Cooperative bidding-based robust optimal energy management of multimicrogrids

Sampath, Lahanda Purage Mohasha Isuru; Krishnan, Ashok; Foo, Eddy Yi Shyh; Gooi, Hoay Beng

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A Cooperative Bidding Scheme for Robust Optimal Energy Management of Multiple-Microgrids

Abstract—This work proposes a cooperative trading scheme for the robust optimal power dispatch and reserve allocation in a multiple-microgrid (MMG) system comprising four microgrids (MGs). This scheme interfaces with a robust optimization (RO) model which accounts for the uncertainties in the renewable energy source generation, the load demand and the energy market prices using a scenario based worst-case exploration technique. A coordinating entity in the MMG system called a power sharing operator manages the day-ahead energy and reserve trading between the MGs and also with the main grid, thereby enabling market clearing within the MMG system. The proposed scheme is based on the iterative sub-gradient method. The results showcase the convergence characteristics of the proposed scheme. Moreover, the trade-off between the energy and reserve costs in each MG are also analysed. Finally, the economic benefits gained by the MMG system under the proposed RO based cooperative trading scheme are evaluated.

Index Terms—Cooperative trading, distributed optimization, economic dispatch, multiple-microgrids, robust optimization.

I. INTRODUCTION

MICROGRIDS are gaining popularity due to their ability to integrate renewable energy sources (RESs) into the electrical power system [1]–[3]. In addition to RESs, a typical MG may include controllable sources such as diesel generators (DGs) and energy storage systems (ESSs) apart from flexible (price-responsive) loads to support critical loads. The increasing levels of RES penetration, the advancements in communication technologies, and the liberalization of energy markets have supported the proliferation of MMG systems. The development of suitable frameworks to enable efficient resource sharing between individual MGs within an MMG system has been an active research area in recent years. In this context, [4] proposed a multi-agent based framework to describe the concept of cooperative MMG operation. More recently, the merits of sharing resources between the MGs constituting an MMG system using a cooperative framework were espoused in [5]–[7]. In every MG, a microgrid operator (MGO) maximizes the utilization of the RESs and optimally dispatches the controllable sources and flexible loads to satisfy the nominal demand. Two major sources of uncertainties affect the economic and reliable operation of MGs. Firstly, the RES generation and critical demand are stochastic and non-dispatchable. Consequently, an arbitrary allocation of reserves to mitigate the uncertainties in the demand and RES generation may result in suboptimal or unreliable MG operation. Secondly, in an energy market (e.g., the National Electricity Market of Singapore), the prices at which electricity is purchased from and sold to the main grid are allowed to change up to 65 minutes before the actual trade [5], [6].

Numerous stochastic optimization and robust optimization (RO) models have been proposed in the literature for jointly optimizing the power dispatch and reserve allocation to efficiently mitigate these uncertainties. For example, a stochastic MG scheduling model was developed in [8] to minimize the

expected operating cost of a MG containing intermittent RESs. The bidding strategy proposed by the authors of [9] used a hybrid stochastic/robust optimization model in a centralized architecture for operating grid-connected MGs. However, stochastic modeling requires the probability distributions of random factors to be known. As shown in [9], this information is difficult to obtain for energy market prices. Conversely, RO procedures characterize uncertainties using confidence bounds which can be computed using historical data and statistical inference techniques [10]. In general, RO procedures minimize the total cost while providing a feasible solution under the worst-case scenario which is realized on the basis of the uncertainties present in the optimization model [5], [6], [11], [12]. Furthermore, the importance of considering the *nonanticipativity* in day-ahead decisions while allocating the reserves under all plausible uncertain scenarios and its impact on the reserve deliverability was highlighted in [13], [14]. In the context of scenario selection, an RO model with a polyhedral uncertainty set was used in [11] and [13] to incorporate a vertex enumerating algorithm for worst-case exploration. Conversely, [12] and [15] adopted a scenario-based RO framework in which the *Taguchi's orthogonal array testing* (TOAT) method was used to select a reduced set of vertex permutations from the uncertainty polyhedron.

In the context of MMG systems, a coordinating entity may be employed to enable power sharing among the constituent MGs [6]. This framework allows individual MGOs to optimize their local resources and cooperatively contribute to the MMG energy and reserve markets via the coordinating entity. Furthermore, this framework is also privacy-preserving by requiring each individual MGO to communicate only bidding (non-critical) information [5]–[7], [16]. The day-ahead power dispatch and the reserve allocation in MMG systems using RO based approaches were recently proposed in [5] and [6]. To facilitate the clearance of the MMG energy and reserve markets, an alternating direction method of multipliers based approach was used in [5] while a game theoretic approach was investigated in [6]. Reference [5] only considered the sharing of energy between the MGs while the reserves were managed locally within each individual MG, thereby diluting the benefits offered by the MMG framework and resulting in a possibly suboptimal dispatch solution. Reference [6] also facilitated the sharing of reserves among the constituent MGs in an MMG system. However, in both [5] and [6], the realized worst-case scenario assumes the lowest RES generation and the highest load demand (and vice-versa) to occur simultaneously for all the constituent MGs over the entire optimization horizon. Such a scenario is highly unlikely in practice. In addition, the RO models in [5] and [6] violate the nonanticipativity in power dispatch and reserve allocations. This potentially restricts the reserve deliverability due to ramping infeasibilities as discussed in [13] and [14].

A. Contributions

This paper proposes a detailed RO model for the day-ahead joint optimal nonanticipative power dispatch and reserve allocation in an MMG system comprising four MGs which perform power trading through a coordinating entity called the power sharing operator (PSO). The PSO adopts the iterative sub-gradient method [17, Ch. 8] to clear the MMG energy market. The sources of uncertainty in the MMG system are characterized by a polyhedral uncertainty set which includes the RES generation and the load demand of each MG and the energy market prices. The TOAT method is used to generate a reduced number of uncertain scenarios for the MMG system. These scenarios are uniformly distributed over the polyhedral uncertainty space. Based on the earlier discussions and compared with the existing works in the literature, the salient contributions of this paper are briefly described below:

- 1) A novel RO model is proposed to jointly optimize the power dispatch and the reserve allocation of MG components in the context of an MMG framework. The proposed RO model resolves the anticipativity issues which restrict the reserve deliverability under uncertain scenarios in the existing MMG related works. The proposed RO model includes detailed models for DGs, ESSs and flexible loads. The nonanticipativity is preserved for the following: i) the power dispatch and the reserve allocation of the DGs and the ESSs and ii) the load shifting of flexible loads. This is achieved without resorting to model simplifications while retaining the convexity and scalability of the RO model.
- 2) A cooperative bidding scheme is proposed to facilitate the optimal sharing of energy and reserves between the constituent MGs in the MMG system which accounts for the aforementioned uncertainties and preserves the privacy of each MG.

The results demonstrate the benefits of sharing energy and reserves between MGs when compared with the isolated operation of individual MGs. The performance of the proposed RO model is also compared with a deterministic optimization (DO) model.

II. UNCERTAINTY MODEL FOR ROBUST OPTIMIZATION

A. Uncertainty Characterization

In RO literature, the uncertain variables are generally assumed to lie within a polyhedral set with known confidence bounds. These confidence bounds can be computed from historical data using statistical inference techniques [10]. To obtain feasible results under the worst-case scenario, the minimum cost resource management problem needs to be *maximized* over the polyhedral uncertainty set. The resulting *max-min* problem is nonconvex and hence, NP-hard to solve in polynomial time. The specific structure of this resource management problem enables the worst-case scenario to be a permutation of the extreme points of the uncertainty polytope [11]. As such, the global solution can be obtained if the resource optimization problem is evaluated at all the vertices of the uncertainty polytope. However, the computational complexity involved in exploring all the vertex (full factorial)

combinations increases exponentially with the dimensions of the uncertainty set [11]. Thus, [11] and [13] propose two alternative tractable solution approaches to capture a reduced set of vertex permutations while considering the correlation between uncertain variables. In the context of MMG systems, the uncertain variables belong to different entities. Hence, the correlations between uncertain variables might not be readily available due to privacy concerns. Conversely, the TOAT method generates a fraction of the full factorial combinations of vertices based on a special set of *orthogonal arrays* (OAs) without requiring any information about the confidence bounds [18]. Furthermore, the set of scenarios generated by the TOAT method combines the least possible vertex permutations which are uniformly distributed over the uncertainty space. Thus, the selected uncertainty set has the potential to represent the impact of the full set of uncertain scenarios. The example in [13, Sec. II] discusses the importance of selecting scenarios which represent the whole space of the uncertainty polyhedron. Moreover, the TOAT method has been widely applied in robust energy management tools for MGs and large power systems, c.f. [12], [15], [18], [19].

B. Scenario Selection based on the TOAT Method

The general representation of an OA is $L_H B^F$, where H is the number of scenarios; F is the number of random factors and B is the number of levels (the two confidence interval bounds) considered for each random factor.

TABLE I
SELECTED SCENARIOS BASED ON THE OA $L_8 2^7$

Scenario h	Levels of each random factor				
	PSO	MG 1	MG 2	MG 3	MG 4
1	+1	+1	+1	+1	+1
2	+1	+1	+1	-1	-1
3	+1	-1	-1	+1	+1
4	+1	-1	-1	-1	-1
5	-1	+1	-1	+1	-1
6	-1	+1	-1	-1	+1
7	-1	-1	+1	+1	-1
8	-1	-1	+1	-1	+1

Let there be an MMG with four MGs. Table I depicts the first five columns of the OA $L_8 2^7$ specifying eight scenarios involving five two-level factors (five cooperative entities) [18]. The reserve requirement of a MG can be either positive or negative depending on the variations in the demand and RES generation. The +1 and -1 levels in Table I represent the corresponding vertices of the uncertainty polyhedron during hour $t \in \mathcal{T}$. Each row is associated with a scenario. In this context, the expected levels of the nominal demand can be defined as shown in (1). Let $\mathcal{H} = \{0, 1, \dots, H\}$ be the set of scenarios ($H = 8$ in Table I). Let $\mathcal{T} = \{1, \dots, T\}$ be the optimization horizon for the study. The superscripts m and t denote the MG number and the optimization interval respectively associated with the corresponding variable or parameter. The subscript h denotes the scenario, wherein the base-scenario is represented by $h = 0$.

$$[P_{ND}^{m,t}]_+ := P_{ND,0}^{m,t} + P_{ND}^{m,t,\zeta^+}; \forall t \in \mathcal{T} \quad (1a)$$

$$[P_{ND}^{m,t}]_- := P_{ND,0}^{m,t} - P_{ND}^{m,t,\zeta^-}; \forall t \in \mathcal{T} \quad (1b)$$

where the nonnegative parameters $P_{ND,0}^{m,t}$, P_{ND}^{m,t,ζ^+} and P_{ND}^{m,t,ζ^-} represent the mean, and the deviations in the upper

and lower confidence bounds of the nominal demand of MG m during hour t respectively. Then, the nominal demand $P_{ND,h}^{m,t}$ of MG m under scenario $h \in \mathcal{H} \setminus \{0\}$ during hour t is a vertex of the uncertain polyhedron as defined below.

$$P_{ND,h}^{m,t} \in \left\{ [P_{ND}^{m,t}]_+, [P_{ND}^{m,t}]_- \right\}; \forall h \in \mathcal{H} \setminus \{0\}, \forall t \in \mathcal{T} \quad (2)$$

Furthermore, the expected levels of the wind power generation can be defined as follows:

$$[P_{W,w}^{m,t}]_+ := P_{W,w,0}^{m,t} - P_{W,w}^{m,t,\zeta^-}; \forall t \in \mathcal{T} \quad (3a)$$

$$[P_{W,w}^{m,t}]_- := P_{W,w,0}^{m,t} + P_{W,w}^{m,t,\zeta^+}; \forall t \in \mathcal{T} \quad (3b)$$

The expected levels of the solar photovoltaic (PV) power generation (denoted by $[P_{PV,s}^{m,t}]_+$ and $[P_{PV,s}^{m,t}]_-$) can also be defined in a similar manner. For the PSO, the +1 and -1 levels represent the upper and lower bounds of the price for purchasing electricity from the main grid respectively.

$$[\gamma_b^t]_+ := \gamma_{b,0}^t + \gamma_b^{t,\zeta^+}, [\gamma_b^t]_- := \gamma_{b,0}^t - \gamma_b^{t,\zeta^-}; \forall t \in \mathcal{T} \quad (4)$$

The expected levels of the price for selling electricity to the main grid (represented by $[\gamma_s^t]_+$ and $[\gamma_s^t]_-$) can also be defined in a similar fashion.

III. ROBUST DAY-AHEAD OPTIMAL ENERGY MANAGEMENT OF MULTI-MICROGRIDS

A. Multi-Microgrids System Structure

An MMG system is a cluster of MGs in which each MG is connected to a common bus called the point-of-common coupling (PCC) via a circuit breaker (see for instance [6, Fig. 1]). Each MG in a MMG system can operate either in islanded or grid-connected mode. The PCC is connected to the main grid. The PSO manages the import and export of electricity through the PCC at predetermined buying and selling prices respectively. Each MG in the MMG system considered in this paper comprises components such as DGs, dispatchable loads, fixed loads, ESSs and RESs. Each MGO optimally utilizes the locally available resources to meet the local load demand while interfacing with the PSO for power trading (buying/selling) whenever it is found to be economically viable. The PSO clears the MMG electricity market based on the supply and demand bids received from the constituent MGs.

B. Microgrid Component Modeling

The MG energy management system solves an optimal day-ahead dispatch problem which is subject to the power balance constraint of the MG and the operational constraints of its components. Furthermore, additional variables are introduced and constraints are imposed on the components to ensure the feasibility of *all the possible* intertemporal power set point transitions under the given set of uncertain realizations/scenarios. Thus, the proposed model accounts for the *nonanticipativity* in the day-ahead scheduling decisions, a feature which is missing in [5], [6]. The superscripts ‘max’ and ‘min’ represent the upper and lower capability bounds respectively of the corresponding variable or parameter.

1) *Energy Storage System (ESS)*: Let $\mathcal{E}^m$ be the set of ESSs in MG m . For all $e \in \mathcal{E}^m$:

$$C_{E,e,h}^{m,t} = a_{E,e}^m \left(P_{E,e,h}^{c,m,t} + P_{E,e,h}^{d,m,t} \right)^2 \quad (5a)$$

$$0 \leq P_{E,e,h}^{c,m,t} \leq (P_{E,e}^{c,m})^{\max}; \forall h \in \mathcal{H} \quad (5b)$$

$$0 \leq P_{E,e,h}^{d,m,t} \leq (P_{E,e}^{d,m})^{\max}; \forall h \in \mathcal{H} \quad (5c)$$

$$E_{e,0}^{m,t} = E_{e,0}^{m,t-\Delta t} + \frac{\Delta t}{B_e^m} \left(\eta_e^c P_{E,e,0}^{c,m,t} - \frac{1}{\eta_e^d} P_{E,e,0}^{d,m,t} \right) \quad (5d)$$

$$(E_e^m)^{\min} \leq E_{e,0}^{m,t} \leq (E_e^m)^{\max} \quad (5e)$$

$$\bar{P}_{E,e,h}^{c,m,t} \geq P_{E,e,h}^{c,m,t}, \quad \underline{P}_{E,e,h}^{c,m,t} \leq P_{E,e,h}^{c,m,t}, \\ \bar{P}_{E,e,h}^{d,m,t} \geq P_{E,e,h}^{d,m,t}, \quad \underline{P}_{E,e,h}^{d,m,t} \leq P_{E,e,h}^{d,m,t}; \forall h \in \mathcal{H} \quad (5f)$$

$$\bar{E}_e^{m,t} = \bar{E}_e^{m,t-\Delta t} + \frac{\Delta t}{B_e^m} \left(\eta_e^c \bar{P}_{E,e}^{c,m,t} - \frac{1}{\eta_e^d} \underline{P}_{E,e}^{d,m,t} \right) \quad (5g)$$

$$\underline{E}_e^{m,t} = \underline{E}_e^{m,t-\Delta t} + \frac{\Delta t}{B_e^m} \left(\eta_e^c \underline{P}_{E,e}^{c,m,t} - \frac{1}{\eta_e^d} \bar{P}_{E,e}^{d,m,t} \right) \quad (5h)$$

$$(E_e^m)^{\min} \leq \{ \bar{E}_e^{m,t}, \underline{E}_e^{m,t} \} \leq (E_e^m)^{\max} \quad (5i)$$

$$E_{e,0}^{m,T} = E_{R,e}^m \quad (5j)$$

$$(1 - \delta) E_{R,e}^{m,T} \leq \{ \bar{E}_e^{m,T}, \underline{E}_e^{m,T} \} \leq (1 + \delta) E_{R,e}^m \quad (5k)$$

where $P_{E,e,h}^{c,m,t}$, $P_{E,e,h}^{d,m,t}$, $E_{e,h}^{m,t}$ and B_e^m are the charging power, the discharging power, the state-of-charge (SOC) and the energy capacity respectively of ESS e under scenario h and $a_{E,e}^m$ is the coefficient of the quadratic degradation cost function in (5a) for ESS e . Finally, η_e^c and η_e^d are the charging and discharging efficiencies of ESS e respectively. The charging and discharging power limits of ESS e are shown in (5b) and (5c) respectively. The time varying SOC of ESS e for the base-case scenario is computed in (5d) and is bounded by (5e). The duration of the optimization interval denoted by Δt is 1 h.

In (5f), the additional variables $\bar{P}_{E,e}^{c,m,t}$, $\underline{P}_{E,e}^{d,m,t}$ and $\underline{P}_{E,e}^{c,m,t}$ in the proposed RO model represent the highest and lowest possible dispatch levels of the variables $P_{E,e,h}^{c,m,t}$ and $P_{E,e,h}^{d,m,t}$ respectively under all the plausible uncertain scenarios (i.e. for all $h \in \mathcal{H}$) during hour t . For instance, $\bar{P}_{E,e}^{c,m,t} \geq \max_{h \in \mathcal{H}} P_{E,e,h}^{c,m,t}$, $\underline{P}_{E,e}^{c,m,t} \leq \min_{h \in \mathcal{H}} P_{E,e,h}^{c,m,t}$ and so on. Equations (5g) and (5h) account for the effects of charging and discharging events on the SOC of ESS e under all uncertain scenarios $h \in \mathcal{H}$. The maximum expected SOC during hour t (denoted by $\bar{E}_e^{m,t}$) is computed in (5g) on the basis of the maximum SOC value during the previous hour and the maximum (or minimum) possible energy that could be stored (or extracted) during hour t under all the plausible uncertain scenarios. The minimum expected SOC (denoted by $\underline{E}_e^{m,t}$) is also computed similarly in (5h). Thus, $\bar{E}_e^{m,t}$ and $\underline{E}_e^{m,t}$ implicitly account for the upper and lower bounds of $E_e^{m,t}$ while considering all the plausible transitions between two adjacent time steps. These two variables are bounded within the physical SOC limits of ESS e by (5i). Thus, the nonanticipativity of the charging power and discharging power dispatch values apart from the SOC of ESS e is preserved under all the plausible uncertain scenarios. Under the base case scenario, (5j) ensures that the SOC of ESS e at the end of the optimization horizon is the same as the initial SOC (denoted by $E_{R,e}^m$). Similarly, the maximum and minimum expected SOC values at the end of

the optimization horizon are constrained around $E_{R,e}^m$ within a predefined radius of δ by (5k) to permit sufficient flexibility for the ESS operation during the following day.

Remark: Binary variables are omitted in the ESS model to preserve the convexity of the constraints. The ESS model accounts for the degradation cost function and the conversion efficiencies. As such, the solutions with simultaneous charging and discharging of the ESS will be naturally eliminated by convex minimization solvers as they increase the cost without impacting the power balance [5], [6].

2) *Diesel Generators (DGs):* Let $\mathcal{G}^m$ be the set of DGs in MG m . For all $g \in \mathcal{G}^m$:

$$C_{G,g,h}^{m,t} = a_{G,g}^m \left(P_{G,g,h}^{m,t} \right)^2 + b_{G,g}^m P_{G,g,h}^{m,t} \quad (6a)$$

$$(P_{G,g}^m)^{\min} \leq P_{G,g,h}^{m,t} \leq (P_{G,g}^m)^{\max}; \forall h \in \mathcal{H} \quad (6b)$$

$$-r_{G,g}^{\text{dn},m} \leq P_{G,g,h}^{m,t} - P_{G,g,0}^{m,t} \leq r_{G,g}^{\text{up},m}; \forall h \in \mathcal{H} \setminus \{0\} \quad (6c)$$

$$\bar{P}_{G,g}^{m,t} \geq P_{G,g,h}^{m,t}, \quad \underline{P}_{G,g}^{m,t} \leq P_{G,g,h}^{m,t}; \forall h \in \mathcal{H} \quad (6d)$$

$$\bar{P}_{G,g}^{m,t} - \underline{P}_{G,g}^{m,t-1} \leq R_{G,g}^{\text{up},m} \quad (6e)$$

$$\bar{P}_{G,g}^{m,t-1} - \underline{P}_{G,g}^{m,t} \leq R_{G,g}^{\text{dn},m} \quad (6f)$$

where $P_{G,g,h}^{m,t}$ is the power output of DG g under scenario h ; $a_{G,g}^m$ and $b_{G,g}^m$ are the quadratic and linear coefficients respectively of the fuel cost function shown in (6a); $r_{G,g}^{\text{up},m}$ and $r_{G,g}^{\text{dn},m}$ are the up and down reserve capability limits respectively of DG g ; $R_{G,g}^{\text{up},m}$ and $R_{G,g}^{\text{dn},m}$ are the up and down ramp rate limits respectively of DG g . Equation (6b) bounds the generation of DG g under scenario h . Constraint (6c) ensures that the power dispatch under scenario h respects the reserve capability bounds. Equations (6e) and (6f) ensure that the up and down operating ramp rate constraints are respected between any two successive time periods under all plausible scenarios h while considering the worst possible ramping rate of DG g . This preserves the nonanticipativity of the day-ahead power dispatch and reserve allocation of DG g .

3) *Flexible Loads:* The MGs support the demand response scheme formulated below.

$$C_{D,h}^{m,t} = a_D^m \left(P_{RD,h}^{m,t} + P_{CD,h}^{m,t} \right)^2 \quad (7a)$$

$$P_{D,h}^{m,t} = P_{RD,h}^{m,t} - P_{CD,h}^{m,t} + P_{ND,h}^{m,t}; \forall h \in \mathcal{H} \quad (7b)$$

$$0 \leq P_{RD,h}^{m,t} \leq (P_{RD}^m)^{\max}; \forall h \in \mathcal{H} \quad (7c)$$

$$0 \leq P_{CD,h}^{m,t} \leq (P_{CD}^m)^{\max}; \forall h \in \mathcal{H} \quad (7d)$$

$$\sum_{t \in \mathcal{T}} \left[P_{RD,0}^{m,t} - P_{CD,0}^{m,t} \right] = 0 \quad (7e)$$

$$P_{RD}^{m,t} \leq P_{RD,h}^{m,t}, \quad \bar{P}_{CD}^{m,t} \geq P_{CD,h}^{m,t}; \forall h \in \mathcal{H} \quad (7f)$$

$$0 \leq \underline{P}_{RD}^{m,t} \leq (P_{RD}^m)^{\max}, \quad 0 \leq \bar{P}_{CD}^{m,t} \leq (P_{CD}^m)^{\max} \quad (7g)$$

$$\Delta t \sum_{t \in \mathcal{T}} \left[\bar{P}_{CD}^{m,t} - \underline{P}_{RD}^{m,t} \right] \leq E_{\text{Shed}}^m \quad (7h)$$

where $P_{ND,h}^{m,t}$, $P_{CD,h}^{m,t}$, $P_{RD,h}^{m,t}$ and $P_{D,h}^{m,t}$ are the nominal (critical), curtailed, redispatched and actual load demands under scenario h respectively and a_D^m is the coefficient of the cost function in (7a) which reflects the sensitivity of the inconvenience felt by the consumers due to the load shifting. The actual load demand in (7b) is considered to be

the nominal load demand after the flexibility adjustment. The demand redispatch and curtailment are constrained by (7c) and (7d) respectively. No load shedding is permitted under the base-case scenario as described in (7e). Additional variables $\underline{P}_{RD}^{m,t}$ and $\bar{P}_{CD}^{m,t}$ are defined for the redispatched and the curtailed load demands respectively as shown in (7f) and (7g). Using these variables, (7h) restricts the worst possible total load shedding below E_{Shed}^m under all the plausible uncertain scenarios, thereby satisfying the nonanticipativity in demand shifting.

4) *Interactions with the PSO:* The PSO supervises the power and price bids submitted by each MGO for buying/selling electricity.

$$C_{\text{PSO},h}^{m,t} = \beta_{b,h}^t P_{\text{PSO},b,h}^{m,t} - \beta_{s,h}^t P_{\text{PSO},s,h}^{m,t} \quad (8a)$$

$$0 \leq P_{\text{PSO},b,h}^{m,t}, P_{\text{PSO},s,h}^{m,t} \leq (P_{\text{PSO}}^m)^{\max}; \forall h \in \mathcal{H} \quad (8b)$$

where $P_{\text{PSO},b,h}^{m,t}$ is the power purchased by MG m from the PSO at $\beta_{b,h}^t$ and $P_{\text{PSO},s,h}^{m,t}$ is the power sold by MG m to the PSO at $\beta_{s,h}^t$. As explained later in Section IV-A, $\beta_{b,h}^t > \beta_{s,h}^t$. This convexifies the power trading cost function in (8a) and avoids the simultaneous buying and selling of electricity. Constraint (8b) bounds the power imported from and exported to the PSO respectively.

C. Energy Management Model for a Single Microgrid

The total operating cost function under scenario h during hour t is formulated as follows.

$$C_h^{m,t}(\Phi_h^{m,t}) = \sum_{g \in \mathcal{G}^m} C_{G,g,h}^{m,t} + \sum_{e \in \mathcal{E}^m} C_{E,e,h}^{m,t} + C_{D,h}^{m,t} + C_{\text{PSO},h}^{m,t} \quad (9)$$

where $\Phi_h^{m,t}$ is the decision variable vector pertaining to the local optimal dispatch problem (as shown below in (11)) of MG m under scenario h during hour t .

To formulate the total expected cost function over the entire optimization horizon, it is assumed that the probability of the base-case scenario is known. However, the worst-case scenario is not known a priori. Therefore, the sampling average approximation method [20] is applied to compute an *average* reserve cost in (10b) assuming same probability of occurrence for all other plausible uncertain scenarios. Accordingly, the energy cost (denoted by C_E^m) and the reserve cost (denoted by C_R^m) for the robust operation of MG m can be formulated as shown below in (10).

$$C_E^m = \sum_{t \in \mathcal{T}} C_0^{m,t}(\Phi_0^{m,t}) \quad (10a)$$

$$C_R^m = \sum_{t \in \mathcal{T}} \left[\frac{1}{H} \sum_{h \in \mathcal{H} \setminus \{0\}} C_h^{m,t}(\Phi_h^{m,t}) - C_0^{m,t}(\Phi_0^{m,t}) \right] \quad (10b)$$

The value of the base-case probability p_0 can be adjusted on the basis of historical data or as the preference of each MGO. However, its value has no impact on the worst-case *feasibility* of the solution. To this end, the robust day-ahead optimal dispatch problem of each MG $m \in \mathcal{M}$ can be formulated as shown below in (11) to obtain the optimal *expected* operating

cost while respecting all the technical constraints under all plausible uncertain scenarios.

$$\min_{\Phi_h^{m,t}} C_{\text{exp}}^m = C_E^m + (1 - p_0) C_R^m \quad (11a)$$

$$\text{s.t.} \quad \sum_{g \in \mathcal{G}^m} P_{G,g,h}^{m,t} + \sum_{e \in \mathcal{E}^m} \left[P_{E,e,h}^{d,m,t} - P_{E,e,h}^{c,m,t} \right] + P_{\text{PSO},b,h}^{m,t} - P_{\text{PSO},s,h}^{m,t} = P_{D,h}^{m,t} - \sum_{w \in \mathcal{W}^m} P_{W,w,h}^{m,t} - \sum_{s \in \mathcal{S}^m} P_{PV,s,h}^{m,t}; \quad \forall h \in \mathcal{H}, \forall t \in \mathcal{T} \quad (11b)$$

$$(5b)-(5k), (6b)-(6f), (7b)-(7h), (8b) \quad (11c)$$

Here, (11a) is the expected total cost function; (11b) is the power balance constraint; and (11c) consolidates the technical constraints explained earlier. The optimization problem in (11) is a quadratic programming (QP) problem which can be solved efficiently using convex optimization solvers. Essentially, in (11a), the behaviour of p_0 is similar to a weight factor representing a trade-off between the base-case (higher p_0) and the worst-case (lower p_0) cost functions. This improves the operational security and the economic efficiency of the MG.

IV. OPTIMAL ENERGY AND RESERVE SHARING VIA COOPERATIVE BIDDING

A. Distributed Algorithm for Market Clearing

The centralized optimization problem (COP) for the MMG system aggregates the sub-problems in (11) for all the MGs constituting the MMG system. The COP turns out to be a convex QP problem having a *unique* optimum owing to the convex characteristics of (11). However, solving the COP requires the full system information of all the MGs to be known. In practice, individual MGs in the MMG system may be owned by separate entities. As such, these entities are often reluctant to share information such as generation costs and quantities owing to privacy concerns. Furthermore, simultaneously accessing large amounts of data may lead to data traffic congestion issues [5].

Algorithm 1 Cooperative Optimal Power Sharing Coordination

```

1: Initialize  $k = 0, \epsilon = 0.005, \lambda_{\text{eq},h}^t = \lambda_h^t(0)$  and  $\Delta P_{N,h}^t(0)$ .
2: while  $\max_{t \in \mathcal{T}} \max_{h \in \mathcal{H}} \left| \Delta P_{\text{PSO},h}^t(k) - \Delta P_{N,h}^t(k) \right| \geq \epsilon$  do
3:    $k = k + 1$ 
4:   Update  $\beta_{b,h}^t$  and  $\beta_{s,h}^t$  using (13).
5:   Receive power exchange preferences  $P_{\text{PSO},b,h}^{m,t}(k)$ 
     /  $P_{\text{PSO},s,h}^{m,t}(k)$  from each MG;  $\forall t \in \mathcal{T}, \forall h \in \mathcal{H}$ .
6:   Compute  $\lambda_h^t(k+1)$  using (12).
7:   if  $\lambda_h^t(k+1) \geq \gamma_{b,h}^t$  then
8:      $\lambda_{\text{eq},h}^t = \gamma_{b,h}^t, P_{N,b,h}^t = \Delta P_{\text{PSO},h}^t(k)$ 
9:   else if  $\lambda_h^t(k+1) \leq \gamma_{s,h}^t$  then
10:     $\lambda_{\text{eq},h}^t = \gamma_{s,h}^t, P_{N,s,h}^t = -\Delta P_{\text{PSO},h}^t(k)$ 
11:   else
12:     $\lambda_{\text{eq},h}^t = \lambda_h^t(k+1), P_{N,b,h}^t = P_{N,s,h}^t = 0$ 
13:   end if
14:    $\Delta P_{N,h}^t(k) = P_{N,b,h}^t - P_{N,s,h}^t$ 
15: end while

```

Algorithm 1 summarizes the cooperative bidding scheme proposed in this paper which mitigates the aforementioned issues. Therein, the COP is decomposed into M local sub-problems of the form in (11). Algorithm 1 is executed by the PSO. Each MG separately solves (11) and communicates its power sharing preferences ($P_{\text{PSO},b,h}^{m,t}/P_{\text{PSO},s,h}^{m,t}$) to the PSO under all the scenarios $h \in \mathcal{H}$ over the optimization horizon $t \in \mathcal{T}$, as described in Step 5 of Algorithm 1. Subsequently, the PSO estimates the difference between the energy demand and supply bids to recalculate the market equilibrium price (MEP) $\lambda_{\text{eq},h}^t$ using (12) as described in Step 6 of Algorithm 1.

$$\Delta P_{\text{PSO},h}^t(k) = \sum_{m \in \mathcal{M}} \left[P_{\text{PSO},b,h}^{m,t}(k) - P_{\text{PSO},s,h}^{m,t}(k) \right] \quad (12a)$$

$$\lambda_h^t(k+1) = \lambda_h^t(k) + \alpha \Delta P_{\text{PSO},h}^t(k) \quad (12b)$$

where k is the current iteration and $\alpha \in \mathbb{R}_{>0}$ is the step-size. The power trading prices (denoted by $\beta_{b,h}^t$ and $\beta_{s,h}^t$) for the MGOs are computed as shown in (13) using the MEP $\lambda_{\text{eq},h}^t$ for scenario h during hour t , wherein τ is the per unit service fee imposed on both the buyer and seller MGOs.

$$\beta_{b,h}^t = \lambda_{\text{eq},h}^t + \tau, \quad \beta_{s,h}^t = \lambda_{\text{eq},h}^t - \tau \quad (13)$$

The aggregated income of the PSO $I_{\text{PSO},h}^t$ under scenario h during hour t in (14) should cover the power transfer losses and any possible expenses incurred for maintaining the system and facilitating the power sharing.

$$I_{\text{PSO},h}^t = \tau \sum_{m \in \mathcal{M}} \left[P_{\text{PSO},b,h}^{m,t} + P_{\text{PSO},s,h}^{m,t} \right] \quad (14)$$

In this model, each MG m solves (11) to minimize its total operating cost for the trading prices provided by the PSO which are denoted as $\beta_{b,h}^t$ (buying) and $\beta_{s,h}^t$ (selling) respectively. Therewith, (12) arrives at a higher MEP for the next iteration if the net demand is higher to encourage more suppliers or fewer buyers. Conversely, (12) arrives at a lower MEP for the next iteration if the net supply is higher to encourage fewer suppliers or more buyers. Accordingly, (12) describes a typical demand and supply market scenario. This can be interpreted as a *market clearing* mechanism since the trading prices are modified with the aim of balancing the net energy demand and supply.

The MMG system considered in this paper is assumed to be operated in the grid-connected mode. The PSO manages the electric power transactions between the MMG system and main grid based on $\gamma_{b,h}^t$ and $\gamma_{s,h}^t$ which represent the per unit spot prices at which the electricity is purchased from and sold to the main grid respectively. In practice, $\gamma_{b,h}^t > \gamma_{s,h}^t$ [5]. If the net supply bid is inadequate to meet the net demand bid at $\lambda_{\text{eq},h}^t \geq \gamma_{b,h}^t$, the resultant shortfall is met through imports from the main grid as described in Steps 7-8 of Algorithm 1, wherein $P_{N,b,h}^t$ is the power purchased from the main grid. Similarly, if the net supply bid exceeds the net demand bid at $\lambda_{\text{eq},h}^t \leq \gamma_{s,h}^t$, the resultant surplus is exported to the main grid as described in Steps 9-10 of Algorithm 1, wherein $P_{N,s,h}^t$ is the power sold to the main grid. Thus, $\lambda_{\text{eq},h}^t$ will lie in between $\gamma_{b,h}^t$ and $\gamma_{s,h}^t$ if the demand and supply bids can be internally matched as shown in Steps 11-12 of Algorithm 1.

B. Convergence Characteristics

The dual problem of the COP can be defined as follows:

$$\max_{\lambda_{eq,h}^t} \sum_{m \in \mathcal{M}} \min_{\Phi_h^{m,t}} C_{exp}^m(\Phi_h^{m,t}, \lambda_{eq,h}^t) \quad (15a)$$

$$\text{s.t. (11b), (11c); } \forall m \in \mathcal{M} \quad (15b)$$

$$\sum_{m \in \mathcal{M}} [P_{PSO,b,h}^{m,t} - P_{PSO,s,h}^{m,t}] = P_{N,b,h}^t - P_{N,s,h}^t; \forall t \in \mathcal{T} \quad (15c)$$

According to (15), the local cost minimization subproblem (11) for each MG m is the contribution of the corresponding MG to the Lagrangian function of (15) at a given $\lambda_{eq,h}^t$. Thus, $\lambda_{eq} = [\lambda_{eq,0}^1, \dots, \lambda_{eq,H}^T]^T$ comprises the Lagrangian multipliers $\lambda_{eq,h}^t$ under scenario h during hour t relative to the coupling constraint (15c), which is the power balance constraint for the MMG system. Algorithm 1 is based on the *iterative sub-gradient method* in [17, Ch. 8]. Moreover, the coupling constraint (15c) is interpreted in (12) and Steps 6-13 of Algorithm 1 as sub-gradients of (15) at $\lambda_{eq,h}^t$. As such, MGs optimize their local resources at a given λ_{eq} as in (11) in every iteration and λ_{eq} is iteratively updated in a direction which satisfies (15c). The *zero duality gap* in convex optimization problems ensures the uniqueness and the global optimality of the solution obtained for (15). Hence, the convergence of the sequence $\{\lambda_{eq}(k)\}$ is guaranteed within a finite number of iterations for iterative sub-gradient methods depending on the selected α in (12).

V. CASE STUDIES

A. Simulation Settings

Numerical simulations are performed on an MMG system comprising four MGs. Each MG contains one DG. The linear cost coefficients of the DGs in the MMG system are listed in Table II. Furthermore, $\forall m \in \mathcal{M}$ and $\forall g \in \mathcal{G}^m$: $a_{G,g}^m = \$5/\text{MW}^2\text{h}$, $(P_{G,g}^m)^{\max} = 1 \text{ MW}$, $(P_{G,g}^m)^{\min} = 0 \text{ MW}$, $R_{G,g}^{\text{up},m} = R_{G,g}^{\text{dn},m} = 0.5 \text{ MW/h}$ and $r_{G,g}^{\text{up},m} = r_{G,g}^{\text{dn},m} = 0.3 \text{ MW}$. ESSs are included with the following parameters $\forall m \in \{2, 3\}$ and $\forall e \in \mathcal{E}^m$: $a_{E,e}^m = \$5/\text{MW}^2\text{h}$, $B_e^m = 2 \text{ MWh}$, $\eta_e^c = \eta_e^d = 0.97$, $(P_{E,e}^m)^{\max} = (P_{E,e}^m)^{\min} = 0.8 \text{ MW}$, $(E_e^m)^{\max} = 0.9$, $(E_e^m)^{\min} = 0.1$, $E_{R,e}^m = 0.4$ and $\delta = 0.2$. Furthermore, dispatchable loads are included with the following parameters $\forall m \in \{1, 4\}$: $a_{FD}^m = \$20/\text{MW}^2\text{h}$, $(P_{RD}^m)^{\max} = (P_{CD}^m)^{\max} = 0.4 \text{ MW}$ and $E_{Shed}^m = 1 \text{ MWh}$.

TABLE II LINEAR COST PARAMETERS OF DGs				
Parameter	MG 1	MG 2	MG 3	MG 4
$b_{G,g}^m$ (\$/MWh)	90	70	80	100

The forecasts for the demand and RES generation are shown in Fig. 1. Symmetrical forecast errors of $[10\%, -10\%]$ and $[5\%, -5\%]$ are considered for the nominal load demand of each MG and the main grid spot prices respectively. The RES generation forecast errors are considered to be $[10\%, -20\%]$. Moreover, $(P_{PSO}^m)^{\max} = 1.5 \text{ MW}$ for all MGs $m \in \mathcal{M}$ and $\tau = \$5/\text{MWh}$. Algorithm 1 and the MG energy management problem described in (11) were programmed on MATLAB. Therein, (11) was solved using CPLEX. The robustness of the results can be verified using techniques such as the Monte

Carlo simulation [15], [19]. Such a study is omitted here for the sake of brevity.

Fig. 1. Forecast for: (a) load demand and (b) aggregate RES generation.

B. Convergence Analysis

The convergence of Algorithm 1 is influenced by the step-size α and the initial market equilibrium price $\lambda_h^t(0)$. Fig. 2 shows the number of iterations required by Algorithm 1 to converge to the optimal solution for different values of α . From Fig. 2, it is observed that Algorithm 1 converges slowly when α is smaller. However, the number of iterations reduces exponentially when α increases. The upper bound of α was found to be approximately 4.5 in the simulation studies. After a few iterations, higher values of α induced toggling in the power mismatch calculated as $\Delta P = \max_{t \in \mathcal{T}, h \in \mathcal{H}} |\Delta P_{PSO,h}^t(k) - \Delta P_{N,h}^t(k)|$. Moreover, it is observed that $\lambda_h^t(0)$ has a minimal impact on the convergence of Algorithm 1. Significantly, it is observed that the cooperative solution always converges to the same solution. Consequently, it can be concluded that the optimal solution attained using the cooperative trading scheme is independent of α and $\lambda_h^t(0)$. Fig. 3 illustrates the evolution of the power mismatch and the objective function value with each iteration for $\alpha = 4$, $\lambda_h^t(0) = 0.5(\gamma_b^t + \gamma_s^t)$ and $p_0 = 0.5$. From Fig. 3, it is observed that the change in the objective function value is marginal after the first few iterations.

Fig. 2. Number of iterations required for Algorithm 1 to converge for different values of α .

Fig. 3. Convergence characteristics of Algorithm 1.

C. Robust and Deterministic Optimization based Operations

In this case study, the optimal dispatches of the MMG system using the DO (wherein the forecasts for the RES generation, load demand and energy market prices are assumed to be 100% accurate) and RO approaches with Algorithm 1 are compared. Fig. 4 shows the dispatches of the DGs in the MMG system at $p_0 = 0.5$ under the aforementioned simulation scenarios. In Fig. 4, a higher utilization of the cheaper DGs is observed which signifies the effectiveness of the cooperative

bidding scheme in optimally sharing cheaper resources across the individual MG boundaries. Furthermore, it is observed that the dispatches obtained using the RO and the DO approaches differ. Therein, the RO model computes hourly reserve margins while ensuring ramping feasibility in delivering reserves. The solution obtained using the RO approach depends on p_0 . Fig. 5 illustrates the trading of energy and reserves between the individual MGOs and the PSO. By and large, it is observed that MG 2 behaves as a seller while MG 4 behaves as a buyer. Conversely, MG 1 and MG 3 act as both buyers and sellers. Table III shows the energy and reserve costs of each MG and the revenue of the PSO while using the RO and DO approaches. The MG operating costs obtained while using the RO approach exceed those obtained while using the DO approach. The cost of MG 4 is the highest since it houses the most expensive DG. Furthermore, a smaller p_0 prioritizes the cost of optimal reserve allocation in MGs 1-3. The PSO income also follows a similar trend. This trend is not observed in MG 4 which is a buyer MG whose operational cost depends on $\gamma_{b,h}^t$ and the prices offered by MGs 1-3.

Fig. 4. Power dispatch profiles of the DGs in the 4 MGs obtained using the DO and RO (base-case dispatch, up and down reserve margins) approaches.

Fig. 5. Power and reserve exchanges between the MGOs and the PSO.

D. Comparison of Cooperative and Isolated Trading Schemes

In this case study, the performances of the cooperative and isolated trading schemes are compared for the RO approach based operation of the MMG system. In the isolated trading scheme, it is assumed that the individual MGs trade with the main grid alone at the predetermined grid selling (γ_s^t) and buying (γ_b^t) prices. Thus, the energy management problem in (11) is executed by each MG at $\beta_s^t = \gamma_s^t - \tau$ and $\beta_b^t = \gamma_b^t + \tau$.

TABLE III
COST ASSOCIATED WITH ROBUST AND DETERMINISTIC OPERATIONS

Market Players	Deterministic Operation C_E^m (\$/day)	Robust Operation (\$/day)			
		$p_0 = 0.5$		$p_0 = 0.1$	
		C_E^m	C_R^m	C_E^m	C_R^m
MG 1	381.25	383.62	200.47	391.56	189.08
MG 2	142.10	158.69	235.61	184.83	209.61
MG 3	541.07	547.64	230.69	577.18	200.29
MG 4	1598.28	1585.70	230.18	1566.52	240.22
PSO	-239.71	-244.35	-56.83	-249.10	-49.28

The dispatch profiles of all the DGs in the MMG system obtained using the isolated trading scheme at $p_0 = 0.5$ are shown in Fig. 6. Compared with the cooperative trading scheme (dispatch profiles shown in Fig. 4), the utilization of the cheapest DGs in MGs 2 and 3 under the isolated trading scheme is lower. From Fig. 6, it is observed that the most expensive DG in MG 4 is dispatched at full capacity during hour 21 while the relatively cheaper DG in MG 3 is partially dispatched under the isolated trading scheme. The comparison illustrates that the bidding framework embedded in the cooperative trading scheme allows MGs 2 and 3 to enhance their revenues while affording MG 4 an opportunity to reduce its expenditure.

Fig. 6. Base-case power dispatch profile and up and down reserve margins of the DGs under the isolated trading scheme in the 4 MGs.

This can be observed in Figs. 7 and 8 which illustrate the MEPs, and the energy and reserve exchanges of the PSO with the main grid over the optimization horizon under the cooperative trading scheme respectively. Under the base-case scenario, the PSO only sells power to the main grid during the hours when the MEP settles at $\gamma_{s,0}^t$. During the other hours, the MEP settles in between $\gamma_{b,0}^t$ and $\gamma_{s,0}^t$ owing to the cooperative trading scheme which accrues economic benefits to both the buyers and sellers when compared with the isolated trading scheme. Furthermore, the grid dependency of the MMG system is reduced, wherein the contracted demand (red dashed line in Fig. 8) is 2.04 MW (41.2% reduction) and the contracted supply (blue dashed line in Fig. 8) is 3.45 MW (5.7% reduction).

Finally, Fig. 9 depicts the variations in the total operating cost incurred with p_0 while using the RO approach under the cooperative and isolated trading schemes. A lower p_0 results in a higher reserve cost which leads to a higher total cost for every MG. Also, it is seen that the cooperative trading

Fig. 7. Market equilibrium price at the base-case of the robust operation.

Fig. 8. Interaction in between PSO and the main grid. Contracted demand and supply are shown with red and blue dashed lines respectively.

scheme enables the sharing of economic resources between the constituent MGs in the MMG system, thereby leading to a lower cost for all the MGs when compared with the isolated trading scheme. In this context, it is observed in Fig. 9(b) that the total cost of MG 2 reduces by 15-18% under the cooperative trading scheme when the p_0 varies.

Fig. 9. Expected total operating cost in cooperative and isolated trading for the 4 MGs along with the percentage cost reduction against p_0 .

VI. CONCLUSIONS

An RO model for the joint optimal dispatch of energy and reserves in an MMG system was presented in this paper. The RO model included a cooperative trading scheme based on the iterative sub-gradient method to enable the trading of energy and reserves between the four MGs within an exemplar MMG system. The nonanticipativity was preserved for the following: i) the power dispatch and the reserve allocation of the DGs and the ESSs and ii) the load shifting of the flexible loads. This guaranteed the reserve deliverability and the reliability of the load scheduling under all plausible uncertain scenarios. The TOAT method was used to identify a reduced set of vertex permutations from the polyhedral uncertainty set which comprises the confidence bounds of the RES generation, demand and energy market prices. Subsequently, a robust optimal resource management problem was solved within each MG. The PSO was used to clear the MMG energy market based on the demand and supply bids submitted by individual MGOs. The results showcased the convergence characteristics of the cooperative trading scheme with respect to the step-size

parameter of the iterative sub-gradient method. The efficacy of the cooperative trading scheme was demonstrated by comparing the total operating cost with that obtained while using the isolated trading scheme. Therein, the cooperative trading scheme resulted in economic benefits to the participating MGs owing to the shared utilization of cheaper resources.

REFERENCES

- [1] A. Hamidi, D. Nazarpour, and S. Golshannavaz, "Multiobjective scheduling of microgrids to harvest higher photovoltaic energy," *IEEE Transactions on Industrial Informatics*, vol. 14, pp. 47–57, Jan. 2018.
- [2] L. Ma, N. Liu, J. Zhang, W. Tushar, and C. Yuen, "Energy management for joint operation of CHP and PV prosumers inside a grid-connected microgrid: A game theoretic approach," *IEEE Transactions on Industrial Informatics*, vol. 12, pp. 1930–1942, Oct. 2016.
- [3] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Agtaie, "Stochastic energy management of microgrids during unscheduled islanding period," *IEEE Transactions on Industrial Informatics*, vol. 13, pp. 1079–1087, Jun. 2017.
- [4] E. J. Ng and R. A. El-Shatshat, "Multi-microgrid control systems (MMCS)," in *IEEE PES General Meeting*, pp. 1–6, Jul. 2010.
- [5] Y. Liu, Y. Li, H. B. Gooi, J. Ye, H. Xin, X. Jiang, and J. Pan, "Distributed robust energy management of a multi-microgrid system in the real-time energy market," *IEEE Transactions on Sustainable Energy*, pp. 1–1, 2018.
- [6] Y. Li, T. Zhao, P. Wang, H. B. Gooi, L. Wu, Y. Liu, and J. Ye, "Optimal operation of multimicrogrids via cooperative energy and reserve scheduling," *IEEE Transactions on Industrial Informatics*, vol. 14, pp. 3459–3468, Aug. 2018.
- [7] Y. Wang, S. Mao, and R. M. Nelms, "On hierarchical power scheduling for the macrogrid and cooperative microgrids," *IEEE Transactions on Industrial Informatics*, vol. 11, pp. 1574–1584, Dec. 2015.
- [8] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Transactions on Smart Grid*, vol. 5, pp. 1876–1883, Jul. 2014.
- [9] G. Liu, Y. Xu, and K. Tomovic, "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization," *IEEE Transactions on Smart Grid*, vol. 7, pp. 227–237, Jan. 2016.
- [10] P. Pinson and G. Kariniotakis, "Conditional prediction intervals of wind power generation," *IEEE Transactions on Power Systems*, vol. 25, pp. 1845–1856, Nov. 2010.
- [11] Y. Zhang, N. Gatsis, and G. B. Giannakis, "Robust energy management for microgrids with high-penetration renewables," *IEEE Transactions on Sustainable Energy*, vol. 4, pp. 944–953, Oct. 2013.
- [12] Y. Xiang, J. Liu, and Y. Liu, "Robust energy management of microgrid with uncertain renewable generation and load," *IEEE Transactions on Smart Grid*, vol. 7, pp. 1034–1043, Mar. 2016.
- [13] Q. Zhai, X. Li, X. Lei, and X. Guan, "Transmission constrained UC with wind power: An all-scenario-feasible MILP formulation with strong nonanticipativity," *IEEE Transactions on Power Systems*, vol. 32, pp. 1805–1817, May 2017.
- [14] N. G. Cobos, J. M. Arroyo, N. Alguacil, and J. Wang, "Robust energy and reserve scheduling considering bulk energy storage units and wind uncertainty," *IEEE Transactions on Power Systems*, vol. 33, pp. 5206–5216, Sep. 2018.
- [15] W. Zhang, Y. Xu, Z. Dong, and K. P. Wong, "Robust security constrained-optimal power flow using multiple microgrids for corrective control of power systems under uncertainty," *IEEE Transactions on Industrial Informatics*, vol. 13, pp. 1704–1713, Aug. 2017.
- [16] D. Gregoratti and J. Matamoros, "Distributed energy trading: The multiple-microgrid case," *IEEE Transactions on Industrial Electronics*, vol. 62, pp. 2551–2559, Apr. 2015.
- [17] D. P. Bertsekas, *Convex Analysis and Optimization*. Athena Scientific, 2003.
- [18] Y. Hong, F. Lin, and T. Yu, "Taguchi method-based probabilistic load flow studies considering uncertain renewables and loads," *IET Renewable Power Generation*, vol. 10, no. 2, pp. 221–227, 2016.
- [19] H. Yu and W. D. Rosehart, "An optimal power flow algorithm to achieve robust operation considering load and renewable generation uncertainties," *IEEE Transactions on Power Systems*, vol. 27, pp. 1808–1817, Nov. 2012.
- [20] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers," *IEEE Transactions on Power Systems*, vol. 32, pp. 3569–3583, Sep. 2017.