiles in different microgrids. Specifically, one microgrid may have excess renewable generation, when another microgrid is deficient in power supply from its local power generation at the same time. Users' power consumption patterns in different microgrids can also be significantly different. For example, measurement data show that the residential users consume more power in the night, while the commercial power usage reaches peak during day time [9]. The diverse renewable power outputs and different demand patterns provide ample opportunities for interconnected microgrids to exchange electricity to enhance their operational performance and reduce operating cost. In this paper, we design a Nash bargaining based incentive mechanism for fair and effective energy trading among multiple microgrids.

The main contributions of this paper are listed as follows.

- *Microgrid modeling*: In Section II, we develop a theoretical model of microgrid, which captures key features of smart grid technologies including local renewable generation, energy storage, and demand response.
- *Energy bargaining*: In Section III, we design a bargaining-based energy trading market for interconnected microgrids, where all the interconnected microgrids cooperatively decide the energy trading amounts and the corresponding payments.
- *Decentralized solution method*: In Section IV, for the purpose of practical implementation, we design a distributed algorithm with limited information exchange to solve the bargaining problem.
- *Simulations and implications*: In Section V, numerical studies based on realistic data demonstrate the effectiveness of the bargaining-based energy trading scheme, which can reduce the total cost up to 22% comparing with the case with no energy trading.

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II. Microgrid Modeling

Consider a radial network of M interconnected microgrids $\mathcal{M} = \{1, ..., M\}$, where microgrids are connected to the main power grid. The microgrids are also interconnected with each other through a power transmission infrastructure and a communication network. The system model is illustrated in Fig. 1.

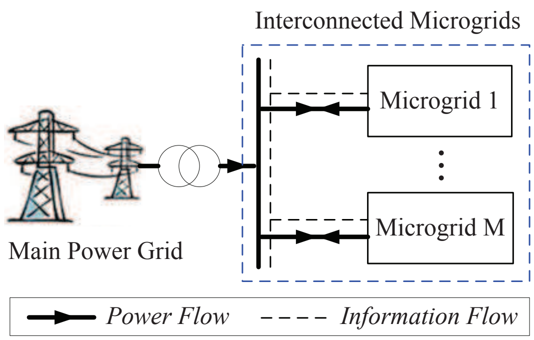

Fig. 1: Interconnected-microgrids system

Before presenting the energy trading model for interconnected microgrids, we first formulate the model for a single microgrid, depicted in Fig. 2. Each microgrid $i \in \mathcal{M}$ contains the following components: local renewable generation, energy storage, and demand responsive users. The local power demand can be served by the local generation and storage discharging, as well as by using power purchased from the main power grid. The microgrid operator is responsible for the power scheduling in the microgrid, and for its energy trading with the main grid and other interconnected microgrids. The operation horizon for the microgrid is one day, which is divided into $T = 24$ time slots (hours), denoted as $\mathcal{T} = \{1, .., T\}$.

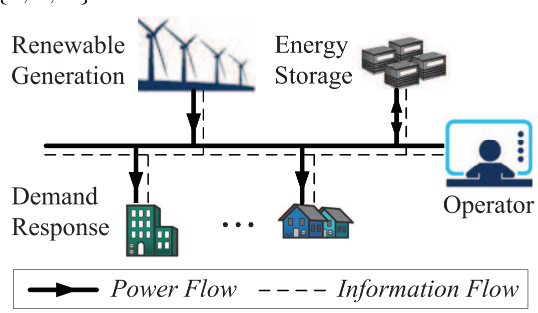

Fig. 2: Microgrid architecture

In the following, we present the detailed formulations for power supply, demand, and energy storage in the microgrid.

A. Power Supply

Power supply in microgrid i can be categorized into local power generation and power drawn from the main grid.

1) Local renewable power generation: There are various types of renewable energy technologies, such as wind, photovoltaic, biomass, and tidal systems. In this paper, we will take the wind energy as a concrete example.[1]

[1]Our theoretic model and analysis are applicable to other renewable sources.

We acquire hourly wind speed data from the Hong Kong Observatory and calculate the corresponding wind power generation based on the model in [11]. Regarding the wind speed, we denote w_{ci} and w_{co} as the cut-in and cut-out wind speed. The wind power will be zero when the speed is less than w_{ci} or above w_{co}. The latter case is due to the protection of wind turbine under a very high wind speed. When the wind speed w_i^t is between w_{ci} and w_{co}, the wind power generation per kW capacity can be calculated as

$$\eta_i^t = \frac{1}{2}\rho C_p A (w_i^t)^3, \ \forall t \in \mathcal{T}, \ \forall i \in \mathcal{M}, \tag{1}$$

where ρ is the density of the air, C_p is a coefficient related to the performance of the wind turbine, and A is the swept area of the turbine blades.

We assume that microgrid i has installed wind turbine generators with a total generation capacity G_i (kW). Based on (1), we have the following constraint for the wind power supply $\boldsymbol{g}_i = \{g_i^t, \ \forall t \in \mathcal{T}\}$:

$$0 \le g_i^t \le \eta_i^t G_i, \ \forall t \in \mathcal{T}, \ \forall i \in \mathcal{M}, \tag{2}$$

where $\eta_i^t G_i$ denotes the maximum available wind power of microgrid i in time slot t.

Different from the conventional power generation, the wind power generation does not consume fuel sources, so for simplicity we will assume a zero generation cost[2].

2) Power drawn from the main grid: When the local wind power generation is not adequate to meet the demand, microgrid i can purchase electricity from the main power grid.[3] Let q_i^t denote the power purchased from the main grid by microgrid i in time slot t. The purchased power cannot be greater than the line capacity, and thus we have

$$0 \le q_i^t \le Q_i^{\max}, \ \forall t \in \mathcal{T}, \ \forall i \in \mathcal{M}, \tag{3}$$

where $Q_i^{\max}$ denotes the line capacity between microgrid i and the main grid.

Let p^t denote the electricity price set by the main grid in time slot t, and let $\boldsymbol{q}_i = \{q_i^t, \ \forall t \in \mathcal{T}\}$ denote power purchased by microgrid i over T time slots. Microgrid i pays time-of-use rate, and the total energy cost of microgrid i in an operation horizon is

$$C_i(\boldsymbol{q}_i) = \sum_{t \in \mathcal{T}} p^t q_i^t, \ \forall i \in \mathcal{M}. \tag{4}$$

B. Power Demand

Let $\mathcal{N}_i$ denote the set of users in microgrid $i \in \mathcal{M}$. We classify the loads of each user $n \in \mathcal{N}_i$ into two categories: inelastic loads and elastic loads.

The inelastic loads, such as refrigerator and illumination demands, cannot be easily shifted over time. We let b_i^t denote

[2]To be more precise, we assume that there is a positive fixed cost for the wind power generation, while the marginal generation cost is zero. The fixed cost is a sunk cost and does not affect the later calculation, and hence is normalized to 0 in the analysis.

[3]For reliability considerations, we assume that microgrids can purchase power from the main grid, but cannot sell power back to the main grid.

the aggregate inelastic load of all the users in microgrid i and time slot t, and denote $\boldsymbol{b}_i = \{b_i^t,\ \forall t \in \mathcal{T}\}$. The elastic loads, such as electric vehicle and washer demands, can be flexibly scheduled over time. For user $n \in \mathcal{N}_i$ in microgrid i, the elastic load is denoted as $\boldsymbol{x}_n = \{x_n^t,\ \forall t \in \mathcal{T}\}$, where x_n^t is user n's elastic power consumption in time slot t.

The demand response program can only control the elastic loads, subject to the following constraints:

$$\sum_{t\in\mathcal{T}} x_n^t = D_n,\ \forall n \in \mathcal{N}_i,\ \forall i \in \mathcal{M}, \tag{5}$$

$$d_n^{t,\min} \leq x_n^t \leq d_n^{t,\max},\ \forall t \in \mathcal{T},\ \forall n \in \mathcal{N}_i,\ \forall i \in \mathcal{M}, \tag{6}$$

where constraint (5) corresponds to the prescribed total energy requirement D_n in the entire operation horizon. Constraint (6) provides a lower bound $d_n^{t,\min}$ and an upper bound $d_n^{t,\max}$ for the power consumption of user n in each time slot t.

Elastic power consumption of user n can be scheduled across time as long as the power consumption satisfies the constraints (5) and (6). However, how the power load is scheduled may affect user's comfort. Let $\boldsymbol{y}_n = \{y_n^t,\ \forall t \in \mathcal{T}\}$ denote the most preferred power consumption of user n. When the actual power consumption $\boldsymbol{x}_n$ deviates from the preferred power consumption $\boldsymbol{y}_n$, user n will experience some discomfort. Similar as the discomfort measure in [12], we define the discomfort cost of user n as

$$C_n(\boldsymbol{x}_n) = \beta_n \sum_{t\in\mathcal{T}} \left| x_n^t - y_n^t \right|, \tag{7}$$

where $|x_n^t - y_n^t|$ measures how much the actual power consumption differs from the preferred power consumption. The coefficient β_n indicates the sensitivity of user n towards the power consumption deviation.

C. Energy Storage

Energy storage (such as batteries) can smooth out the intermittent wind power generation, flatten the power load (by charging when the load is low and discharging during peak load times), and exploit time-varying electricity prices for arbitrage. We assume that microgrid i has installed energy storage devices with a total capacity $S_i^{\max}$, and let s_i^t, $r_{c,i}^t$, and $r_{d,i}^t$ denote the amount of electricity stored, charged, and discharged in time slot t, respectively.

First, the charging and discharging power levels in each time slot t are bounded, and satisfy the following constraints:

$$0 \leq r_{c,i}^t \leq r_{c,i}^{\max},\ \forall t \in \mathcal{T},\ \forall i \in \mathcal{M}, \tag{8}$$

$$0 \leq r_{d,i}^t \leq r_{d,i}^{\max},\ \forall t \in \mathcal{T},\ \forall i \in \mathcal{M}, \tag{9}$$

where $r_{c,i}^{\max} > 0$ and $r_{d,i}^{\max} > 0$ denote the maximum charging and discharging rates, respectively.

Second, there are power losses when electricity is charged into and discharged from the battery. We denote $\eta_{c,i} \in (0,1]$ and $\eta_{d,i} \in (0,1]$ as the conversion efficiencies of charging and discharging. Therefore, we obtain the energy storage dynamics of microgrid i in time slot t as

$$s_i^t = s_i^{t-1} + \eta_{c,i} r_{c,i}^t - \frac{r_{d,i}^t}{\eta_{d,i}},\ \forall t \in \mathcal{T},\ \forall i \in \mathcal{M}. \tag{10}$$

Third, the stored energy should be non-negative and no greater than the battery capacity $S_i^{\max}$, and thus satisfies the following constraint:

$$0 \leq s_i^t \leq S_i^{\max},\ \forall t \in \mathcal{T},\ \forall i \in \mathcal{M}. \tag{11}$$

Last, repeated charging and discharging cause ageing of the energy storage devices. Usually, the life-time of energy storage is characterized by the number of charging/discharging cycles that an energy storage drive can sustain. Therefore, we let c_s denote the unit cost of charging and discharging, and model the cost of energy storage operation [13] as

$$C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) = c_s \left(\sum_{t\in\mathcal{T}} r_{c,i}^t + \sum_{t\in\mathcal{T}} r_{d,i}^t \right), \tag{12}$$

where $\boldsymbol{r}_{c,i} = \{r_{c,i}^t,\ \forall t \in \mathcal{T}\}$ and $\boldsymbol{r}_{d,i} = \{r_{d,i}^t,\ \forall t \in \mathcal{T}\}$ denote the charging and discharging amount over the operation horizon $\mathcal{T}$ in microgrid i, respectively.

D. Single microgrid's Cost Minimization Problem

The microgrid operator coordinates the power supply, energy storage charging, discharging, and elastic load scheduling. First of all, it is essential to keep the power supply and demand balanced, and thus we have the following constraint:

$$g_i^t + q_i^t + r_{d,i}^t = r_{c,i}^t + b_i^t + \sum_{n\in\mathcal{N}_i} x_n^t,\ \forall t \in \mathcal{T},\ \forall i \in \mathcal{M}, \tag{13}$$

where the left-hand side represents the total power supply in time slot t, including the wind power generation g_i^t, power drawn from the main grid q_i^t, and power discharged from the battery $r_{d,i}^t$. The right-hand side represents the total power demand in time slot t, including power charged into the battery $r_{c,i}^t$, aggregate inelastic load b_i^t, and aggregate elastic load $\sum_{n\in\mathcal{N}_i} x_n^t$ from all the users.

We assume that the microgrid operator owns both renewable energy generators and energy storage facilities, and can schedule the elastic loads through demand response programs. The objective of each microgrid operator is to minimize its total operating cost, including the costs of purchasing main grid power, energy storage operation, and users' discomfort costs. Therefore, we formulate the microgrid operator's operating cost minimization problem as

Cost minimization problem for microgrid i (P-MG$_i$)

$$\begin{aligned} \min_{\boldsymbol{g}_i, \boldsymbol{q}_i, \boldsymbol{x}_n, \boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}} \quad & C_i(\boldsymbol{q}_i) + \sum_{n\in\mathcal{N}_i} C_n(\boldsymbol{x}_n) + C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) \\ \text{subject to} \quad & (2), (3), (5), (6), (8) - (11) \text{ and } (13). \end{aligned}$$

We can verify that the objective function and constraints of problem **P-MG**$_i$ are affine. Therefore, problem **P-MG**$_i$ is a linear programming problem that can be efficiently solved by the simplex method or interior point method [14]. We let u_i^* denote the optimal value of the objective function in problem **P-MG**$_i$, which indicates the minimum cost that microgrid i can achieve without trading energy with other microgrids.

III. Interconnected-Microgrids Interactions

After formulating the cost minimizing problem for one single microgrid, we model the energy trading interaction among interconnected microgrids. Microgrids in different locations have different renewable generations and local load profiles. Through trading energy with each other, interconnected microgrids can exploit the diversities of supply and demand patterns, and improve their operational performance. In this section, we aim at designing an effective energy trading mechanism for interconnected microgrids.

We assume that microgrids own their local generation and energy storage facilities, and are operated in a decentralized manner. In other words, microgrids are independent players, such that each microgrid interacts with other microgrids to optimize its own performance. We will study the microgrid interactions based on the Nash bargaining theory, which is a cooperative game theoretical framework that helps distributed decision makers achieve fair and Pareto optimal benefit sharing [15].

Each microgrid $i \in \mathcal{M}$ bargains with other interconnected microgrids to determine the amount of energy trading $\boldsymbol{e}_i = \{e_{i,j}^t,\ \forall t \in \mathcal{T},\ \forall j \in \mathcal{M}\backslash i\}$ and the associated payment $\boldsymbol{\pi}_i = \{\pi_{i,j},\ \forall j \in \mathcal{M}\backslash i\}$. Specifically, $e_{i,j}^t$ denotes the amount of energy that microgrid i exchanges with microgrid j in time slot t, and $\pi_{i,j}$ denotes the associated payment for energy trading between microgrid i and microgrid j. If microgrid i purchases energy from microgrid j in time slot t, then $e_{i,j}^t > 0$; otherwise, microgrid i sells energy to microgrid j and $e_{i,j}^t < 0$. Similarly, if microgrid i makes payment to microgrid j, then $\pi_{i,j} > 0$; otherwise microgrid i receives payment from microgrid j and $\pi_{i,j} < 0$.

The energy trading and payments among microgrids should satisfy the market clearing constraints:

$$e_{i,j}^t + e_{j,i}^t = 0,\ \forall t \in \mathcal{T},\ \forall i,j \in \mathcal{M}, \tag{14}$$

$$\pi_{i,j} + \pi_{j,i} = 0,\ \forall i,j \in \mathcal{M}. \tag{15}$$

Different from the single microgrid operation, in the interconnected-microgrids system, microgrids not only coordinate their local energy supplies and demands, but also conduct energy trading with each other. This leads to the following new power balance constraint:

$$g_i^t + q_i^t + r_{d,i}^t + \sum_{j \in \mathcal{M}\backslash i} e_{i,j}^t = r_{c,i}^t + b_i^t + \sum_{n \in \mathcal{N}_i} x_n^t, \quad \forall t \in \mathcal{T},\ \forall i \in \mathcal{M}, \tag{16}$$

where $\sum_{j\in\mathcal{M}\backslash i} e_{i,j}^t$ is the net energy traded between microgrid i and all the other microgrids in time slot t.

Though the interconnected microgrids cooperate and trade energy with each other, they are still selfish entities. In other words, each microgrid aims to optimize it own performance, in terms of minimizing its operating cost through energy trading. Compared with the cost function of microgrid i in Problem **P-MG**$_i$, an interconnected microgrid has an extra cost, which equals to the payment to other microgrids. Let $C_e(\boldsymbol{\pi}_i) = \sum_{j\in\mathcal{M}\backslash i} \pi_{i,j}$ denote the net payment that microgrid i gives to all the other microgrids over the operation horizon. In Section II, we formulated the cost minimization problem for a microgrid, which does not interconnect and trade energy with other microgrids. However, in the interconnected-microgrids system, each selfish microgrid expects to benefit from energy trading. This means that

$$C_i(\boldsymbol{q}_i) + \sum_{n\in\mathcal{N}_i} C_n(\boldsymbol{x}_n) + C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) + C_e(\boldsymbol{\pi}_i) \le u_i^*, \quad \forall i \in \mathcal{M}, \tag{17}$$

where the left-hand side of the inequality equals to the total cost of microgrid i when participating in the energy trading. The right-hand side u_i^* denotes the minimized cost of microgrid i when it does not trade energy with other microgrids.

Applying Nash bargaining theory [15], we formulate the energy trading problem among interconnected as

Nash bargaining problem for energy trading (NBP)

$$\begin{aligned} \max \quad & \prod_{i\in\mathcal{M}} \Big[u_i^* - \Big(C_i(\boldsymbol{q}_i) + \sum_{n\in\mathcal{N}_i} C_n(\boldsymbol{x}_n) \\ & \qquad + C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) + C_e(\boldsymbol{\pi}_i)\Big)\Big] \\ \text{subject to} \quad & (2),(3),(5),(6),(8)-(11) \text{ and } (14)-(17), \\ \text{Variables:} \quad & \{\boldsymbol{g}_i, \boldsymbol{q}_i, \boldsymbol{x}_n, \boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}, \boldsymbol{e}_i, \boldsymbol{\pi}_i,\ i \in \mathcal{M}\}, \end{aligned}$$

where the objective of Problem **NBP** is the product of performance improvements of all the microgrids through energy trading.

Problem **NBP** can be solved centrally if a centralized optimization entity is available. However, this may not be feasible in practice, as each microgrid is an independent entity, and thus may not be directly controlled by some common power grid operator. Therefore, we will design a decentralized algorithm to solve Problem **NBP** in Section IV.

IV. Solution Method

In this section, we design a decentralized solution method, which enables autonomous microgrids to coordinate with each other to solve Problem **NBP**.

First, by taking the logarithm of the objective function, we transform Problem **NBP** into an equivalent problem as

Equivalent problem of NBP (EP)

$$\begin{aligned} \max \quad & \sum_{i\in\mathcal{M}} \ln \Big[u_i^* - \Big(C_i(\boldsymbol{q}_i) + \sum_{n\in\mathcal{N}_i} C_n(\boldsymbol{x}_n) \\ & \qquad + C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) + C_e(\boldsymbol{\pi}_i)\Big)\Big] \\ \text{subject to} \quad & (2),(3),(5),(6),(8)-(11) \text{ and } (14)-(17), \\ \text{Variables:} \quad & \{\boldsymbol{g}_i, \boldsymbol{q}_i, \boldsymbol{x}_n, \boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}, \boldsymbol{e}_i, \boldsymbol{\pi}_i,\ i \in \mathcal{M}\}. \end{aligned}$$

We notice that Problem **EP** is not in a separable form, because it contains coupling constraints (14) and (15). Therefore, we apply dual decomposition [14] to deal with the coupling constraints and design a decentralized solution method.

We write the partial Lagrangian function of Problem **EP** as

$$
\begin{aligned}
&L(\boldsymbol{g}_i, \boldsymbol{q}_i, \boldsymbol{x}_n, \boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}, \boldsymbol{e}_i, \boldsymbol{\pi}_i, \boldsymbol{\lambda}, \boldsymbol{\gamma}) \\
&= \sum_{i \in \mathcal{M}} \Bigg\{ \ln \bigg[u_i^* - \Big(C_i(\boldsymbol{q}_i) + \sum_{n \in \mathcal{N}_i} C_n(\boldsymbol{x}_n) \\
&\quad + C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) + C_e(\boldsymbol{\pi}_i) \Big) \bigg] \\
&\quad + \sum_{j \in \mathcal{M} \setminus i} \sum_{t \in \mathcal{T}} \lambda_{i,j}^t \left(e_{i,j}^t + e_{j,i}^t \right) \\
&\quad + \sum_{j \in \mathcal{M} \setminus i} \gamma_{i,j} \left(\pi_{i,j} + \pi_{j,i} \right) \Bigg\},
\end{aligned}
$$

where $\boldsymbol{\lambda} = \{\lambda_{i,j}^t, \forall t \in \mathcal{T}, \forall i, j \in \mathcal{M}\}$ and $\boldsymbol{\gamma} = \{\gamma_{i,j}, \forall i, j \in \mathcal{M}\}$ are dual variables associated with coupling constraints (14) and (15).

Moreover, the Lagrangian is a separable function with respect to the decision variables of each microgrid i. We can write the dual problem of **EP** as

$$
\min_{\boldsymbol{\lambda}, \boldsymbol{\gamma}} \quad \sum_{i \in \mathcal{M}} g_i(\boldsymbol{\lambda}, \boldsymbol{\gamma}),
$$

where $g_i(\boldsymbol{\lambda}, \boldsymbol{\gamma})$ is obtained by solving the corresponding subproblem:

Local optimization problem for microgrid i (LOP-MG$_i$)

$$
\begin{aligned}
\max \quad & \ln \bigg[u_i^* - \Big(C_i(\boldsymbol{q}_i) + \sum_{n \in \mathcal{N}_i} C_n(\boldsymbol{x}_n) + C_s(\boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}) \\
& + C_e(\boldsymbol{\pi}_i) \Big) \bigg] + \sum_{j \in \mathcal{M} \setminus i} \sum_{t \in \mathcal{T}} \lambda_{i,j}^t e_{i,j}^t + \sum_{j \in \mathcal{M} \setminus i} \gamma_{i,j} \pi_{i,j} \\
\text{subject to} \quad & (2), (3), (5), (6), (8) - (11), (16), (17), \\
\text{Variables:} \quad & \boldsymbol{g}_i, \boldsymbol{q}_i, \boldsymbol{x}_n, \boldsymbol{r}_{c,i}, \boldsymbol{r}_{d,i}, \boldsymbol{e}_i, \boldsymbol{\pi}_i.
\end{aligned}
$$

We verify that **EP** is a convex optimization problem, and thus the duality gap between Problem **EP** and its dual problem is zero. We can solve Problem **EP** by solving its dual problem. Then we design a distributed algorithm to solve **EP**, based on a two-level separation. The lower level problem is to solve each local optimization problem **LOP-MG**$_i$ based on fixed dual variables. The upper level problem is to solve the dual problem using the subgradient method, and update the dual variables using the results from the low level problems **LOP-MG**$_i$. The distributed algorithm is given as follows.

We use a diminishing stepsize (*i.e.* $\mu(k) = \frac{\mu_0}{k}$, where $\mu_0 > 0$ is a constant), such that **Algorithm 1** is guaranteed to converge to the optimal solution [17]. The decentralized energy trading algorithm only requires limited information exchange among microgrids. For each pair of microgrids in bargaining, say microgrid i and microgrid j, they only need to exchange the information on the dual variables $\lambda_{i,j}^t$, $\gamma_{i,j}$. As for the local power supply, demand scheduling, and energy storage charging/discharging, each microgrid will make its own optimal decision, and won't share with other microgrids. Therefore, **Algorithm 1** solves the energy trading problem **EP** with minimum information exchange without releasing microgrid's private power schedules.

Algorithm 1 Decentralized energy trading algorithm

Initialization: iteration index $k = 0$, error tolerance $\epsilon > 0$, stepsize $\mu(k) > 0$, and initial multipliers $\boldsymbol{\lambda}(0)$ and $\boldsymbol{\gamma}(0)$.
repeat
  At k-th iteration, microgrid i solves Problem **LOP-MG**$_i$ based on the present value of dual variables $\boldsymbol{\lambda}(k)$ and $\boldsymbol{\gamma}(k)$.
  Microgrid i updates $\boldsymbol{\lambda}(k)$ and $\boldsymbol{\gamma}(k)$ according to the following rules:

$$
\begin{aligned}
&\lambda_{i,j}^t(k+1) = \lambda_{i,j}^t(k) - \mu(k) \left(e_{i,j}^t(k) + e_{j,i}^t(k) \right), \\
&\gamma_{i,j}(k+1) = \gamma_{i,j}(k) - \mu(k) \left(\pi_{i,j}(k) + \pi_{j,i}(k) \right).
\end{aligned}
$$

  $k = k + 1$;
until terminal conditions are satisfied, i.e. $\parallel \lambda_{i,j}^t(k) - \lambda_{i,j}^t(k-1) \parallel \leq \epsilon$, and $\parallel \gamma_{i,j}(k) - \gamma_{i,j}(k-1) \parallel \leq \epsilon$.
end

V. Simulation Evaluations

As an illustrative example, we consider a distribution network with two interconnected microgrids. To model real renewable generations, we acquire meteorological data from the Hong Kong Observatory. As shown in Fig. 3, we use wind power productions (on July 3, 2013) in Sai Kung and Tate's Cairn of Hong Kong [10] to simulate the local renewable generations in microgrid 1 and microgrid 2, respectively. From Fig. 3, we can see that the wind power in microgrid 1 has a peak at noontime, while wind power in microgrid 2 is often adequate during night time. Therefore, wind power generations in these two microgrids have a complementary relation on the chosen day. The electricity price of the main power grid is retrieved from ISO New England [16] and is depicted in Fig. 4. We can see that the power grid price has one spike during evening, corresponding to heavy power loads in the entire power grid. Other system parameters are summarized as follows: $\rho = 1.225$, $C_p = 0.593$, $A = 6.15$, $c_s = 0.01$, $Q_i^{\max} = 1000$, $\beta_n = 0.01$, $r_{c,i}^{\max} = r_{d,i}^{\max} = 20$, $S_i^{\max} = 100$, $\eta_{c,i} = \eta_{d,i} = 0.95$, for both $i = 1, 2$.

We consider two typical load profiles: residential load and commercial load, to imitate preferred power load profiles in microgrid 1 and 2 respectively. Fig. 5 and Fig. 6 show the load profiles before and after load scheduling in microgrid 1 and 2.

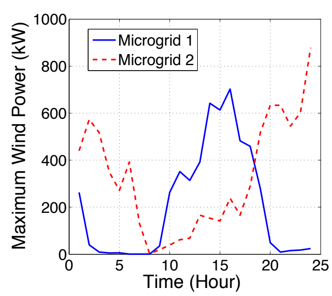

Fig. 3: Wind power in Microgrid 1 & 2

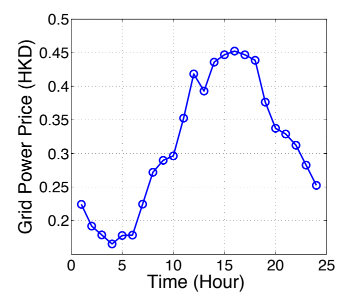

Fig. 4: Power grid price

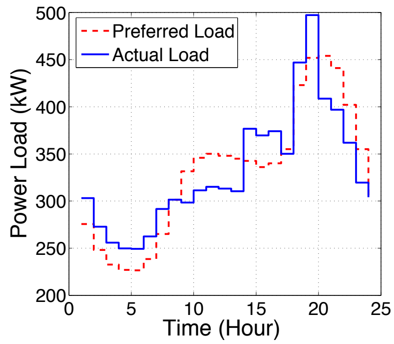

Fig. 5: Load scheduling in Microgrid 1 (Residential Load)

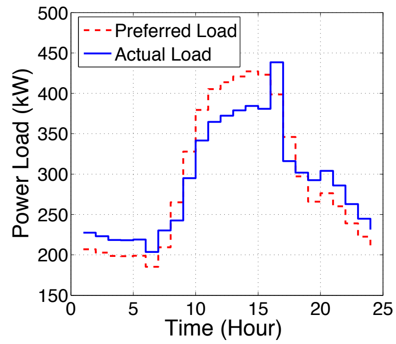

Fig. 6: Load scheduling in Microgrid 2 (Commercial Load)

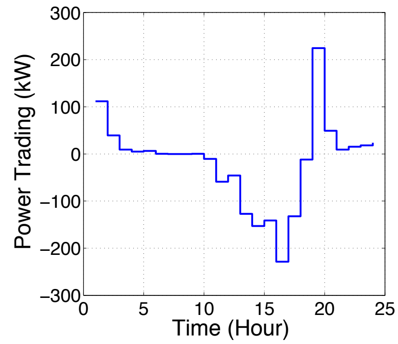

Fig. 7: Power traded between Microgrid 1 & 2

Compare the preferred residential load and commercial load profiles (in dash lines), we see that the residential load peaks appear in the morning and evening; in contrast, the commercial load peaks occur during daytime. After load scheduling, from Fig. 5, we see that some morning and evening power demands in microgrid 1 have been shifted to night time. Similarly, peak power consumption in microgrid 2 has been shifted to low-consumption period (7PM-7AM).

From Fig. 3, 5, and 6, we see that both wind power generations and load profiles in microgrid 1 and 2 reveal different patterns. The difference provides an opportunity for the two interconnected microgrids to bargain with each other. Fig. 7 shows the power acquired by microgrid 1 from microgrid 2. We see that the traded power during hour 10-18 is negative, implying that microgrid 1 sells power to microgrid 2 during this period, because microgrid 1 has surplus of wind power production. Microgrid 1 purchases power from microgrid 2 during other time slots, especially during night time, because microgrid 2 has adequate wind power generation (more than its own local demand) in the night. Through energy trading, both microgrid 1 and microgrid 2 purchase less power from the main grid, and improve the utilization of local renewable energy, such that the total cost of the interconnected microgrids is reduced by up to 22%.

Table 1 shows the operating costs of microgrids 1 and 2 and their payments for energy trading. It is clear that trading reduces the operating costs of both microgrids. Microgrid 2 gains more benefit than microgrid 1, hence microgrid 2 pays microgrid 1 during the energy trading.

TABLE I: Costs and payments

Merits	Microgrid 1	Microgrid 2
Cost (no trading)	985.3	896.7
Cost (with energy trading)	943.2	530.1
Payment (for energy trading)	-162.3	162.3

VI. Conclusion

In this paper, we designed a bargaining-based energy trading market to incentivize interactions among interconnected microgrids, and proposed a decentralized algorithm to compute the trading result in practice. Numerical simulations demonstrated the effectiveness of the energy trading mechanism. Through energy trading, interconnected microgrids can significant reduce their costs comparing with the case where they do not trade with each other.

References

[1] F. Katiraei, R. Iravani, N. Hatziargyriou, and A. Dimeas, "Microgrids management," *IEEE Power and Energy Magazine*, 6(3): 54-65, 2008.

[2] A.G. Tsikalakis and N.D. Hatziargyriou, "Centralized control for optimizing microgrids operation," *IEEE Trans. on Energy Conversion*, 23(1): 241-248, 2008.

[3] Y. Huang, S. Mao, and R.M. Nelms, "Adaptive electricity scheduling in microgrids," in *Proc. of IEEE INFOCOM*, 2013.

[4] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Trans. on Smart Grid*, 5(4): 1876-1883, 2014.

[5] M. Fathi and H. Bevrani, "Statistical cooperative power dispatching in interconnected microgrids," *IEEE Trans. on Sustainable Energy*, 4(3): 586-593, 2013.

[6] K. Rahbar, C.C. Chai, and R. Zhang, "Real-time energy management for cooperative microgrids with renewable energy integration," in *Proc. of IEEE SmartGridComm*, 2014.

[7] G.E. Asimakopoulou, A.L. Dimeas, and N.D. Hatziargyriou, "Leader-follower strategies for energy management of multi-microgrids," *IEEE Trans. on Smart Grid*, 4(4): 1909-1916, 2013.

[8] L. Zhang, Z. Li, and C. Wu, "Randomized auction design for electricity markets between grids and microgrids," in *Proc. of ACM SIGMETRICS*, 2014.

[9] https://www.sce.com/wps/portal/home/regulatory/load-profiles

[10] Summary of Wind and Solar Meteorological Data in Hong Kong, http://jianwei.ie.cuhk.edu.hk/energy.html

[11] Y. Li, V.G. Agelidis, and Y. Shrivastava, "Wind-solar resource complementarity and its combined correlation with electricity load demand," in *Proc. of IEEE ICIEA*, 2009.

[12] L. Jiang and S.H. Low, "Multi-period optimal energy procurement and demand response in smart grid with uncertain supply," in *Proc. of IEEE CDC*, 2011.

[13] R. Urgaonkar, B. Urgaonkar, M.J. Neely, and A. Sivasubramanian, "Optimal power cost management using stored energy in data centers," in *Proc. of ACM SIGMETRICS*, 2011.

[14] S. Boyd and L. Vandenberghe, "Convex optimization," Cambridge University Press, 2004.

[15] M.J. Osborne and A. Rubinstein, "Bargaining and markets," Academic Press, 1990.

[16] http://www.iso-ne.com

[17] S. Boyd, L. Xiao, A. Mutapcic, and J. Mattingley, "Notes on decomposition methods," 2008.