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Framework for Network-Constrained Cooperative Trading of Multi-Microgrid Systems

Mohasha Isuru, Ashok Krishnan, Eddy Y. S. Foo and H. B. Gooi

Abstract—The rising penetration of renewable energy sources (RESs) has led to increased research interest in the optimal scheduling and management of multi-microgrid (MMG) systems. This is due to the potential economic benefits which can be derived from the sharing of resources between the MGs which constitute the MMG. Advanced optimization procedures such as robust optimization (RO) frameworks have been proposed in the literature to handle any uncertainties caused by the stochastic nature of the RES generation, the load demand, and the electricity prices. However, the existing works in the literature do not consider the nonlinear network constraints of individual MGs which might significantly impact the power balance and the power sharing between MGs in MMG systems. This paper proposes a cooperative trading scheme including a two-stage network-constrained robust energy management system to optimize the resource utilization within each MG and the sharing of resources between the constituent MGs of a MMG system. The results clearly highlight the performance of the proposed approach and the impact of including the AC network constraints on the optimal dispatch of the MMG system under varying uncertainties.

I. INTRODUCTION

Multi-microgrid systems (MMGs) have attracted growing research interest in recent years due to the liberalization of energy markets, increasing penetration of RESs and advancements in communication technologies. There are two major sources of uncertainties involved in the operation of MMG systems - i) the stochastic natures of the RES generation and the load demand, and ii) the electricity prices.

Several optimization frameworks have been proposed to efficiently share resources between individual MGs in an MMG. Specifically, to deal with the aforementioned uncertainties, RO approaches have been proposed in the literature for dispatching the energy and reserves in MMG systems. In many MMG optimization frameworks such as [1]–[3], individual MGs optimize their local resources and cooperatively contribute to the MMG energy and reserve markets via an independent coordinating entity. The interaction of each MG with the coordinating entity is privacy-preserving as only the power sharing (buying or selling) preferences are communicated. To facilitate the clearance of the MMG energy and reserve markets, recent works have proposed approaches such as the dual-decomposition method [4] and the alternating direction method of multipliers (ADMM) method [5]. The ADMM method was also used by the authors of [6] to

develop an optimization framework to perform the day-ahead scheduling of a local energy community comprising multiple prosumers. An approximated, rudimentary mechanism was developed in [6] to apportion the network losses to each transaction. However, the authors of [6] did not address any of the issues surrounding uncertain RES generation and load demand forecasts in their optimization framework. A bi-level 'system-of-systems' approach was adopted by the authors of [7] to perform the robust optimal scheduling of a multi-microgrid system. The approach in [7] maintained the power balance within each MG using a centralized MG level controller. Each MG controller then coordinated with a distribution management system to enable power sharing with the other MGs constituting the MMG. A cooperative, stochastic optimization approach was used to schedule the operations of the MMG system in [8]. The optimization model in [8] had multiple objectives which led to a reduction in the CO₂ emissions from the MMG system. The optimization model in [8] included a demand response scheme and was solved using the compromised program method. DC power flow constraints were also included in the optimization model formulated in [8]. Recently, game-theoretic approaches which enable peer-to-peer trading among power system entities have also gained prominence [9]. A distributed, two-layer MMG control model was proposed in [10] with agents as the top layer and the MMG network as the bottom layer. Two communication subgraphs were defined in [10] - within MGs and between MGs. Control laws were derived for the agents. The control laws for the MG subgraph ensured power balance within the MG while also setting the outputs of the dispatchable DGs proportional to their capacities. The control law for the MMG subgraph tried to ensure power balance within the MMG through the cooperation of the constituent MGs.

Microgrids are generally multi-bus systems. As a result, the network power losses and the power transfer limits might significantly impact the power balance and/or power sharing in an MG [11], [12]. However, none of the optimization models in the aforementioned works related to MMGs incorporate a day-ahead power and reserve dispatch framework which considers the impact of the AC network constraints within each MG constituting the MMG system. To this end, the major contributions of the proposed optimization framework in this paper are as follows:

- 1) A cooperative trading scheme including a two-stage network-constrained robust energy management system (EMS) is proposed for optimally utilizing the

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resources within each MG constituting the MMG system. The proposed scheme also facilitates optimal power sharing between the MGs constituting the MMG system. The two-stage EMS accounts for uncertainties in the RES generation, load demand and electricity market price forecasts via a robust optimization model. The two stages are designed in a manner which enhances the computational properties of the EMS.

- 2) The impact of including the network constraints (NCs) in the optimal scheduling model of the MMG system is analyzed under various degrees of uncertainties in the RES generation and load demand forecasts.

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

A. Uncertainty Characterization

In general, uncertain variables such as the nominal load demand, generation from the RESs, and the electricity prices offered by the utility grid can be assumed using polyhedral uncertainty sets over the optimization horizon [3], [5]. It has been shown in [13] that the worst uncertainty which is unknown a priori occurs at a vertex combination of the (polyhedral) uncertainty sets. The *Taguchi's orthogonal array testing* (TOAT) method is a widely used scenario generation approach which has a higher potential for representing the worst uncertain scenario. The TOAT method uses a special set of *orthogonal arrays* (OAs) to select a fraction of all the vertex combinations.

Table I depicts the *transpose* of the first five columns of the OA L_{82^7} specifying eight scenarios (columns) involving five (cooperative entities) two-level factors [14].

TABLE I
SELECTED SCENARIOS BASED ON THE OA L_{82^7}

Scenario ω	Levels of each Random Factor							
Price	+	+	+	+	-	-	-	-
MG 1	+	+	-	-	+	+	-	-
MG 2	+	+	-	-	-	-	+	+
MG 3	+	-	+	-	+	-	+	-
MG 4	+	-	+	-	-	+	-	+

Let $\Upsilon = \{0, 1, \dots, \mathcal{W}\}$ be the set of scenario indices wherein the base scenario (set of nominal values) is represented by the entry 0. In Table I, $\mathcal{W} = 8$ and the + and - signs symbolically represent the upper and lower vertices of the polyhedrons of the uncertain variables during each hour. Let $\mathcal{M}$ be the set of MGs constituent in the MMG system. Then, the nominal demand $P_{ND,\omega}^{m,t}$ of MG $m \in \mathcal{M}$ under scenario $\omega \in \Upsilon \setminus \{0\}$ during hour $t \in \mathcal{T} = \{1, \dots, T\}$ is a vertex of the uncertain polyhedron as defined below:

$$P_{ND,\omega}^{m,t} \in \left\{ [P_{ND}^{m,t}]_+, [P_{ND}^{m,t}]_- \right\} \quad (1)$$

The two vertices during hour t are defined below:

$$[P_{ND}^{m,t}]_+ = P_{ND,0}^{m,t} + P_{ND}^{m,t,\zeta+}, [P_{ND}^{m,t}]_- = P_{ND,0}^{m,t} - P_{ND}^{m,t,\zeta-} \quad (2)$$

where $P_{ND}^{m,t,\zeta+}$ and $P_{ND}^{m,t,\zeta-}$ represent the (nonnegative) deviations in the upper and lower confidence bounds respectively of the nominal demand of MG m during hour $t \in \mathcal{T}$.

The vertices of the power output of RES $f \in \mathcal{F}^m$ (set of wind and solar PV power plants in MG m) during hour t can be defined as follows:

$$[P_{F,f}^{m,t}]_+ = P_{F,f,0}^{m,t} - P_{F,f}^{m,t,\zeta-}, [P_{F,f}^{m,t}]_- = P_{F,f,0}^{m,t} + P_{F,f}^{m,t,\zeta+} \quad (3)$$

Then, the RES generation $P_{F,f,\omega}^{m,t}$ of RES f in MG m under scenario $\omega \in \Upsilon \setminus \{0\}$ during hour t is a vertex of the uncertain polyhedron as defined below:

$$P_{F,f,\omega}^{m,t} \in \left\{ [P_{F,f}^{m,t}]_+, [P_{F,f}^{m,t}]_- \right\} \quad (4)$$

where $P_{F,f}^{m,t,\zeta+}$ and $P_{F,f}^{m,t,\zeta-}$ represent the (nonnegative) deviations in the upper and lower confidence bounds respectively of the power output of RES f in MG m during hour t .

The upper and lower vertices of the price at which electricity is bought from the utility grid (denoted by $[\lambda_{UG}^{B,t}]_+$ and $[\lambda_{UG}^{B,t}]_-$ respectively) during hour t are defined below.

$$[\lambda_{UG}^{B,t}]_+ = \lambda_{UG,0}^{B,t} + \lambda_{UG}^{B,t,\zeta+}, [\lambda_{UG}^{B,t}]_- = \lambda_{UG,0}^{B,t} - \lambda_{UG}^{B,t,\zeta-} \quad (5)$$

The upper and lower vertices of the price at which electricity is sold to the utility grid (denoted by $[\lambda_{UG}^{S,t}]_+$ and $[\lambda_{UG}^{S,t}]_-$ respectively) can also be defined in a similar fashion.

The power requirement $\zeta_{\omega}^{m,t}$ under scenario ω during hour t is given in (6), where $P_{L,\omega}^{m,t}$ is the total power loss.

$$\zeta_{\omega}^{m,t} = P_{ND,\omega}^{m,t} - \sum_{f \in \mathcal{F}^m} P_{F,f,\omega}^{m,t} + P_{L,\omega}^{m,t}; \forall t \in \mathcal{T}, \forall \omega \in \Upsilon \quad (6)$$

B. Microgrid Component Modeling

1) *Energy Storage System (ESS)*: For all $e \in \mathcal{E}^m$:

$$C_{E,e,\omega}^{m,t} = a_{E,e}^m (P_{E,e,\omega}^{C,m,t})^2 + a_{E,e}^m (P_{E,e,\omega}^{D,m,t})^2 \quad (7a)$$

$$0 \leq P_{E,e,\omega}^{C,m,t} \leq (P_{E,e}^{C,m})^{\max}; \forall \omega \in \Upsilon \quad (7b)$$

$$0 \leq P_{E,e,\omega}^{D,m,t} \leq (P_{E,e}^{D,m})^{\max}; \forall \omega \in \Upsilon \quad (7c)$$

$$E_{e,\omega}^{m,t} = E_{e,\omega}^{m,t-1} + \frac{\Delta t}{B_e^m} \left(\eta_e^C P_{E,e,\omega}^{C,m,t} - \frac{1}{\eta_e^D} P_{E,e,\omega}^{D,m,t} \right) \quad (7d)$$

$$E_{e,\omega}^{m,1} = \frac{\Delta t}{B_e^m} \left(\eta_e^C P_{E,e,\omega}^{C,m,1} - \frac{1}{\eta_e^D} P_{E,e,\omega}^{D,m,1} \right) + E_{I,e}^m \quad (7e)$$

$$(E_e^m)^{\min} \leq E_{e,\omega}^{m,t} \leq (E_e^m)^{\max}; \forall \omega \in \Upsilon \quad (7f)$$

$$E_{e,0}^{m,T} = E_{I,e}^m \quad (7g)$$

$$(1 - \delta) E_{I,e}^m \leq E_{e,\omega}^{m,T} \leq (1 + \delta) E_{I,e}^m; \forall \omega \in \Upsilon \setminus \{0\} \quad (7h)$$

$$P_{E,e,\omega}^{D,m,t} - P_{E,e,\omega}^{C,m,t} = P_{E,e,0}^{D,m,t} - P_{E,e,0}^{C,m,t} + \sigma_{E,e}^{m,t} (\zeta_{\omega}^{m,t} - \zeta_0^{m,t}); \forall \omega \in \Upsilon \setminus \{0\} \quad (7i)$$

where e is the ESS index and $\mathcal{E}^m$ is the set of ESSs. $P_{E,e,\omega}^{C,m,t}$, $P_{E,e,\omega}^{D,m,t}$, $E_{e,\omega}^{m,t}$ and B_e^m are the charging power, the discharging power, the state of charge (SoC) and the energy capacity of the ESS respectively; $a_{E,e}^m$ is the coefficient of

the quadratic degradation cost function in (7a); η_e^C and η_e^D are the charging and discharging efficiencies respectively. The charging and discharging power limits are expressed in (7b) and (7c) respectively. The time varying SoC under scenario ω is computed using (7d)-(7e) and is bounded by (7f). Under the base scenario, (7g) ensures that the SoC at the end of the optimization horizon, i.e., $E_{e,0}^{m,T}$ is the same as the initial SoC $E_{1,e}^m$. For the other scenarios, it is constrained to be within a predefined radius δ around $E_{1,e}^m$ by (7h). The duration of each optimization interval (denoted by Δt) is 1 h. Equation (7i) enforces the participation factors (PFs) $\sigma_{E,e}^{m,t}$ of the charging/discharging powers to deal with any power mismatches caused due to the aforementioned uncertainties and power loss variations.

2) *Diesel Generators (DGs)*: For all $g \in \mathcal{G}^m$:

$$C_{G,g,\omega}^{m,t} = a_{G,g}^m (P_{G,g,\omega}^{m,t})^2 + b_{G,g}^m P_{G,g,\omega}^{m,t} \quad (8a)$$

$$\underline{P}_{G,g}^m \leq P_{G,g,\omega}^{m,t} \leq \bar{P}_{G,g}^m; \forall \omega \in \Upsilon \quad (8b)$$

$$-\hat{r}_{G,g}^m \leq P_{G,g,\omega}^{m,t} - P_{G,g,0}^{m,t} \leq \hat{r}_{G,g}^m; \forall \omega \in \Upsilon \setminus \{0\} \quad (8c)$$

$$P_{G,g,\omega}^{m,t} = P_{G,g,0}^{m,t} + \sigma_{G,g}^{m,t} (\zeta_{\omega}^{m,t} - \zeta_0^{m,t}); \forall \omega \in \Upsilon \setminus \{0\} \quad (8d)$$

$$\hat{R}_{G,g}^m \leq P_{G,g,\omega}^{m,t} - P_{G,g,\omega}^{m,t-1} \leq \hat{R}_{G,g}^m; \forall \omega \in \Upsilon \quad (8e)$$

where g is the DG index and $\mathcal{G}^m$ is the set of DGs. $P_{G,g,\omega}^{m,t}$ is the power dispatch and $a_{G,g}^m$ and $b_{G,g}^m$ are the quadratic and linear coefficients respectively of the fuel cost function shown in (8a). Equation (8b) bounds $P_{G,g,\omega}^{m,t}$ within its upper and lower bounds which are denoted by $\bar{P}_{G,g}^m$ and $\underline{P}_{G,g}^m$ respectively. Equation (8c) ensures that the power dispatch respects the up and down reserve capability bounds which are denoted by $\hat{r}_{G,g}^m$ and $\hat{r}_{G,g}^m$ respectively. Constraint (8d) enforces the PFs $\sigma_{G,g}^{m,t}$ of the DGs to mitigate any power mismatch due to the aforementioned uncertainties and power loss variations. Equation (8e) ensures that the up and down operating ramp rate constraints denoted by $\hat{R}_{G,g}^m$ and $\hat{R}_{G,g}^m$ respectively, are respected between any two successive time periods under all plausible scenarios.

3) *Dispatchable Loads*:

$$C_{D,\omega}^{m,t} = a_D^m (P_{RD,\omega}^{m,t})^2 + a_D^m (P_{CD,\omega}^{m,t})^2 \quad (9a)$$

$$0 \leq P_{RD,\omega}^{m,t} \leq \bar{P}_{RD}^m; \forall \omega \in \Upsilon \quad (9b)$$

$$0 \leq P_{CD,\omega}^{m,t} \leq \bar{P}_{CD}^m; \forall \omega \in \Upsilon \quad (9c)$$

$$\sum_{t \in \mathcal{T}} [P_{RD,0}^{m,t} - P_{CD,0}^{m,t}] = 0 \quad (9d)$$

$$\Delta t \sum_{t \in \mathcal{T}} [P_{CD,\omega}^{m,t} - P_{RD,\omega}^{m,t}] \leq E_{Shed}^m; \forall \omega \in \Upsilon \setminus \{0\} \quad (9e)$$

$$P_{CD,\omega}^{m,t} - P_{RD,\omega}^{m,t} = P_{CD,0}^{m,t} - P_{RD,0}^{m,t} + \sigma_D^{m,t} (\zeta_{\omega}^{m,t} - \zeta_0^{m,t}); \forall \omega \in \Upsilon \setminus \{0\} \quad (9f)$$

where $P_{CD,\omega}^{m,t}$ and $P_{RD,\omega}^{m,t}$ are the curtailed and redispatched load demands respectively. a_D^m is the coefficient of the cost function in (9a) which reflects the inconvenience experienced by the consumers due to the load shifting. The demand redispatch and curtailment are constrained by (9b) and (9c) respectively. Equation (9d) prevents load shedding under the base scenario. Constraint (9e) restricts the total load

shedding below E_{Shed}^m under all the plausible uncertain scenarios. Equation (9f) enforces the PFs $\sigma_D^{m,t}$ of the demand redispatch/curtailment to mitigate any power mismatches caused by the aforementioned uncertainties and power loss variations.

4) *Power Imports/Exports*: The energy and reserve trading by each MG m depends on the market equilibrium price (MEP) $\lambda_{O,\omega}^t$.

$$C_{O,\omega}^{m,t} = [\lambda_{O,\omega}^t + \tau] P_{B,\omega}^{m,t} - [\lambda_{O,\omega}^t - \tau] P_{S,\omega}^{m,t} \quad (10a)$$

$$P_{O,\omega}^{m,t} = P_{B,\omega}^{m,t} - P_{S,\omega}^{m,t}; \forall \omega \in \Upsilon \quad (10b)$$

$$P_{O,\omega}^{m,t} = P_{O,0}^{m,t} + \sigma_O^{m,t} (\zeta_{\omega}^{m,t} - \zeta_0^{m,t}); \forall \omega \in \Upsilon \setminus \{0\} \quad (10c)$$

$$0 \leq P_{B,\omega}^{m,t}, P_{S,\omega}^{m,t} \leq \bar{P}_O^m; \forall \omega \in \Upsilon \quad (10d)$$

where $P_{B,\omega}^{m,t}$ ($P_{S,\omega}^{m,t}$) is the power purchased (sold) by MG m from (to) the MMG coordinating entity (MCE) and τ is the service fee per unit of electricity. The convex power trading cost function is shown in (10a). Constraints (10b) and (10c) enforce the PFs $\sigma_O^{m,t}$ of the power imports/exports to mitigate any power mismatches caused due to the aforementioned uncertainties. Constraint (10d) bounds the power imported or exported by MG m below the capacity limit $\bar{P}_O^m$ respectively.

C. Energy Management Model for a Single Microgrid

The total operating cost (TOC) function under scenario ω during hour t is formulated as follows:

$$C_{\omega}^{m,t}(\Phi_{\omega}^{m,t}) = \sum_{g \in \mathcal{G}^m} C_{G,g,\omega}^{m,t} + \sum_{e \in \mathcal{E}^m} C_{E,e,\omega}^{m,t} + C_{D,\omega}^{m,t} + C_{O,\omega}^{m,t} \quad (11)$$

The overall robust day-ahead optimal dispatch problem of each MG $m \in \mathcal{M}$ can be formulated as shown in (12).

$$\min_{\Phi_{\omega}^{m,t}} C_{\exp}^m = \sum_{t \in \mathcal{T}} \left[C_0^{m,t} + \frac{1}{W} \sum_{\omega \in \Upsilon \setminus \{0\}} C_{\omega}^{m,t} \right] \quad (12a)$$

$$\text{s.t. } \mathbf{1}^T P_{G,0}^{m,t} + \mathbf{1}^T [P_{E,0}^{D,m,t} - P_{E,0}^{C,m,t}] + P_{O,0}^{m,t} = P_{RD,0}^{m,t} - P_{CD,0}^{m,t} + \zeta_0^{m,t}; \forall t \in \mathcal{T} \quad (12b)$$

$$\mathbf{1}^T \sigma_G^{m,t} + \mathbf{1}^T \sigma_E^{m,t} + \sigma_D^{m,t} + \sigma_O^{m,t} = 1; \forall t \in \mathcal{T} \quad (12c)$$

$$\underline{V}^m \leq \hat{V}_{V,\omega}^{m,t} \Delta \Phi_{\omega}^{m,t} + \hat{V}_{\omega}^{m,t} \leq \bar{V}^m; \forall \omega \in \Upsilon, \forall t \in \mathcal{T} \quad (12d)$$

$$\hat{J}_{X,\omega}^{m,t} \Delta \Phi_{\omega}^{m,t} + \hat{\Psi}_{X,\omega}^{m,t} \leq [\mathbf{I}, \mathbf{I}]^T \bar{S}^X; \forall \omega \in \Upsilon, \forall t \in \mathcal{T} \quad (12e)$$

$$(6), (7b)-(7i), (8b)-(8e), (9b)-(9f), (10b)-(10d) \quad (12f)$$

where $\Delta \Phi_{\omega}^{m,t} = \Phi_{\omega}^{m,t} - \hat{\Phi}_{\omega}^{m,t}$; $\mathbf{1}$ is a vector of ones with an appropriate dimension; $\mathbf{I}$ is the unit matrix with an appropriate dimension; $(\cdot)^T$ is the transpose of vector/matrix $(\cdot)$; $\hat{(\cdot)}$ is the value of $(\cdot)$ during the previous iteration; (12a) is the *expected* TOC function formulated using the sampling average approximation method; (12b) is the power balance constraint; (12c) constrains the sum of the PFs to be equal to 1 during every hour so that the total power mismatch is proportionally compensated through optimal contributions from the MG components; (12d) and (12e) are linearized voltage and power flow constraints at a known optimal

power flow (OPF) solution so that the updated day-ahead optimal dispatch solution satisfies the linearized NCs. The optimization problem in (12) is a quadratic convex program which can be solved efficiently using commercial solvers.

III. TWO-STAGE NETWORK-CONSTRAINED MICROGRID ENERGY MANAGEMENT SYSTEM

In this section, a two-stage EMS is proposed to determine the optimal day-ahead power and reserve dispatches for each MG constituting the MMG system while satisfying the NCs. The proposed RO framework is illustrated by the flowchart in Fig. 1 and it comprises two sequential stages to minimize the total MG operating cost and to examine the feasibility of the NCs. This two-stage approach reduces the complexity of the overall optimization problem, thereby ensuring that it is solved in a reasonable time using off-the-shelf commercial solvers.

Fig. 1. Flowchart of the two-stage network-constrained MG EMS.

In Stage 1, the robust day-ahead optimal dispatch (RDAO) problem (12) is initiated with the given $\lambda_O = [\lambda_{O,1}^1, \dots, \lambda_{O,W+1}^T]^T$. Then, the feasibility of the day-ahead generation schedule Φ^m is examined in Stage 2 by solving OPF problems which are formulated for each scenario $\omega \in \Upsilon$ during each hour $t \in \mathcal{T}$.

A. Optimal Power Flow Formulation

The OPF problems in Stage 2 are formulated by *fixing* the power dispatch values of the MG components such as the DGs, the ESSs, and dispatchable loads to the values determined in Stage 1. The critical demand and the RES generation are fixed to the values corresponding to the scenario and the hour. The power import/export limits are sufficiently adjusted using a prespecified parameter $\chi (= 0.25)$ to account for the power losses. For power injections at the point-of-common-coupling (PCC):

$$-(1 + \chi)\bar{P}_O^m \leq P_{O,\omega}^{m,t} \leq (1 + \chi)\bar{P}_O^m; \forall t \in \mathcal{T}, \forall \omega \in \Upsilon \quad (13)$$

For each MG, let $\mathcal{N}$ and $\mathcal{L}$ represent the sets of buses and lines respectively. Let $\delta \in \mathbb{R}^{|\mathcal{N}|}$ and $V \in \mathbb{R}^{|\mathcal{N}|}$ represent the vectors of bus voltage angles and magnitudes respectively with $\Theta = [\delta^T, V^T]^T$. Equations (14a) and (14b) constitute the active and reactive power exchanges (denoted by Ψ_n^P and Ψ_n^Q) respectively at bus $n \in \mathcal{N}$. The subscripts of the

variables denote the bus indices and $\delta_{n,i} = \delta_n - \delta_i$. $Y_{n,i}^G$ and $Y_{n,i}^B$ represent the real and imaginary parts respectively of element (n, i) of the *bus admittance matrix* [15].

$$\Psi_n^P(\Theta) = V_n \sum_{i \in \mathcal{N}} V_i [Y_{n,i}^G \cos(\delta_{n,i}) + Y_{n,i}^B \sin(\delta_{n,i})] \quad (14a)$$

$$\Psi_n^Q(\Theta) = V_n \sum_{i \in \mathcal{N}} V_i [Y_{n,i}^G \sin(\delta_{n,i}) - Y_{n,i}^B \cos(\delta_{n,i})] \quad (14b)$$

Equation (15) formulates the active ($\vec{P}_l^X$), reactive ($\vec{Q}_l^X$) and apparent ($\vec{\Psi}_l^X$) power flows through line $l \in \mathcal{L}$ from bus $i \in \mathcal{N}$ to bus $j \in \mathcal{N}$ ($i \neq j$).

$$\vec{P}_l^X = -V_i^2 Y_{i,j}^G + V_i V_j [Y_{i,j}^G \cos(\delta_{i,j}) + Y_{i,j}^B \sin(\delta_{i,j})] \quad (15a)$$

$$\vec{Q}_l^X = V_i^2 Y_{i,j}^B + V_i V_j [Y_{i,j}^G \sin(\delta_{i,j}) - Y_{i,j}^B \cos(\delta_{i,j})] \quad (15b)$$

$$\vec{\Psi}_l^X(\Theta) = \sqrt{(\vec{P}_l^X)^2 + (\vec{Q}_l^X)^2} \quad (15c)$$

Similarly, the corresponding equations for power flows $\overleftarrow{P}_l^X$, $\overleftarrow{Q}_l^X$, and $\overleftarrow{\Psi}_l^X$ from bus j to bus i can also be formulated. It should be noted that indices m , t , and ω has been dropped in (14) and (15) for the sake of brevity. Therewith, the OPF problem for MG m during hour t under scenario ω can be formulated as follows.

$$\min_{\Theta_{\omega}^{m,t}, P_{I,\omega}^{m,t}, Q_{I,\omega}^{m,t}} C_{O,\omega}^{m,t} (P_{B,\omega}^{m,t}, P_{S,\omega}^{m,t}) \quad (16a)$$

$$\text{s.t. (10b), (13), (14); } \forall n \in \mathcal{N}, (15); \forall l \in \mathcal{L} \quad (16b)$$

$$P_{I,n,\omega}^{m,t} = \Psi_n^P(\Theta_{\omega}^{m,t}), Q_{I,n,\omega}^{m,t} = \Psi_n^Q(\Theta_{\omega}^{m,t}); \forall n \in \mathcal{N} \quad (16c)$$

$$\vec{\Psi}_l^X(\Theta_{\omega}^{m,t}) \leq \bar{S}_l^X, \overleftarrow{\Psi}_l^X(\Theta_{\omega}^{m,t}) \leq \bar{S}_l^X; \forall l \in \mathcal{L} \quad (16d)$$

$$V^m \leq V_{\omega}^{m,t} \leq \bar{V}^m, Q_I^m \leq Q_{I,\omega}^{m,t} \leq \bar{Q}_I^m \quad (16e)$$

where $P_{I,\omega}^{m,t}$, $Q_{I,\omega}^{m,t}$ are the active and reactive nodal power injections from MG components; (16c) is the nodal power balance; (16d) represents that the line flows are limited by the capacity limits $\bar{S}_l^X$; and (16e) represents that the bus voltage is bounded by the voltage limits V^m and $\bar{V}^m$, and the reactive power dispatch is bounded by the capability bounds Q_I^m and $\bar{Q}_I^m$. Based on the OPF solution $\Theta_{\omega}^{m,t}$,

$$P_{L,\omega}^{m,t} = \sum_{n \in \mathcal{N}} \Psi_n^P(\Theta_{\omega}^{m,t}); \forall t \in \mathcal{T}, \forall \omega \in \Upsilon \quad (17)$$

B. Jacobian Matrix-based Linear Approximations

In the proposed two-stage MG energy management problem, the nonlinear NCs are separated from the RDAO problem. This allows the RDAO problem to remain convex and tractable. Furthermore, this allows the NC evaluations to be decomposed into individual OPF problems which have the potential of being solved in parallel. To include the voltage and power transfer constraints in the RDAO problem, linearized NCs are included as shown in (12d) and (12e) [15]. Let Γ_n^P , Γ_n^Q , $\vec{\Gamma}_l^X$, and $\overleftarrow{\Gamma}_l^X$ be the Jacobian (first order derivative) matrices of Ψ_n^P , Ψ_n^Q , $\vec{\Psi}_l^X$, and $\overleftarrow{\Psi}_l^X$ respectively at a given voltage-angle

solution Θ of the OPF problem in (16). Let $\mathbf{I}$ be the $|\mathcal{N}|$ -dimension unit matrix, $\mathcal{I}$ be the matrix that maps the power injections/extractions from the MG components to the buses, $\Gamma^{\text{PQ}} = \left[(\Gamma_1^{\text{P}})^{\text{T}}, \dots, (\Gamma_{|\mathcal{N}|}^{\text{P}})^{\text{T}}, (\Gamma_1^{\text{Q}})^{\text{T}}, \dots, (\Gamma_{|\mathcal{N}|}^{\text{Q}})^{\text{T}} \right]^{\text{T}} \in \mathbb{R}^{2|\mathcal{N}| \times 2|\mathcal{N}|}$, and $\Gamma^{\text{X}} = \left[(\tilde{\Gamma}_1^{\text{X}})^{\text{T}}, \dots, (\tilde{\Gamma}_{|\mathcal{L}|}^{\text{X}})^{\text{T}}, (\tilde{\Gamma}_1^{\text{X}})^{\text{T}}, \dots, (\tilde{\Gamma}_{|\mathcal{L}|}^{\text{X}})^{\text{T}} \right]^{\text{T}} \in \mathbb{R}^{2|\mathcal{L}| \times 2|\mathcal{N}|}$. Let $\tilde{\mathbf{I}}$ and $\tilde{\mathcal{I}}$ be the matrices formed by removing the columns which correspond to the slack bus (i.e., the PCC in each MG) from $\mathbf{I}$ and $\mathcal{I}$ respectively. Let $\tilde{\Gamma}^{\text{PQ}}$ be the square matrix formed by removing the columns and rows which correspond to the slack bus from Γ^{PQ} . Let $\tilde{\Gamma}^{\text{X}}$ be the matrix formed by removing the columns which correspond to the slack bus from Γ^{X} . Then,

$$\mathcal{J}_{\text{V}} = [\mathbf{O}, \tilde{\mathbf{I}}] \left(\tilde{\Gamma}^{\text{PQ}} \right)^{-1} [\tilde{\mathcal{I}}^{\text{T}}, \mathcal{O}^{\text{T}}]^{\text{T}} \quad (18a)$$

$$\mathcal{J}_{\text{X}} = \tilde{\Gamma}^{\text{X}} \left(\tilde{\Gamma}^{\text{PQ}} \right)^{-1} [\tilde{\mathcal{I}}^{\text{T}}, \mathcal{O}^{\text{T}}]^{\text{T}} \quad (18b)$$

where $\mathbf{O} = \{0\}^{|\mathcal{N}| \times |\mathcal{N}| - 1}$; $\mathcal{O}$ is another zero matrix with dimensions equivalent to $\tilde{\mathcal{I}}$.

As illustrated in Fig. 1, Θ , P_{L} , $\mathcal{J}_{\text{V}}$, $\mathcal{J}_{\text{X}}$, and Ψ_{X} are iteratively updated until the convergence of the two-stage network-constrained robust EMS, where $\Psi_{\text{X}} = \left[\tilde{\Psi}_1^{\text{X}}(\Theta), \dots, \tilde{\Psi}_{|\mathcal{L}|}^{\text{X}}(\Theta), \tilde{\Psi}_1^{\text{X}}(\Theta), \dots, \tilde{\Psi}_{|\mathcal{L}|}^{\text{X}}(\Theta) \right]^{\text{T}}$. As such, the two stages are mainly coupled via the outer-approximations of the power flows and the voltage constraints. The power flow and voltage constraints are expressed in (16c)-(16e), while their outer approximations are included in the RDAOD problem via (12d) and (12e). This procedure follows the general convergence behaviour described in [16]. In addition, P_{L} is also added to the power balance constraints of the RDAOD problem to further improve the convergence characteristics. In case an OPF problem is found to be *infeasible*, it is solved again by relaxing (16d). This is referred to as *Relaxed-OPF* in Fig. 1. The algorithm terminates when the maximum power loss variation is less than the tolerance ϵ ($= 1\%$).

IV. COOPERATIVE MARKET CLEARING FOR MULTI-MICROGRIDS

A. Multi-Microgrid System Structure

An MMG system is a cluster of MGs, each of which is connected to a PCC as shown in Fig. 2. Each microgrid op-

Fig. 2. The typical structure of an MMG system.

erator strives to optimally utilize locally available resources to meet the internal load demand via the aforementioned network-constrained MG EMS in Fig. 1, while also interfacing with a MCE for buying and selling electricity. The MCE collects all the supply/demand bids from the constituent MGs and determines the MEP. Subsequently, the MCE imports (exports) the electricity deficit (surplus) from (to) the utility grid at predetermined buying (selling) prices.

B. Cooperative Trading Algorithm

Algorithm 1 Optimal Power Sharing Coordination

```

1: Initialize  $k \leftarrow 0$ ;  $\epsilon_{\text{P}} \leftarrow 10^{-3}$ ;  $\lambda_{\text{O}}(1)$ ;  $\Delta P_{\text{M},\omega}^t(0) \leftarrow \infty$ 
2: while  $\max_{t \in \mathcal{T}} \max_{\omega \in \mathcal{Y}} |\Delta P_{\text{M},\omega}^t(k)| \geq \epsilon_{\text{P}}$  do
3:    $k \leftarrow k + 1$ 
4:   Send  $\lambda_{\text{O}}(k)$  to MGs.
   /* Waiting for the response from all MGs. */
5:   Receive  $P_{\text{O}}^m(k)$  from each MG.
6:   Compute  $\lambda_{\text{O},\omega}^t(k+1)$  using (19).
7:   if  $\lambda_{\text{O},\omega}^t(k+1) \geq \lambda_{\text{UG},\omega}^{\text{B},t}$  then
8:      $\lambda_{\text{O},\omega}^t(k+1) = \lambda_{\text{UG},\omega}^{\text{B},t}$ ,  $\Delta P_{\text{M},\omega}^t(k) = 0$ 
9:      $P_{\text{UG},\omega}^{\text{B},t}(k) = \sum_{m \in \mathcal{M}} P_{\text{O},\omega}^m(k)$ ,  $P_{\text{UG},\omega}^{\text{S},t}(k) = 0$ 
10:  else if  $\lambda_{\text{O},\omega}^t(k+1) \leq \lambda_{\text{UG},\omega}^{\text{S},t}$  then
11:     $\lambda_{\text{O},\omega}^t(k+1) = \lambda_{\text{UG},\omega}^{\text{S},t}$ ,  $\Delta P_{\text{M},\omega}^t(k) = 0$ 
12:     $P_{\text{UG},\omega}^{\text{B},t}(k) = 0$ ,  $P_{\text{UG},\omega}^{\text{S},t}(k) = - \sum_{m \in \mathcal{M}} P_{\text{O},\omega}^m(k)$ 
13:  else
14:     $\Delta P_{\text{M},\omega}^t(k) = \sum_{m \in \mathcal{M}} P_{\text{O},\omega}^m(k)$ 
15:     $P_{\text{UG},\omega}^{\text{B},t}(k) = P_{\text{UG},\omega}^{\text{S},t}(k) = 0$ 
16:  end if
17: end while

```

Algorithm 1 summarizes the cooperative bidding scheme executed by the MCE to facilitate the clearing of the MMG market. During every iteration k , each MG separately executes the two-stage network-constrained MG EMS shown in Fig. 1 at the given MEPs λ_{O} and communicates P_{O}^m to the MCE in between the Steps 4 and 5 of Algorithm 1. Subsequently, the MCE estimates the difference between the power demand and supply bids to recalculate the MEP $\lambda_{\text{O},\omega}^t$ under scenario ω during hour t using (19) as shown in Steps 6-16 of Algorithm 1.

$$\lambda_{\text{O},\omega}^t(k+1) = \lambda_{\text{O},\omega}^t(k) + \alpha \sum_{m \in \mathcal{M}} P_{\text{O},\omega}^m(k) \quad (19)$$

where α is the (nonnegative) step-size. In this model, the operators in each MG m solves (12) to minimize its TOC for $\lambda_{\text{O},\omega}^t$ provided by the MCE. Consequently, if the net demand is higher, (19) arrives at a higher MEP for the next iteration to encourage more supply or less demand. Conversely, if the net supply is higher, (19) arrives at a lower MEP for the next iteration to encourage less supply or more demand. Accordingly, (19) 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 power demand and supply. The MMG system considered in this paper is assumed to be operated in the grid-connected mode. The MCE manages the electric power transactions between the MMG system and the utility grid based on the per unit spot prices $\lambda_{UG,\omega}^{B,t}$ and $\lambda_{UG,\omega}^{S,t}$. In practice, $\lambda_{UG,\omega}^{B,t} > \lambda_{UG,\omega}^{S,t}$ to avoid energy arbitrage [5]. As explained in Steps 7-16, the MEP is maintained in between $\lambda_{UG,\omega}^{B,t}$ and $\lambda_{UG,\omega}^{S,t}$ and the resulting net power deficit/surplus of the MMG system is imported ($P_{UG,\omega}^{B,t}$)/exported ($P_{UG,\omega}^{S,t}$) from/to the utility grid. Algorithm 1 terminates when the power balance in the MMG system is achieved within a tolerance ϵ_P under every scenario over the optimization horizon. Interested readers can refer to [2], [4] for more details regarding the convergence of Algorithm 1.

V. CASE STUDIES AND RESULTS

A. System Parameters and Simulation Settings

Numerical simulations are performed on an exemplar MMG system comprising four MGs each of which contains two DGs, two ESSs, dispatchable loads, fixed loads, and RESs. $b_{G,g}^m = \{85, 75, 80, 95\}$ (\$/MWh) for the four MGs respectively. Furthermore, for all $m \in \mathcal{M}, g \in \mathcal{G}^m$: $a_{G,g}^m = \$5/\text{MW}^2\text{h}$, $\bar{P}_{G,g}^m = 0.5 \text{ MW}$, $\underline{P}_{G,g}^m = 0 \text{ MW}$, $\hat{R}_{G,g}^m = \hat{R}_{G,g}^m = 0.25 \text{ MW/h}$ and $\hat{r}_{G,g}^m = \hat{r}_{G,g}^m = 0.2 \text{ MW}$. The ESSs have the following parameters for all $m \in \mathcal{M}$ and $e \in \mathcal{E}^m$: $a_{E,e}^m = \$5/\text{MW}^2\text{h}$, $B_e^m = 1 \text{ MWh}$, $\eta_e^C = \eta_e^D = 0.97$, $\bar{P}_{E,e}^{C,m} = \bar{P}_{E,e}^{D,m} = 0.2 \text{ MW}$, $\bar{E}_e^m = 0.9$, $\underline{E}_e^m = 0.1$, $E_{R,e}^m = 0.5$, and $\delta = 0.2$. The dispatchable loads have the following parameters for all $m \in \mathcal{M}$: $a_{FD}^m = \$15/\text{MW}^2\text{h}$, $\bar{P}_{RD}^m = \bar{P}_{CD}^m = 0.4 \text{ MW}$, and $E_{Shed}^m = 0.75 \text{ MWh}$. Finally, $\bar{P}_O^m = 1.5 \text{ MW}$ for all $m \in \mathcal{M}$.

The four MGs are all assumed to be IEEE 9-bus systems [17] with certain modifications. The base value used in the computations is 1 MVA. The line flow capacities in the original test case are modified accordingly. The resistance of the lines are increased by 4 times. For all the lossless lines, a resistance of 0.02 p.u. is considered. Bus 1 is defined as the PCC and its voltage magnitude is fixed at 1 p.u.. The loads are located at buses 5, 7, and 9. Instead of the sources considered in the original IEEE 9-bus test case, two DGs are connected to buses 3 and 6; two ESSs are connected to buses 2 and 8 while the wind and solar PV plants are connected to buses 9 and 7 respectively.

The load demand and RES generation forecasts are shown in Fig. 3. $\lambda_{UG,0}^{B,t}$ for all $t \in \mathcal{T}$, are the hourly average values extracted from [18]. $\lambda_{UG,0}^{S,t} = \lambda_{UG,0}^{B,t} - \20 for all $t \in \mathcal{T}$. Symmetrical forecast errors of $[10\%, -10\%]$ and $[5\%, -5\%]$ are considered for the nominal load demand of each MG and the utility grid spot prices respectively. The RES generation forecast errors are considered to be within the range $[10\%, -40\%]$. Moreover, the value of τ is equal to $\$3/\text{MWh}$ for cooperative trading.

Algorithm 1 and the RDAOD problem in (12) were programmed in MATLAB and solved using GUROBI. The OPF problems were solved using MATPOWER [17]. All the simulations were performed on a notebook PC with an

Fig. 3. Forecasts for (a) load demand and (b) aggregated RES generation.

Intel®Core i7-8565U four-core CPU processor running at 1.80 GHz with 16 GB of RAM.

B. Comparison of the Significance of Network Constraints

Fig. 4 shows the power losses of each MG under the base scenario. It is observed that the power losses are significant in MGs 1 and 2 during some hours. Therefore, avoiding the power losses while optimally scheduling the MG operation might result in insufficient resources for maintaining the power balance during real-time operation.

Fig. 4. Power losses of the MGs under the base scenario.

Furthermore, there are some noticeable differences between the power dispatch trajectories (curves 1 and 4) of DG 1 in the four MGs when the NCs are considered and ignored as shown in Figs. 5(a)-(d). There are also some noticeable differences between the hourly generation PFs of DG 1 in all the four MGs (curves 5 and 6) when the NCs are considered and ignored as shown in Fig. 5(e)-(h). This highlights the importance of having a cooperative trading framework including network-constrained power and reserve management for MMG systems. Therein, the shaded area in Figs. 5(a)-(d) represents the reserves allocated for mitigating any real-time power mismatches. Moreover, the MEPs are also significantly different for the two cases as observed in Fig. 6. The MEP increases during some hours as the power demand increases due to transfer losses.

C. Validation of the Network-Constrained Power and Reserve Dispatch against Plausible Real-Time Variations

An out-of-sample analysis is used to validate the network-constrained optimal power and reserve (via the PFs) dispatches of the MGs constituting the MMG system. The simulations are performed under four degrees of uncertainty, wherein the sizes of the uncertain bounds are varied as follows:

- 1) 50% for both load demand and RES generation,
- 2) 50% for load demand and 100% for RES generation,
- 3) 100% for load demand and 50% for RES generation and
- 4) 100% (original) for both load demand and RES generation.

Fig. 5. (a)-(d) 1 is the base scenario power dispatch profile while 2 and 3 are the up and down reserve margins respectively of DG 1 in the four MGs which are obtained while considering the NCs; 4 is the base scenario power dispatch profile of DG 1 in the 4 MGs which are obtained without considering the NCs. (e)-(h) 5 and 6 are the PFs of DG 1 in the four MGs which are obtained while considering and ignoring the NCs.

Fig. 6. 1 is the shaded area between $\lambda_{U,G,0}^{B,t}$ and $\lambda_{U,G,0}^{S,t}$; 2 and 3 are $\lambda_{O,0}^t$ obtained while considering and ignoring the NCs respectively.

In each case, a set of scenarios comprising 1,000 uncertain realizations is randomly and independently generated following a uniform probability distribution. Hourly redispatch decisions for each MG component are computed under each scenario while considering the optimal base scenario power dispatch values and the PFs.

Table II shows the expected TOCs and the percentages of scenarios (out of the 4,000 samples for the four MGs) which violate any constraint. It is observed that the network-constrained power and reserve dispatches are feasible against the complete pool of samples under all the degrees of uncertainties. Conversely, a significant number of infeasible samples suggests that feasibility cannot be guaranteed for power and reserve dispatches (and hence for power sharing amounts) which are determined without considering the NCs in practice.

D. Convergence and Computational Analysis

Fig. 7 illustrates the convergence of the power losses in MG 1 under the base scenario during the first iteration of Algorithm 1. Fig. 8 illustrates the computation time required for each MG during each iteration of Algorithm 1, i.e. the time taken to execute the two-stage network-constrained MG EMS at given MEPs with $\alpha = 5$. The RDAOD problem

TABLE II
VALIDATION OF THE OPTIMAL DISPATCH SOLUTIONS UNDER DIFFERENT DEGREES OF UNCERTAINTIES

Case	Without NCs [2]		With NCs	
	TOC (\$/day)	Infeasible Samples	TOC (\$/day)	Infeasible Samples
1	3,052	25.00%	4,181	0%
2	3,945	25.00%	5,076	0%
3	3,099	22.75%	4,227	0%
4	4,003	19.00%	5,111	0%

Fig. 7. Power loss convergence of MG 1 under the base scenario during the first iteration of Algorithm 1, where i is the iteration counter of two-stage network-constrained MG EMS given in Fig. 1.

can be initiated with the power losses computed during a previous run of Algorithm 1. It is reduced during the later iterations due to the convergence of power losses. As illustrated in Fig. 9, the number of iterations required for the convergence of Algorithm 1 is 169 when the NCs are considered and 155 when the NCs are not considered. These numbers are not too far apart and are well comparable. However, the total computation time when considering the NCs is around 1,226 s, whereas the total computation time when ignoring the NCs is around 25 s (communication delays have been ignored while estimating both values). Hence, it is observed that considering the NCs involves significant computational challenges.

Fig. 8. Computation time $T^m[k]$ taken by each MG to execute two-stage network-constrained MG EMS at given MEPs over the iterations of Algorithm 1.

Fig. 9. Convergence characteristics of the Algorithm 1. Curves 1 and 2 are $\max_{t \in \mathcal{T}} \max_{\omega \in \Omega} |\Delta P_{M,\omega}^t(k)|$ with and without NCs respectively. Curves 3 and 4 are TOC with/without NCs respectively.

VI. CONCLUSIONS

In this paper, a cooperative trading scheme including a two-stage network-constrained energy management system was proposed for optimal resource utilization and power sharing among the constituent microgrids in multi-microgrid systems. The approach proposed in this paper decomposed the resource optimization and the network constraint evaluations of each microgrid into two sequential stages which reduced the computational complexity. The results demonstrated noticeable differences in the power dispatches and the generator participation factors of the microgrid components, apart from the market equilibrium prices when the network constraints were considered and ignored. Subsequently, an out-of-sample analysis was carried out to validate the power dispatch and reserve allocations (determined via generator participation factors) against the plausible real-time variations of the renewable energy source outputs and the load demand. It was observed that all the samples were feasible with the day-ahead decisions determined via the proposed two-stage network-constrained energy management system. Conversely, a significant number of samples were infeasible with the day-ahead decisions determined without considering the network constraints. As such, network-constrained energy management is essential in guaranteeing the practicality of optimal power sharing and resource management within multi-microgrid systems. Furthermore, the computation time and the convergence characteristics of the proposed two-stage network-constrained energy management system was found to be reasonable in the context of day-ahead computations.

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