On Stochastic Optimal Bidding Strategy for Microgrids

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***Abstract*—In this paper, we addressed the issue of a stochastic optimal bidding problem for a system with microgrids (MGs). The optimal bidding problem is formulated as a two-stage stochastic programming process, which aims to minimize the system operation cost and to expand energy interactions among local MGs that are geographically close. Uncertainties come from both energy supply and demand sides (e.g., wind, solar, and load demand) are considered in the stochastic model and random parameters to represent those uncertainties are captured by using the Monte Carlo method. To enable an optimal electricity trading between local MGs, we presented two bidding schemes: (i) Cournot equilibrium based Dynamic Backtrack Energy Trading (DBET), and (ii) double auction based Dual Decomposition Auction (DDA). Experimental results on an IEEE-33 bus based system with MGs were presented to show the effectiveness of our proposed schemes. Experimental results show that our proposed bidding schemes can reduce the operation cost of the system, while the DDA scheme achieves better performance in terms of system social welfare than the DBET scheme.**

***Keywords*—Microgrids, biding, uncertainties, stochastic programming, double auction.**

I. Introduction

MGs in the smart grid are commonly operated in an island, connected to the utility grid, and are integrated with distributed energy resources, loads and batteries, and other electric components [1]. In a MG, energy resources generated locally in the MG can be used to serve load demands and improve the efficiency of energy delivery by reducing energy distribution losses. Through being connected to the utility grid, as denoted as the grid-connected mode, MGs can sell extra power to the utility grid and buy power from it whenever necessary. The Microgrids Center Controller (MGCC), also acting as an aggregator, aims at minimizing the operation cost of microgrids, while satisfying the market efficiency and the responsibility of individual parties.

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There have been a number of research efforts devoted to address this issue. For example, Parisio and Glielmo in [2] formalized the energy scheduling problem as a linear programming problem in order to minimize the operation cost of the system with MGs. In such a system, variabilities and uncertainties raised by renewable energy resources and load demands make the energy resource management challenging. To deal with this issue, stochastic energy management methods have been developed [3] and bidding strategies for MGs have been studied as well [4].

Nonetheless, existing research efforts on energy resources management in the system with MGs mainly focus on interactions between MGs and the utility grid. Because of the large number of renewable energy resources in MGs, the amount of locally generated energy can be larger than the local demand in MGs. Due to that transmitting power from MGs (which commonly operate in low voltages) to the utility gird (which commonly operates in high voltages) will incur a high transmission cost and line losses. Therefore, it will be more efficient that MGs can trade the surplus energy to both the utility grid and other MGs directly. How to develop techniques to enable the efficient trading between GMs and the utility grid, as well as the trading among local MGs directly remain an opening issue. To address this issue, in this paper we consider that local MGs are operated as an energy supplier when locally generated energy is excess, or local MGs are operated as an energy consumer when the locally generated energy is insufficient. We proposed a secondary market to enable the trading among MGs and proposed two novel energy bidding schemes to provide an optimal energy trading in the secondary market.

The main contributions of this paper can be summarized as follows:

First, we presented a stochastic model for optimizing the operation of MGs, which considers energy interactions not only between MGs and the utility grid, but also among local MGs. The proposed model aims to minimize the operation cost

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of the system. To address uncertainties from both renewable energy resources and demands, the optimal bidding problem is formalized as a two-stage stochastic programming process, in which uncertainty factors are captured through the Monte-Carlo method.

Second, we proposed to develop a secondary electricity market, in which MGs are treated in the same manner as other market entities. The market will be used when there exists surplus and insufficient MGs simultaneously, and energy trading among geographically closed MGs is allowed. The operation of the secondary electricity market is enabled by the coordination of local agents in MGs and the MGCC.

Third, we presented the following two bidding schemes that enable the efficient energy trading among local MGs: (i) Cournot equilibrium based Dynamic Backtrack Energy Trading (DBET), and (ii) double auction based Dual Decomposition Auction (DDA) mechanisms. In the first scheme, we consider surplus MGs as independent power suppliers so that the schedule of power delivery from surplus MGs to insufficient MGs is based on the distance of power transmission for the sake of energy delivery cost. The clearing price in the secondary market is determined by the Cournot equilibrium. Nonetheless, in this first scheme, insufficient MGs are purely price-takers so that the efficiency of the market is limited. To overcome this limitation, we then proposed an enhanced scheme, which is the double auction based DDA scheme. In this scheme, we took all MGs social welfare into a consideration and proposed a double auction DDA mechanism, in which surplus and insufficient MGs are considered as buyers and sellers, respectively. We formalized the double auction problem as a winner determination problem, which is NP-hard. We then developed an efficient algorithm to solve this problem by decomposing it to a linear programming problem. Our experimental results show that, when our proposed bidding schemes are used, the operation cost of system can be reduced. In addition, the double auction based DDA scheme achieves better performance than the Cournot Equilibrium based DBET scheme in terms of social welfare.

The remainder of this paper is organized as follows. In Section II, we present system models. In Section III, we present our approach, including the basic idea, problem formalization, and our schemes. In Section IV, we give performance evaluation and results. We conduct literature reviews in Section V. Finally, we conclude the paper in Section VI.

II. System Models

In this section, we first describe the multi-microgrids model and then describe the electricity market model.

A. System Model

In this paper, we consider that a smart grid consists of multiple MGs and the MGs operate in a grid-connected mode. In this system, the capacity of selling surplus electricity or buying them from an electricity market is allowed. Figure 1 shows the system model. As we can see, the system is composed of a cluster of MGs, the agents of MGs, and the MGCC. In this system, local MGs consists of several renewable generation units, conventional energy generation units, a number of residential consumers who demand loads, and a battery storage facility. The MG agent is responsible for collecting the energy usage information and interacting with the MGCC. We assume that the electricity can be transported among MGs, especially MGs that are geographically close to each other.

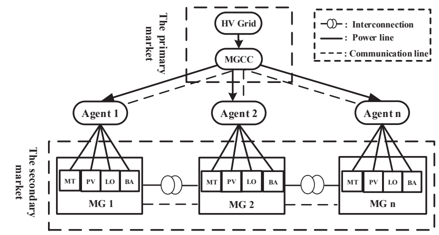

Fig. 1: System Model

Generally speaking, the MGCC tends to minimize the cost of a system with MGs by collecting information such as energy generation and demand of local MGs, and energy delivery among local MGs, between MGs and the utility grid. The MGCC can make decisions on purchasing the electricity from the market or selling the electricity to the market based on status of local units, as well as other factors (e.g., the electricity price, states of conventional units, and the operation cost, etc.).

B. Market Model

The basic electricity market in this paper is a deregulation market. The electricity market is divided into two parts: the primary market and the secondary market. The primary market is assumed to be a price-taker energy market, which consists of energy trading between MGs and the utility grid through the coordination of the MGCC. In this market, trading prices are day-ahead or real-time electricity prices. In each day, agents of local MGs need to forecast demands and the amount of renewable energy resources generated, and then submit hourly bids to the day-ahead market before real-time delivery. Bids from the agent include selling and buying electricity bids, denoted as tuples $\{amount, price\}$.

Recall that MG agents usually provide selling bids at a relatively low price, which is usually far below than the generation cost of local units [5], while offering buying bids at high prices in order to guarantee that bids are always admissible. In addition, because of the low voltage characteristics of MGs, a relatively frequent power transmission to the utility grid will incur line losses, posing an increased operation cost. For this purpose, to guarantee energy interactions among local MGs, we define the secondary market as a supplement of the primary market. We assume that there must exist some MGs that want to purchase power which denoted as insufficient MGs, while others want to sell power which denoted as surplus MGs in a time duration. When are both insufficient MGs and surplus MGs in the system, the secondary market can be used to enable the trading between surplus and insufficient MGs. The trading process can be determined by the MGCC based on our proposed bidding schemes in Section III.

III. Our Approach

In this section, we first present the problem formalization, and then present two new bidding schemes.

A. Problem Formulation

We now present the two-stage stochastic programming problem [6] to minimize the operation cost of the system with MGs. In our two-stage stochastic programming process, the input and output of the problem are parameters, which are used to capture uncertainties and decisions for both the first and second stage. At the beginning, the initial decision on day-ahead energy bids should be made in the first stage. Then, the uncertainty factors are mimicked based on scenarios constructed by the Monte-Carlo method, which affect the outcome of the first-stage decision. Decisions will then be made at the second stage in order to compensate for uncertainties. The optimal decision in the first stage has an objective to identify the amount of optimal power to be purchased or sold, as well as the commitment of distributed energy generation units over the next 24 hours. Decisions in the second stage consists of the power dispatch of all local generating units, the amount of electricity purchased or sold, and decisions for battery charging and discharging.

We now describe the stochastic problem. The objective function is described as follows:

$$\begin{aligned}\min \sum_{N}\sum_{M}\sum_{T} C^G P_{i,t}^k + \sum\sum\sum (SU_{i,t}+SD_{i,t}),\\ +\sum_{s} r_s \sum\sum \{P_{i,t}^{sch} r_{da} + I\,(P_{i,t}^{sch} < P_{i,t}^{D}),\\ \left(P_{i,t}^{B,MGCC} r_{rt} + P_{i,t}^{B,MG} r_B^{MG}\right) - I(P_{i,t}^{sch} > P_{i,t}^{D}),\\ (P_{i,t}^{S,MGCC} r_s^{MGCC} + P_{i,t}^{S,MG} r_s^{MG}),\\ -Cost(battery)\ -\delta_{i,t}\left|P_{i,t}^{D} - P_{i,t}^{sch}\right|\}. \quad (1)\end{aligned}$$

The first and second parts of the objective function 1 corresponds to the startup and shutdown cost, and the generation cost associated with local generators, respectively. The generation cost consists of the cost for both local conventional generators and renewable energy generators. In our model, renewable energy resources are wind and solar. Therefore, corresponding uncertainties are wind speed and ambient temperature, respectively.

The third, fourth, and fifth parts in the objective function 1 are associated with the cost of day-ahead bids, the amount of electricity purchased and sold with the utility grid and among local MGs. Here, $P_{i,t}^{sch}$ is referred to as the amount of energy purchased or sold for day-ahead bids. $I(.)$ is referred to as an indicator function, where positive and negative parts represent the amount of electricity purchased from the utility grid or surplus MGs, and the amount of electricity sold to the utility grid or insufficient MGs, respectively. Here, $Cost_t^{B,MG}$ and $Rev_t^{S,MG}$ are the cost and revenue for the energy trading associated with individual MG.

TABLE I: Notations

$\boldsymbol{\lambda}$:	Lagrangian vector which are price in double auction mechanism
τ:	Termination criterion of iteration
$\delta_{i,t}$:	Penalty factor of deviation between day-ahead bids and real-time delivery
γ_{cha}, γ_{dis}:	Charing/Discharging efficiency of storage battery
ω_{cha}, ω_{dis}:	Cost for battery Charing/Discharging degradation
Δ_T:	Duration of time slot (h)
λ_i:	Generation cost of MG i under Cournot Equilibrium ($/kWh)
π_i:	Profit of MG i under Cournot Equilibrium (/kWh)
ζ_s:	Probability of monte-carlo scenario s
a_i, b_i, ci:	The coefficient of MG i's local units generation cost
$c_{b,i}, c_{s,j}$:	Bids from buyer and seller agents in double auction mechanism
$d_{i,j}$:	Distance matrix of local MGs
$q_{b,i}, q_{s,j}$:	Trading amount from buyer requests and seller offers in double auction mechanism
r_{da}, r_{rt}:	Day-ahead and real-time electricity price in primary market ($/kWh)
r_B^{MG}, r_s^{MG}:	Buying and selling electricity price among MGs ($/kWh)
r_s^{MGCC}:	Price of MG selling to MGCC in secondary market ($/kWh)
$u(b,i), u(s,j)$:	Utility functions of buyer and seller
x_i, y_j:	Binary variables 0,1 which represent winning the bid or not
C^G:	Generation cost of local units ($/kWh)
$CU_{i,t}$, $CD_{i,t}$:	Shutdown/startup offer cost of unit ($)
$E_{i,t}$:	Capacity of battery i at time slot t (kWh)
E_i^{min}, E_i^{max}:	Lower/Upper bound of battery capacity (kWh)
$I(.)$:	Energy status of MG, "1" means surplus and "0" means sufficient
$I(i,t)$:	Status of local units i at time slot t
M, N, K, T, S:	Number of local units, MGs, renewable energy resources, time slots and scenarios
$P_{i,t}^m$:	Power generation of local unit m (kW)
$P_{i,t}^{sch}$, $P_{i,t}^D$:	Scheduled bids and real-time power delivery (kW)
$P_{i,t}^{B,MGCC}$, $P_{i,t}^{B,MG}$:	Purchasing power from MGCC and other MG (kW)
$P_{i,t}^{S,MGCC}$, $P_{i,t}^{S,MG}$:	Selling power to MGCC and other MG (kW)
$P_{i,t}^k$:	Power generation of renewable energy resource k (kW)
$P_{i,t}^{cha}$, $P_{i,t}^{dis}$:	Charging/Discharging power of battery (kW)
P_m^{min}, P_m^{max}:	Minimum/maximum power generation of unit(kW)
P_i^{min}, P_i^{max}:	Maximum power of battery i charging/discharging unit(kW)
P_{grid}^{min}, P_{grid}^{max}:	Lower/Upper bound of MG interaction with main gird (kWh)
$SU_{i,t}^m$, $SD_{i,t}^m$:	Start-up and shutdown cost of unit m ($)
$U(i,t)$:	Status of battery i, "1" if charging/discharging

The last three parts in the objective function 1 are battery charging and discharging costs, the penalty cost for the deviation between day-ahead schedule and real time delivery, and the transmission cost between two local MGs. Here, $\delta_{i,t}$ is referred to as the penalty factor for electricity transactions deviation. Recall that due to aforementioned uncertainties in the system, it is possible to over-commit on the day-ahead schedule. The penalty factor is to reduce the difference between real time electricity delivery and day-ahead scheduling through minimizing over-commitment.

In the optimization problem, we need to consider constraints as well. The first constraint is to balance power. For each MG in the system, the following power balance constraint needs to be satisfied:

$$\sum_m P_{i,t}^m + \sum_k P_{i,t}^k + \sum_j P_{j,t}^{dis} = \sum_j P_{j,t}^{cha} + \sum P_{i,t}^D, \quad (2)$$

$$\begin{aligned} &\sum_m P_t^{B,MGCC} + \sum_m P_t^{B,MG} - (\sum_m P_t^{S,MGCC} + \sum_m P_t^{S,MG}), \\ &= P_{i,t}^D - P_{i,t}^{sch}. \end{aligned} \quad (3)$$

In any time duration, the power balance constraint should be satisfied. This means that the sum of the amount of total power generation from all local generation units and the discharging power from battery units, and the amount of total power sold to the utility grid, and other MGs, must be equal to the sum of the amount of purchased power from the utility grid and other MGs, and amount of battery charged. In Equation (3), the left side is the amount of electricity that MGs trade in the real-time market, which is equal to the difference between day-ahead scheduling and real-time delivery in the right side.

The second constraint is related to conventional unit constraints. The operating cost of conventional unit can be modeled approximately by,

$$C^G P_{i,t} = a_i + b_i P_{i,t} + c_i P_{i,t}^2, \quad (4)$$

where $P_{i,t}$ is output power, a_i, b_i, and c_i are generation cost factors of local conventional generation unit i. The output power generation should also be limited by

$$P_{\min}^m \leq P_{m,t} \leq P_{\max}^m. \quad (5)$$

The third constraint is associated with the start-up cost and shut-down cost, which are listed as follows: $SU_{i,t} \geq CU_{i,t}(I_{i,t} - I_{i,t-1})$; $SU_{i,t} \geq 0$, and $SD_{i,t} \geq CD_{i,t}(I_{i,t-1} - I_{i,t})$; $SD_{i,t} \geq 0$, where I is the indictor function with a value of 0 or 1, CU and CD are the cost for the startup and shutdown of conventional generation unit.

The fourth constraint is related to the capacity of storage in each MG, which should satisfy the following constraint:

$$\begin{aligned} &0 \leq P_{i,t}^{dis} \leq U_{i,t} u_s P_{i,\max}, \\ &0 \leq P_{i,t}^{cha} \leq (1 - U_{i,t}) u_s P_{i,\max}, \\ &E_{i,t+1} = E_{i,t} + \gamma_{cha} P_{i,t}^{cha} \Delta T - \frac{P_{i,t}^{dis} \Delta T}{\gamma_{dis}}, \\ &E_{i,\min} \leq E_{i,t} \leq E_{i,\max}. \end{aligned} \quad (6)$$

For the battery in each MG i, the above constraint considers charging and discharging limit, the battery state, and the upper and lower bounds of battery capacity, respectively. Here, $U_{i,t}$ is an indicator function with a value of 0 or 1, representing the battery is either in charging or discharging state. One purpose of using the charging and discharging state is to ensure that charging and discharging processes are not be performed simultaneously. Also, γ_{cha} and γ_{dis} are referred to as the efficiency of charging and discharging process, respectively.

In the objective function 1, the degradation cost of battery charging and discharging is also denoted as $Cost(battery)$, which can be derived by $Cost(battery) = \gamma_{cha}\omega_{cha} P_{i,t}^{cha} \Delta T - \frac{P_{i,t}^{dis} \Delta T \omega_{dis}}{\gamma_{dis}}$.

At last, the maximum capacity of electricity interactions between MGs and the utility grid cannot exceed the capacity limit of physical transmission line. Then, we have $P_{grid}^{\min} \leq P_{i,t}^D, P_{i,t}^{sch} \leq P_{grid}^{\max}$.

B. Curnot Equilibrium based DBET Scheme

To design an effective electricity interaction among MGs, we introduce the Cournot Equilibrium [7] based DBET scheme in the secondary market. In a time duration, we consider that surplus and insufficient MGs are allowed to participate in the secondary electricity market as second-tier suppliers. The secondary market will be cleared by obtaining the Cournot Equilibrium based on the generation cost of individual MGs. The bidding process belongs to a static game with incomplete information because MGs do not hold the complete information of generation cost of other MGs. Notice that insufficient MGs are only price takers, and electricity purchasing prices are determined by surplus MGs.

We now describe the market clearing process in detail. Assume that there are N surplus MGs in a time duration. Agents of MGs can compute their generation costs based Equation (4). Nonetheless, due to the electricity market competition and imperfect monopoly characteristics, agents will join scaling factor in the cost function on their own, before the offer, to ensure the maximum benefit from the game. Therefore, the generation cost of Equation (4) can be rewritten as, $C_i^{'} = (1 + \lambda_i) \left[a_i (P_i(t))^2 + b_i P_i(t) + d_i \right]$.

Also, the generation cost of MG j can be estimated by MG i by $C_j^{i'} = \left(1 + \lambda_j^i\right) \left[a_i^j \left(P_j^i(t)\right)^2 + b_i^j P_j^i(t) + d_i^j \right]$. Then, the profit π of MG i can be expressed by $\pi_i = \rho P_i(t) - C_i$.

Based on the Cournot equilibrium conditions, we know that if the surplus MGs want to maximize their own profits, the following condition needs to be satisfied: $\frac{\partial \pi_i^{'}}{\partial P_i(t)} = \frac{\partial \pi_j^{(i)'}}{\partial P_j^{(i)}(t)} = 0$.

According to the prediction of power output in each MG, we have $P_L^i = \sum_{j=1}^{n} P_{Gj}^i$.

According to above equations, we can estimate the optimal bidding, which consists of the price and the amount of power for MG i based on estimating the price and the amount of power for other competitors as follows: $P_i(t)_{\text{opt}} =$

$\frac{P_L^{(i)} + \sum_{i=1}^{N-1} \frac{b^j{}_i}{2a^j{}_i} - \frac{(1+\lambda_i)}{(1+\lambda_j^i)} \sum_{i=1}^{N-1} \frac{b_i}{2a^j{}_i}}{1 + \frac{(1+\lambda_i)}{(1+\lambda_j^i)} \sum_{i=1}^{N-1} \frac{b_i}{2a^j{}_i}}$, where $P_i(t)_{\text{opt}}$ is the optimal bidding power of MGi. Correspondingly, the expected amount of bidding power for MG j, which is estimated by MG i, is $P^i_{j\,\text{opt}} = \frac{1+\lambda}{1+\lambda_j^i} \bullet \frac{\rho - b^j{}_i}{2a^j{}_i}$, where $P^i_{j\,\text{opt}}$ is the expected bidding power, and $j = 1, \cdots, N$ are the MGs and electricity companies participated in the bidding process. After that, the MGCC sorts all bidding prices and the largest one is considered as the market clearing price.

After obtaining the clearing price for the secondary market, the amount of energy traded among local MGs needs be determined. To this end, we proposed a Dynamic Backtrack Energy Trading algorithm (DBET). Recall that from the objective function 1, the difference between optimal day-ahead scheduling bids and real-time demand is the amount of energy that MG should purchase or sell. The amount of purchased or sold energy for each MG at a given time duration needs to be derived first. Also, positive and negative values represent energy selling and purchasing actions. Then, in each time duration, the amount of energy traded between surplus MGs and insufficient MGs are determined by the transmission distance between them for the sake of power delivery cost. This means that each surplus MG preferentially transmits the electricity to insufficient MGs, which are geographically close first. This process continues until the energy gap of insufficient MGs is fulfilled or surplus energy in surplus MGs is sold out. Finally, after finishing the trading among local MGs, the remaining energy or the shortage of energy will be either purchased from the utility grid or sold to it, which has a higher voltage than the one in MGs. Algorithm 1 shows the detailed procedure of our proposed DBET algorithm.

Algorithm 1 Dynamic Backtrack Energy Trading (DBET)

Require: $P^{sch}_{i,t}$, $P^D_{i,t}$; Distance Matrix $dis(i,j)$, which is distance between MGs i and j;
Ensure: Energy trading amount among each MG;
initializing the energy matrix $E_{i,t} = P^{sch}_{i,t} - P^D_{i,t}$;
if There exist a time duration t, for a given MG i, $E_{i,t} \geq 0 || E_{i,t} < 0$ **then**
    ALL MGs sell the amount of energy $E_{i,t}$ to the utility grid or buy the same amount of energy from the utility grid; **break**
else
    Set C_{Buy}={Group of MGs purchasing energy $\left| E_{i,t} < 0 \right\}$;
    Set C_{Sell}={Group of MGs selling energy $\left| E_{i,t} \geq 0 \right\}$;
    Set $Sort(dis)$: descending of distance between C_{Buy} and C_{Sell};
    $MGs(m,n)$: MGs corresponds to the minimum one in $Sort(dis)$;
    if $E_{m,t} + E_{n,t} \geq 0$ **then**
        argmin ($E_{m,t}$, $E_{n,t}$)=0; argmax($E_{m,t}$, $E_{n,t}$)=$E_{m,t} + E_{n,t}$;
        trading amount between MG m and n is: $|argmin(E_{m,t}, E_{n,t})|$;
    else
        argmin ($E_{m,t}$, $E_{n,t}$)=$E_{m,t} + E_{n,t}$; argmax($E_{m,t}$, $E_{n,t}$)=0;
        trading amount between MG m and n is: argmax($E_{m,t}$, $E_{n,t}$);
    end if
    return to 2
end if

C. Double Auction DDA Scheme

1) Double Auction Bidding Model: Recall that in the Cournot Equilibrium based DBET scheme, the surplus MGs are oligarch and only their profits are considered. Nonetheless, sufficient MGs in the secondary market are only price-takers and their benefits are ignored. To overcome this limitation and provide a more efficient trading market, we proposed a double auction based DDA scheme. This scheme makes both surplus and insufficient MGs fully participate in the market, where surplus and sufficient MGs are treated as sellers and buyers, respectively. In this scheme, through the agent in each MG, potential buyers submit their bids with amounts and price of energy and sellers submit their requests with amounts and price of electricity to the MGCC. Then, a price will be determined by the MGCC to clear the market. By doing so, the secondary market is bilateral and competitive, where utilities (i.e., social welfare) [8] of all MGs in the system can be maximized.

Considering that in a time duration t, there are p surplus MGs in the system, which are referred to as sellers $\{1, 2, \ldots, p\}$ (denoted as sellers $\{1, 2, \cdots, p\}$) and q insufficient MGs (defined as buyers $1, 2, \ldots, q$). Electricity prices for a buy and a seller in their bids are $c_{b,j}$ and $c_{s,j}$ per unit, while the maximum demand and the available electricity are d_i and s_j, respectively. In this paper, we assume that the amount of excess electricity of all surplus MGs is less than the sum of all the electricity needed by insufficient MGs, and can be sold out in the auction process. This means that the selling amount of electricity is equal to the buying amount of electricity in the double auction strategy. The remaining part of insufficient electricity will be provided by the utility grid through the primary market. Denote c_o^k as the clearing price of double auction mechanism. Then, the utility of the sellers and buyer can be expressed. For a buyer, we have $u_{b,i} = \left(c_{b,i} - c_o^k\right) q_{b,i}$ and and for a seller, we have $u_{s,j} = \left(c_o^k - c_{s,j}\right) q_{s,j}$, where the amount of purchasing and selling electricity from a buyer and to a seller are $q_{b,i}$ and $q_{s,j}$, respectively. Obviously, objectives of buyers and sellers are conicting with each other due to natural selfishness. If both buyers and sellers decide the amount of electricity to purchase or to sell independently, it is very difcult to reach an agreement. Therefore, there is a need for the MGCC to intervene and ensure that the market operates efciently. To this end, as bids and offers are processed in the double auction process, the winner determination problem (WDP), which represents the difference between buyers' payment and sellers' revenue, can be formalized as an integer linear programming (ILP) problem to maximize the social welfare. The objective function of the WDP is formalized as follows:

$$\max: \sum_i x_i c_{b,i} q_{b,i} - \sum_j y_j c_{s,j} q_{s,j}, \tag{7}$$

$$s.t. \sum y_j q_{s,j} - \sum x_i q_{b,i} = 0, \tag{8}$$

$$x_i \in \{0,1\}, \forall i \in [M], \forall t \in [T], \tag{9}$$

$$y_i \in \{0,1\}, \forall j \in [M], \forall t \in [T], \tag{10}$$

where x_i and y_j are binary variables $0, 1$, showing the winning bid of buyer i and seller j. Notice that the first constraint imposes the balance between demand and supply in the double auction process.

2) Dual Decomposition Auction (DDA) Scheme: Recall that as the ILP problem 7 formulated is NP-hard, it is hard to obtain the optimal solution due to the high computation cost when the number of MGs is large. To address this issue, we proposed a multi-agent dual decomposition (DDA) scheme to solve the problem in an efficient way. In this scheme, we rst decompose the ILP problem to a linear programming problem, which can then be solved in a polynomial time by using the sub-gradient algorithm [9]. After that, we introduced the Lagrangian Multiplier to relax the constraint of ILP. The Lagrangian relaxation problem can be formalized as follows:

$$Lp(\lambda) = \max_{\substack{x_i \in \{0,1\} \\ y_i \in \{0,1\}}} L(x, y, \lambda), \tag{11}$$

where $L(x, y, \lambda)$ is the Lagrangian function, and is defined by,

$$\begin{aligned} L(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\lambda}) = \sum_i x_i c_{b,i} q_{b,i} - \sum_j y_j c_{s,j} q_{s,j}, \\ +\boldsymbol{\lambda}(\sum x_i q_{b,i} - \sum y_j q_{s,j}), \end{aligned} \tag{12}$$

where $\boldsymbol{\lambda}$ is the Lagrangian vector, and $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_k)$ represents transaction prices between winning MGs in the double auction process. For a given λ, the original WDP is decomposed into a couple of sellers (i.e., surplus MGs) and buyers (i.e., insufficient MGs) sub-problems, which can be solved by individual MGs' agents independently.

The seller's sub-problems can be presented by

$$\begin{aligned} & L_{s,j}(\lambda) = -\sum y_j c_{s,j} q_{s,j} - \lambda_k \sum y_j q_{s,j}, \\ & s.t. \quad \lambda_k > 0, y_j \in \{0, 1\}, \end{aligned} \tag{13}$$

and the buyer's sub-problems can be represented by

$$\begin{aligned} & L_{b,i}(\lambda) = \sum x_i c_{b,i} q_{b,i} + \lambda_k \sum x_i q_{b,i}, \\ & s.t. \quad \lambda_k > 0, x_i \in \{0, 1\}. \end{aligned} \tag{14}$$

In this way, dual decomposition results in each sub-problem can be solved. For a given λ_k, the optimal solution to above subproblems is

$$\begin{aligned} x^*_{b,i} &= \arg\max L_{b,i}(\lambda_k), \\ y^*_{s,j} &= \arg\max L_{s,j}(\lambda_k). \end{aligned} \tag{15}$$

Also, the Lagrange multipliers can be determined by solving the following master dual problem:

$$\begin{aligned} & Dp = \min Lp(\lambda), \\ & s.t. \;\; \lambda_k > 0. \end{aligned} \tag{16}$$

Notice that this problem is abbreviated as the master problem, and the solution corresponds to the trading price, which can balance demand and supply between buyers and sellers. In order to solve the above dual problem 16, the Lagrange multiplier $\boldsymbol{\lambda}$ can be updated by the sub-gradient mechanism [9]. Therefore, λ_k is updated based on, $\lambda_k^{q+1} = (\lambda_k^q - \sigma^q \frac{\partial L(\cdot)}{\partial \lambda_k}\Big))$, where the positive parameter σ^i is the learning rate of the sub-gradient mechanism. By updating x_i, y_j and price λ_k iteratively, the numerical solution of the dual problem can be obtained. As the solution of the dual problem is also a solution for the primal problem, the WDP is addressed and social welfare of the MGs in the secondary market can be maximized. Algorithm 2 presents the detail procedure of dual decomposition auction (DDA) algorithm.

Algorithm 2 Dual Decomposition Auction Algorithm (DDA)

Require: $P^{sch}_{i,t}$, $P^D_{i,t}$, τ
Ensure: $\boldsymbol{x^*}$, $\boldsymbol{y^*}$, $\boldsymbol{\lambda_k}$

```
q ← 0;
E_{m,t} = P^{sch}_{m,t} − P^D_{m,t}, x_i^0, y_j^0, λ_k^0;
repeat
    Set C_Buyer={Group of MGs buying energy |E_{m,t} < 0};
    Set C_Seller={Group of MGs selling energy |E_{m,t} ≥ 0};
    MGCC broadcasts price λ_k^q, buyers C_Buyer and sellers C_Seller;
    q ← q + 1;
    Each agent in C_Seller obtains optimal y_j^q by solving 13;
    Each agent in C_Buyer obtains optimal x_i^q by solving 14;
    Agents submit y_j^q and x_i^q to MGCC;
    MGCC solves the dual problem 16;
    MGCC updates the dual variable:
    λ_k^{q+1} = ((λ_k^q − σ^q ∂L(·)/∂λ_k))^+;
until The termination criterion is satisfied:
    |L(λ_k^q) − L(λ_k^{q−1})| / L(λ_k^{q−1}) < τ
return The optimal price λ_k^q, transact x_i^q, y_j^q.
```

IV. Performance Evaluation

In our evaluation, we consider a system based on a modified IEEE 33-bus power distribution system [10], which consists of five residential MGs connected. For each MG, we consider residential houses and buildings with different sizes, and local power generators, renewable energy resources and storage batteries are included. In addition, the penalty cost, the efficiency of battery charging and discharging process, the cost of battery charging and discharging in the objective function 1 are set to 0.01, 0.95, 0.9, and 0.03, respectively. The load demand of individual MGs are all based on residential houses loads. All experiments were conducted on a computer with 3.5 GHz Intel Core i7-3770 CPU and 8G RAM.

Recall that the proposed model that considers various uncertainties and bidding among MGs in Section III-A can be formalized as a typical stochastic programming problem. Notice that the generation cost of the local energy generation unit can be formalized based on Equation (4), which is a quadratic function, but it can be approximately as a piecewise linear function [11]. In this way, our stochastic programming problem can be converted to a Mixed-Integer Linear Problems (MILP) [11] and solved by methods implemented in Matlab. Moreover, the uncertainties parameters, including day-ahead and real-time prices, load demand from residential houses, and wind and PV generation capacity should be predicted. For the prediction of electricity demands, our previous work in [12] showed that loads of MG users in a time window follow a Gaussian distribution, and the distribution parameters can be estimated by using statistical methods.

In our simulations, we used the Monte Carlo method to generate 1000 scenarios for each uncertainty parameter, Each

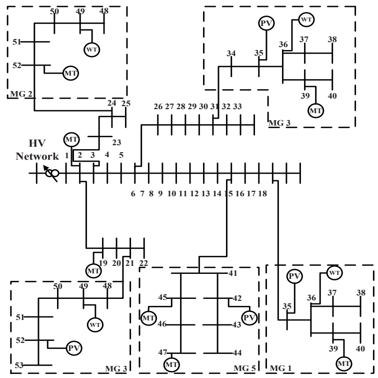

Fig. 2: IEEE-33 bus based test system

scenario contains the hourly load, real-time price, and wind and PV generated capacity. Notice that in practice, a large number of scenarios will lead to the increase of computation time and complexity, while a small number of scenarios generated by the Monte Carlo method will result in the decline of accuracy. To balance computation time and accuracy, we used the fast-forward scenario reduction mechanism [13] to shrink 1000 scenarios to 10 ones.

Figure 3 represents the operation cost of the system with MGs, where the bidding is not used, and the Cournot Equilibrium based DBET scheme and the double auction based DDA scheme are used. We can see that after two bidding schemes for the energy trading among local MGs are in place, the operation cost declines dramatically. Notice that, the operation cost of two bidding schemes are equal. This is because the sum of MGs buying cost and selling revenue from or to each other are equal to zero in the objective function 1. Therefore, to evaluate the effectiveness of two bidding schemes, we introduced the social welfare 7 in Section III-C1 into the third and fourth parts of the reversed objective function 1, as the social welfare (utility) of the system. Figure 4 shows the utility of the system when our proposed bidding schemes are used. From the figure, we can observe that the utility is higher when the double auction based DDA scheme is used. This is because that optimal bids of sellers and buyers sub-problems, which maximize the social welfare, are obtained by agents in each iteration in the DDA scheme, while only the utility of sellers are taken into consideration in the DBET algorithm.

Furthermore, Figure 5 and 6 illustrate the variation of the total cost in the system versus the penalty factor $\delta_{i,t}$ and battery degradation parameter. Figure 5 shows that a higher penalty parameter of the deviation between day-ahead scheduling and real-time delivery will result in a higher total cost for the system. Recall that a higher penalty cost will lead to a smaller deviation between day-ahead bids and real-time delivery of electricity, which poses less agility for the MGCC and agents to carry out energy trading among local MGs. This leads to a higher operation cost. Figure 6 shows that the total cost increases as the battery degradation increases. The reason is that a higher degradation parameter that makes the use of benefits of energy storage in local MGs will not balance out the cost raised by its charging/discharging degradation.

In addition, to evaluate the performance of various parameters in the objective function, we carried out the sensitivity evaluation. Figure 7 illustrates the impact of the deviation penalty parameter $\delta_{i,t}$ on the utility when two bidding schemes are used. The results show that the utility decreases as the penalty increases. This is because as the penalty factor increases, the penalty cost is expected to keep at a small level, making the deviation between day-ahead scheduling bids closer to real-time delivery. Therefore, the energy trading among local MGs in the secondary market will be reduced. In addition, the impact of battery degradation factors on the system utility was also performed. For the sake of simplicity, we assume $\omega_{cha} = \omega_{dis}$. As shown in Figure 8, we observe that the utility decreases as the degradation cost of battery increases. This is because as the degradation parameters increases, the battery "dare not" charging and discharging frequently if we want to keep a low degradation cost. In this way, the flexibility of energy trading among local MGs can be reduced, leading to the reduction of the utility. Both figures also confirm that the DDA scheme achieves a higher utility than the DBET scheme.

V. Related Work

Due to limited space, we only list most relevant of literatures in this section. The energy management in the smart grid system with MGs has attracted growing attention. For example, Chaouachi *et al.* in [14] formalized the intelligent energy management of MGs through artificial intelligence techniques, jointly with the linear programming-based multi-objective optimization. There have been some research efforts on addressing interactions among MGs [15], [16].To address uncertainties in the smart grid, stochastic programming models have been used to manage energy resources in MGs [17], [18]. For example, Yang *et al.* in [17] proposed a stochastic framework, which considers uncertainties of wind power generation and statistical PEV driving patterns. In addition, bidding and auction schemes for MGs in energy markets have been studied [4], [19].

Different from existing research efforts, in this study, we addressed the operation challenge in the system with MGs and proposed two novel bidding schemes. Our proposed scheme can not only tackle various uncertainties in both supply and demand sides, but also consider local MGs as energy supplier and allow efficient energy trading among them to minimize the operation cost and improve the efficiency of energy delivery.

VI. Conclusion

In this paper, we addressed the energy management issue in the system with MGs. Particularly, we first formalized the optimal bidding problem as a two-stage stochastic programming process, which aims to minimize the operation cost and obtain the optimal delivery of electricity, while uncertainties from both supply and demand sides need to be considered. To enable the energy trading among local MGs,

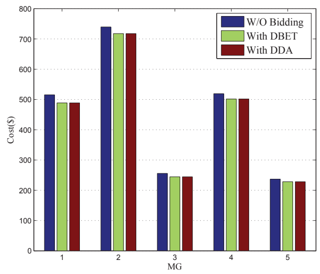

Fig. 3: Operation cost Comparison

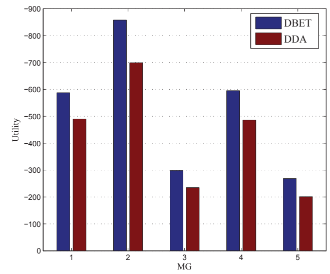

Fig. 4: utility under DBET and DDA

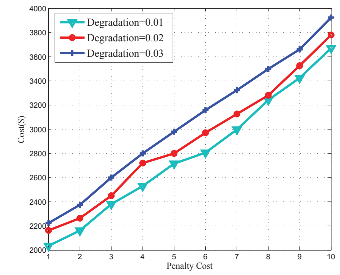

Fig. 5: Operation cost vs. penalty factor

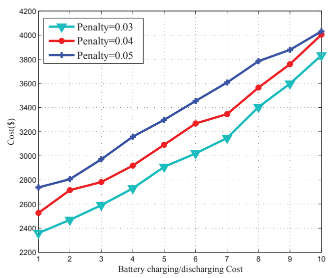

Fig. 6: Cost vs. degradation factor

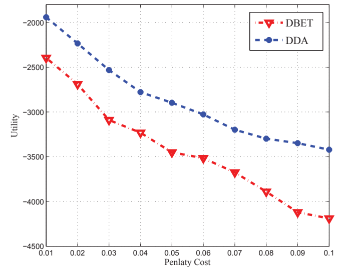

Fig. 7: Utility vs. penalty factor

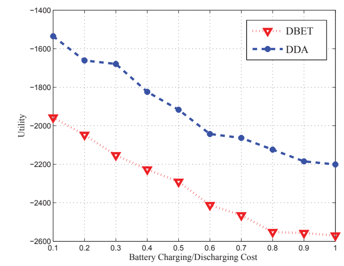

Fig. 8: Utility vs. degradation factor

we proposed the secondary electricity market. To derive the optimal energy trading in the secondary market, we proposed two new bidding schemes: Cournot Equilibrium based DBET scheme and double auction based DDA scheme. We used the Monte Carlo method to generate scenarios that capture uncertainties, and conducted experiments on a modified IEEE-33 bus based system. Our experimental results show that, when our proposed bidding schemes are in place, the operation cost of the system can be reduced significantly. Also, the double auction based DDA scheme achieves better performance than the Cournot Equilibrium based DBET scheme in terms of social welfare.

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