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Decentralized Energy Management System for Networked Microgrids in Grid-Connected and Islanded Modes

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***Abstract*—This paper proposes a decentralized energy management system for the coordinated operation of networked microgirds (MGs) in a distribution system. In the grid-connected mode, the distribution network operator and each MG are considered as distinct entities with individual objectives to minimize their own operation costs. It is assumed that both dispatchable and renewable energy source-based distributed generators (DGs) exist in the distribution network and the networked MGs. In order to coordinate the operation of all entities, we apply a decentralized bi-level algorithm to solve the problem with the first level to conduct negotiations among all entities and the second level to update the non-converging penalties. In the islanded mode, the objective of each MG is to maintain a reliable power supply to its customers. In order to take into account the uncertainties of DG outputs and load consumption, we formulate the problems as two-stage stochastic programs. The first stage is to determine base generation setpoints based on the forecasts and the second stage is to adjust the generation outputs based on the realized scenarios. Case studies of a distribution system with networked MGs demonstrate the effectiveness of the proposed methodology in both grid-connected and islanded modes.**

***Index Terms*—Distributed generator (DG), microgrids (MGs), power distribution system, stochastic optimization.**

NOMENCLATURE

Acronyms

WT	Wind turbine.
PV	Photovoltaic generator.
MT	Micro turbine.
MG	Microgrid.

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Sets

S	Set of scenarios.
M^m/D	Set of nodes in mth MG/distribution network operator (DNO).

Indices

m	Index for MGs.
i	Index for nodes.
g	Index for distributed generator (DG) types (WTs and solar panels).
s	Index for scenarios.
j	Iteration step in the first level.
k	Iteration step in the second level.

Parameters

r_i	Line resistance between nodes i and $i+1$.
x_i	Line reactance between nodes i and $i+1$.
p_i^D	Active demand at node i.
q_i^D	Reactive demand at node i.
S_{base}	Power base for the system.
$p_{i,g}^R$	Predicted active power output of a DG.
$p_i^{\max}$	Maximum allowed active output of an MT.
$q_i^{\max}$	Maximum allowed reactive output of an MT.
ε	Maximum allowed voltage deviation.
γ_s	Probability of sth scenario.
c^G	Generation cost of an MT ($/kW).
$c^{\Delta G}$	Redispatch cost of an MT ($/kW).
c^E	Power exchange price.
c^D	Price for selling electricity to consumers.
$\Delta p_{i,s,g}^R$	Prediction error of DG output.
ω_i	Priority index of the load at node i.
α, β	Shape parameters of beta distribution.
ς	Convergence error.
ψ	Updating factor for penalty function.
$\mathbf{c}_l/\mathbf{d}_l/\mathbf{b}_l/\mathbf{A}_l/\mathbf{B}_l$	Parameter vectors of lth entity.

Variables

V_i	Voltage magnitude at node i.
P_i	Active power flow from node i to $i+1$.
Q_i	Reactive power flow from node i to $i+1$.
p_i^G	Active power generation at node i.

q_i^G	Reactive power generation at node i.
$p_i^{G,\mathrm{MT}}$	Base active power output of the MT at node i.
$q_i^{G,\mathrm{MT}}$	Base reactive output of the MT at node i.
ϕ/η^m	Power deficiency of DNO/mth MG.
μ/θ^m	Power surplus of DNO/mth MG.
π^m	Penalty function for mth MG.
λ	Penalty factor.
$\Delta(\cdot)_s$	Adjustment of $(\cdot)$ in scenario s.
$\mathbf{x}_s$	Shared variable vector in scenario s.
$\mathbf{y}_{l,s}$	Unique variable vector of lth entity in scenario s.

I. Introduction

MICROGRIDS (MGs) are integrated distribution systems consisting of DGs, loads, energy storage systems, and other onsite electric components. MGs can be considered as intelligent distribution systems with two different modes of operation: the islanded mode and the grid-connected mode [1], [2].

An MG may consist of both dispatchable and renewable energy source (RES)-based DGs. An energy management system (EMS) is essential for the operation of MGs in both grid-connected and islanded modes. The main responsibilities of an EMS are to assign generation references to dispatchable DGs and manage controllable loads so as to control the power production and energy consumption in an MG [3]. Many studies have been made in the literature on the intelligent energy management of MGs. Falahi *et al.* [3] proposed a model predictive control-based EMS to regulate the active and reactive power in an MG. Jiang *et al.* [4] proposed a double-layer EMS for an MG with a schedule layer to obtain an economic operation plan based on forecasted data, and a dispatch layer to control the DG outputs based on real-time data. Palma-Behnke *et al.* [5] presented an EMS based on a rolling horizon algorithm for an MG. The optimal dispatch of DGs was formulated as a mixed integer program and solved based on forecasting models. It should be noted that the above work assumes that DGs are dispatchable. However, RES-based DGs are mostly nondispatchable power sources with intermittent output. Arefifar *et al.* [6] presented a systematic approach for optimal construction of MGs in a distribution system. The distribution system was decomposed into several MGs considering the importance of both reliability and supply-security aspects. Su *et al.* [7] proposed a stochastic energy scheduling model for an MG with intermittent RESs and plug-in electric vehicles so as to minimize the operation costs and power losses. Chaouachi *et al.* [8] presented a generalized formulation for the EMS of an MG considering the uncertainties related to the forecasted RES-based DG outputs. A fuzzy logic expert system was used to solve the problem. Tan *et al.* [9] combined the MG power dispatch and network reconfiguration to benefit the whole system. The bio-inspired algorithms were adopted to solve the problem.

The above studies only considered one single MG, the interactions among different MGs and between MGs and DNOs were not taken into account. A smart distribution system may consist of multiple MGs. It has been shown that connecting multiple MGs to a distribution system can facilitate the powerful and reliable control and operation in the future distribution systems [6], [10]. The DNO and MG owners can benefit from the lower operation costs. The customers can benefit from a more reliable and economical power supply. Therefore, it is necessary to consider the DNO and networked MGs altogether. Kumar Nunna and Doolla [11] applied multiagent systems (MASs) to the energy management of networked MGs so that different entities could participate in the market. Marvasti *et al.* [12] proposed a hierarchical deterministic optimization algorithm to coordinate the operations of DNO and multiple MGs. This paper only considered the grid-connected mode. Moreover, the uncertainties of RES-based DGs and load consumption were not taken into account. Wu and Guan [13] proposed a decentralized Markov decision process to model the optimal control problem of networked MGs and to minimize the operation costs of MGs. Nunna and Doolla [14] proposed an MAS-based EMS to control the operation of networked MGs and allow customers to participate in demand response. Fathi and Bevrani [15] presented a cooperative power dispatching algorithm to minimize the operational costs of networked MGs. The coordination between DNO and the connected networked MGs brings new challenges to the power system operation. The uncertainties introduced by the RES-based DG outputs and load consumption make it more difficult to realize optimal energy management. Since all entities (DNO or MGs) are interconnected and have their own operation objectives, the operating decisions made by one entity may impact the operation of others. Therefore, the traditional centralized EMS is not suitable be used for the energy scheduling of a distribution system with networked MGs due to the operational independence of different entities. At the same time, it can be seen that the stochasticity of RES-based DGs and load consumptions as well as the decentralized coordinated control of networked MGs and DNOs have not been captured simultaneously in the above-mentioned literature.

In this paper, the energy management of MGs is divided into grid-connected mode and islanded mode for different operation requirements. In the grid-connected mode, the DNO and MGs are considered as different entities with their individual objectives. Since the supply-demand balance can always be met for MGs connected with a utility system, the main objective of the DNO and each MG is to minimize the operation costs. The costs of an MG include the operation costs of MG-owned DGs and the cost of purchasing electricity from the DNO; the revenues of an MG result from selling electricity to MG consumers and the DNO. The costs of a DNO can be classified into operation costs of DNO-owned DGs and the cost of purchasing electricity from MGs and the connected higher-level system; the revenues include selling electricity to DNO consumers and MGs. The interrelating variables between DNO and MGs are power exchanges. In the islanded mode, the operating priority is to maintain the sound power supply to consumers.

This paper proposes a decentralized EMS for the coordinated control of the distribution system and the networked MGs. The EMS is based on a decentralized bi-level stochastic

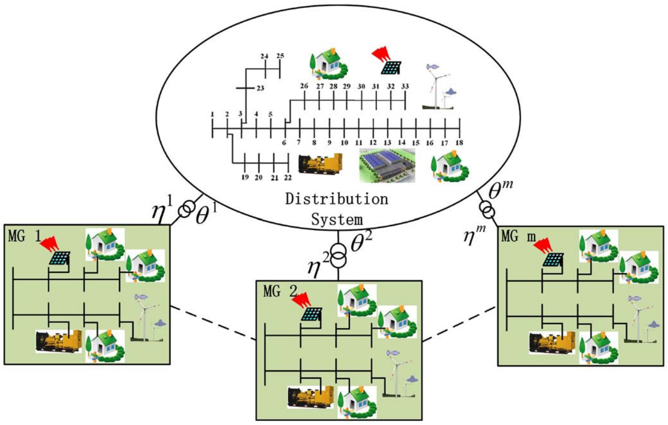

Fig. 1. Distribution system with networked MGs.

optimization algorithm that offers autonomy to each entity to optimize its own objectives subject to an entity-specific set of constraints. The algorithm has two levels: the first level is to solve the optimization problem of each entity and conduct negotiations based on the current penalty factor until no further negotiations can be achieved; the second level is to update the penalty functions representing the mutual impacts between different entities until the optimal coordinated operation point is found. Three types of DGs are considered in this paper: 1) MTs; 2) WTs; and 3) PVs. In order to consider the stochasticity of RES-based DGs and load consumption, the power outputs of WTs and PVs and the load consumption are described by scenarios generated from Monte Carlo simulations. A scenario reduction method is applied to increase the calculation speed while maintaining the accuracy of the solution. When an MG is separated from the upstream utility grid and operated in the islanded mode, the operational objective is to provide a stable and reliable power supply to customers instead of increasing its economic profits. The loads can be divided into sensitive loads and interruptible loads with different penalty factors. The optimization objectives of the EMS are to minimize bus voltage deviations and the penalty cost of load shedding while taking into account the constraints of power balance. The major contribution of this paper is to propose a stochastic bi-level optimization algorithm to coordinate the operation of MGs and DNO in a completely distributed fashion.

The remainder of this paper is organized as follows. Section II introduces the decentralized EMS and the corresponding bi-level algorithm. Section III presents the local stochastic optimization problems of the DNO and MGs. In Section IV, the numerical results on a test distribution system with networked MGs are provided. Section V concludes this paper with the major findings.

II. Decentralized Energy Management System

As shown in Fig. 1, both DNO and MGs have generators and consumers. Because of the close connection of DNO and grid-connected MGs, the decision-making problem of DNO is interrelated with the ones of MGs. The decisions of one entity will impact those of others. The interrelating variables are the power exchanges between DNO and the networked MGs. Each independent system has its distinct variables and objectives. It has been shown that the all-in-one optimization problem can be decomposed into several local optimization problems corresponding to different independent systems [16], [17]. The general formulation of lth entity in a stochastic multientity problem can be described as follows:

$$\begin{aligned} \min_{x, y_l} \quad & \mathbf{c}_l^T \mathbf{x}_s + \mathbf{d}_l^T \mathbf{y}_{l,s} \\ \text{s.t.} \quad & \mathbf{A}_l \mathbf{x}_s + \mathbf{B}_l \mathbf{y}_{l,s} \leq \mathbf{b}_l. \end{aligned} \tag{1}$$

In this paper, we propose an algorithm based on the deterministic decomposition algorithm introduced in [16] and the concept of progressive hedging [18]. Progressive hedging is used to solve two-stage stochastic programming problems. It decomposes the stochastic program into several sub-problems where decisions are made for each scenario. Penalty is added to the objective function of each scenario to force the first-stage solutions of all scenarios to converge to the same point.

In our algorithm, instead of decomposing the problem based on scenarios, we decompose it based on entities. Each entity makes its own optimal decisions. Penalty is added to the objective function of each entity to force the shared variables $\mathbf{x}_s$ of the interconnected entities to converge to the same point under all scenarios.

The interactions among entities will be modeled using a stochastic decentralized bi-level optimization method. Different convergence conditions are applied to the two levels. When both levels converge, the shared variables (power exchanges) between systems are identified and the optimal coordinated operation point can be found. In order to consider the stochasticity of RES-based DGs and load consumption, Monte Carlo simulations are run based on the forecasted power and uncertain prediction errors to generate scenarios for DG outputs and the load consumption. Fig. 2 shows the flowchart of the algorithm.

The complete steps can be described as follows.

Step 1: Initialization. Set the initial values for $\theta^{m*}_{k,j,s}$, $\eta^{m*}_{k,j,s}$, $\theta^{m}_{k,j,s}$, $\eta^{m}_{k,j,s}$, and λ_k.

Step 2: Solve the stochastic optimization problems for the networked MGs with $\theta^{m}_{k,j-1,s}$ and $\eta^{m}_{k,j-1,s}$ to obtain $\theta^{m*}_{k,j,s}$ and $\eta^{m*}_{k,j,s}$. $\theta^{m*}_{k,j,s}$ and $\eta^{m*}_{k,j,s}$ represent the power exchange requested by the mth MG in the sth scenario in the current iteration, $\theta^{m}_{k,j-1,s}$ and $\eta^{m}_{k,j-1,s}$ represent the power exchange requested by the DNO in the previous first-level iteration.

Step 3: Solve the stochastic optimization problems for the DNO with $\theta^{m*}_{k,j,s}$ and $\eta^{m*}_{k,j,s}$ to obtain $\theta^{m}_{k,j,s}$ and $\eta^{m}_{k,j,s}$.

Step 4: Check the convergence of the first level as follows:

$$\begin{aligned} \left|\theta^{m*}_{k,j,s} - \theta^{m*}_{k,j-1,s}\right| &\leq \varsigma_1 \\ \left|\eta^{m*}_{k,j,s} - \eta^{m*}_{k,j-1,s}\right| &\leq \varsigma_1, \quad \forall m, s \end{aligned} \tag{2a}$$

$$\begin{aligned} \left|\theta^{m}_{k,j,s} - \theta^{m}_{k,j-1,s}\right| &\leq \varsigma_1 \\ \left|\eta^{m}_{k,j,s} - \eta^{m}_{k,j-1,s}\right| &\leq \varsigma_1, \quad \forall m, s. \end{aligned} \tag{2b}$$

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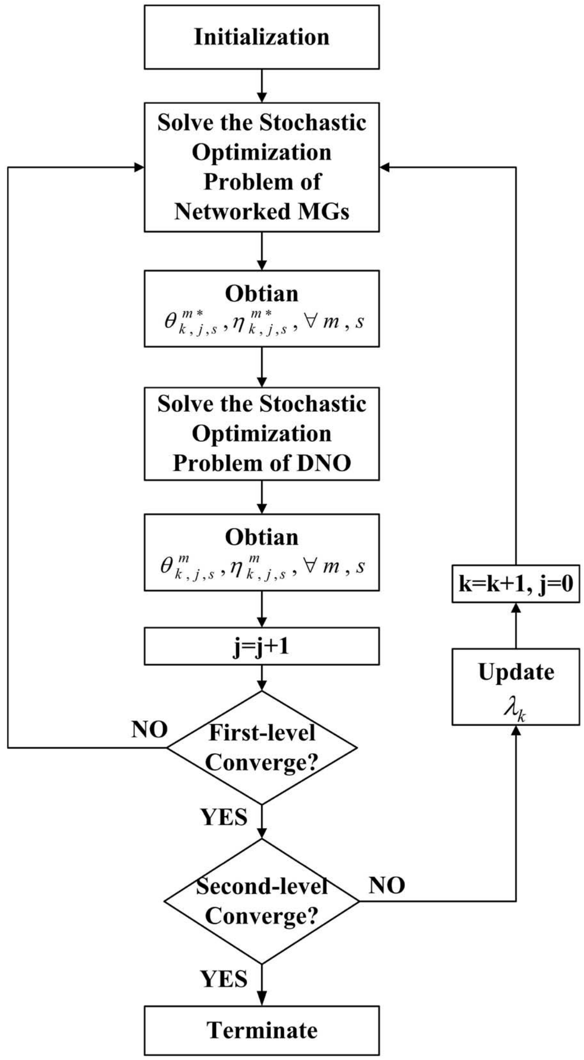

Fig. 2. Flowchart of the algorithm.

It can be seen that the first-level convergence checks whether the negotiation between DNO and MGs finishes (no further negotiation can be conducted) with the current penalty factor, the algorithm goes back to step 2 if it is not converged.

Step 5: Check the convergence of the second level as follows:

$$\left|\theta^{m*}_{k,j,s} - \theta^{m}_{k,j,s}\right| \le \varsigma_2, \left|\eta^{m*}_{k,j,s} - \eta^{m}_{k,j,s}\right| \le \varsigma_2, \quad \forall m, s. \tag{3}$$

It can be seen that the second-level convergence checks whether agreements between DNO and MGs are reached, the algorithm goes to step 6 if it is not converged.

Step 6: Update the penalty factor and go to step 2.

More details on penalty functions will be discussed in Section III-D.

III. Mathematical Modeling of Individual Systems

This section introduces a widely used electrical network model and provides the local optimization formulation for individual systems. The uncertainties of RES-DGs are also discussed.

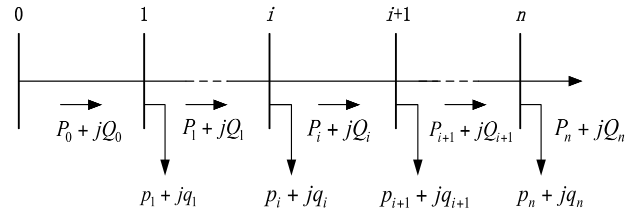

Fig. 3. Diagram of a radial electrical network.

A. Distribution System Model

Consider an electrical network as shown in Fig. 3, there are n buses indexed by i. DistFlow [19] equations can be used to describe the complex power flows at each node i

$$P_{i+1} = P_i - r_i\left(P_i^2 + Q_i^2\right)\Big/V_i^2 - p_{i+1} \tag{4}$$

$$Q_{i+1} = Q_i - x_i\left(P_i^2 + Q_i^2\right)\Big/V_i^2 - q_{i+1} \tag{5}$$

$$V_{i+1}^2 = V_i^2 - 2(r_iP_i + x_iQ_i) + \left(r_i^2 + x_i^2\right)\left(P_i^2 + Q_i^2\right)\Big/V_i^2 \tag{6}$$

$$p_i = p_i^D - p_i^G, q_i = q_i^D - q_i^G. \tag{7}$$

In the above equations, we assume p_i^G is generated by both RES-based DG units which are subject to uncertainties and controllable DG units, q_i^G is generated by controllable DG units [20]. The DistFlow equations can be simplified using linearization. The linearized power flow equations have been extensively used and justified in both traditional distribution systems and MGs [9], [19], [21]. Details on applying DistFlow equations to a feeder with laterals can be found in [19]

$$P_{i+1} = P_i - p_{i+1} \tag{8}$$

$$Q_{i+1} = Q_i - q_{i+1} \tag{9}$$

$$V_{i+1} = V_i - (r_iP_i + x_iQ_i)/V_1 \tag{10}$$

$$p_i = p_i^D - p_i^G, q_i = q_i^D - q_i^G. \tag{11}$$

B. Optimization Problem for MGs in Grid-Connected Mode

In this paper, WTs and PVs are considered as RES-based DGs, while MTs are considered as dispatchable DGs. The general optimization problem of the mth MG in the grid-connected mode can be formulated as follows (denote the formulation as M):

$$\begin{aligned}\min \sum_i c^G p_i^{G,\mathrm{MT}} - \sum_i c^D p_i^D + \left(c^E\eta^m - c^E\theta^m\right) \\ + \pi^m + \sum_s \gamma_s \sum_i \left(C_{i,s}^{\Delta G} + c^D \Delta p_{i,s}^D\right) \\ + \sum_s \gamma_s\left(c^E\Delta\eta_s^m - c^E\Delta\theta_s^m\right) + \sum_s \gamma_s \Delta\pi_s^m\end{aligned} \tag{12}$$

$$\text{s.t.} \quad P_{i+1} = P_i - p_{i+1}^D + p_{i+1,g}^R + p_{i+1}^{G,\mathrm{MT}} \quad \forall i \in M^m, \forall g \tag{13}$$

$$Q_{i+1} = Q_i - q_{i+1}^D + q_{i+1}^{G,\mathrm{MT}}, \quad \forall i \in M^m \tag{14}$$

$$V_{i+1} = V_i - (r_iP_i + x_iQ_i)/V_1, \quad \forall i \in M^m \tag{15}$$

$$1 - \varepsilon \le V_i \le 1 + \varepsilon, \quad \forall i \in M^m \tag{16}$$

$$0 \le p_i^{G,\mathrm{MT}} \le p_i^{\max}, \quad \forall i \in M^m \tag{17}$$

$$\sum_i p_i^{G,\mathrm{MT}} + \sum_{i,g} p_{i,g}^R + \eta^m \geq \sum_i p_i^D + \theta^m \tag{18}$$

$$\Delta P_{i+1,s} = \Delta P_{i,s} + \Delta p_{i+1,s,g}^R + \Delta p_{i+1,s}^{G,\mathrm{MT}} - \Delta p_{i+1,s}^D \quad \forall i \in M^m, \forall s \in S, \forall g \tag{19}$$

$$\Delta Q_{i+1,s} = \Delta Q_{i,s} + \Delta q_{i+1,s}^{G,\mathrm{MT}} - \Delta q_{i+1,s}^D \quad \forall i \in M^m, \forall s \in S \tag{20}$$

$$\Delta V_{i+1,s} = \Delta V_{i,s} - \left(r_i \Delta P_{i,s} + x_i \Delta Q_{i,s}\right) / V_1 \quad \forall i \in M^m, \forall s \in S \tag{21}$$

$$1 - \varepsilon \leq V_i + \Delta V_{i,s} \leq 1 + \varepsilon, \quad \forall i \in M^m, \forall s \in S \tag{22}$$

$$0 \leq p_i^{G,\mathrm{MT}} + \Delta p_{i,s}^{G,\mathrm{MT}} \leq p_i^{\max}, \quad \forall i \in M^m, \forall s \in S \tag{23}$$

$$0 \leq q_i^{G,\mathrm{MT}} + \Delta q_{i,s}^{G,\mathrm{MT}} \leq q_i^{\max}, \quad \forall i \in M^m, \forall s \in S \tag{24}$$

$$\sum_i \Delta p_{i,s}^{G,\mathrm{MT}} + \sum_{i,g} \Delta p_{i,g,s}^R + \Delta \eta_s^m \geq \sum_i \Delta p_{i,s}^D + \Delta \theta_s^m \quad \forall s \in S \tag{25}$$

$$C_{i,s}^{\Delta G} \geq c^{\Delta G} \Delta p_{i,s}^{G,\mathrm{MT}}, \quad \forall i \in M^m, \forall s \in S \tag{26a}$$

$$C_{i,s}^{\Delta G} \geq -c^{\Delta G} \Delta p_{i,s}^{G,\mathrm{MT}}, \quad \forall i \in M^m, \forall s \in S. \tag{26b}$$

In the above formulation, the objective function (12) consists of costs and revenues (C&R) as well as the penalty function of the MG. The first four items in the objective function represent C&R relative to the base generation schedule made based on the forecasts of loads and RES generation. The first item in (12) represents the generation costs of all MTs in the MG. The second item in (12) describes the revenue of the MG by selling electricity to customers within the MG. The third and fourth items in (12) represent the costs of power exchange between the MG and DNO. Buying electricity from the DNO is considered as positive cost, while selling electricity to the utility grid is considered as negative cost. The fifth item represents the penalty function with the base generation. However, RES generation outputs and load consumptions are stochastic in nature. The outputs of dispatchable DGs should be adjusted according to the realized scenario of RES-based DG outputs and load consumptions. The sixth to ninth items in (12) represent the expected adjustments of C&R. The tenth item in (12) represents the adjustments of the penalty function. In other words, if loads and RES generation are deterministic and can be accurately forecasted, the last five items should be zero. The details of the penalty function will be discussed later. Constraints (13)–(15) are linearized DistFlow equations as discussed in the previous section. Constraint (16) guarantees that the voltage level of each node is within a predefined range, ε is usually set to be 0.05. Constraint (17) guarantees the active output of an MT is within its maximum allowable value. Constraint (18) describes that the total generation should be equal to or larger than the total load. In the formulation (13)–(18), P, Q, V, p^G, q^G, η, and θ are first-stage variables determined based on the forecasts. Since the output of RES-based DGs and load consumption are stochastic, a forecast is usually used for scheduling purposes. In this paper, the uncertain nature of prediction errors is considered as random variables with certain distributions, e.g., the normal distribution and beta distribution are used by previous papers to represent the load consumption and wind/solar power prediction errors [22]–[24], respectively. The second-stage variables should be adjustable in order to deal with the variations of loads and RES generation [25], [26].

Constraints (19)–(26) describe the second-stage variables ΔP, ΔQ, ΔV, Δp^G, Δq^G, $\Delta\eta$, and $\Delta\theta$ which are adjusted with the realization of scenarios. Constraints (19)–(21) are adjustable linearized DistFlow equations for the sth scenario. Constraint (22) guarantees the voltage level at each node is within the permissible range after the generation is adjusted. In constraints (23) and (24), the sum of the base generation schedule and the adjusted outputs should be less than or equal to the rated capacity of an MT. Constraint (25) describes that the total adjusted generation should be equal to or larger than the total adjusted load. We also consider the redispatch cost which is for the generation adjustment between the base generation and the generation in scenarios. Constraints (26a) and (26b) guarantee the redispatch cost of an MT is positive [e.g., if $\Delta p_{i,s}^G \geq 0$, which indicates a generation increase, constraint (26b) becomes redundant and the redispatch cost $C_{i,s}^{\Delta G}$ becomes equal to $c^{\Delta G} \Delta p_{i,s}^G$ due to the minimization formulation].

C. Optimization Problem for MGs in Islanded Mode

In the islanded mode, the highest priority it to maintain a reliable and stable power supply to customers. Thus, the optimization problem of an islanded MG can be formulated as follows:

$$\begin{aligned} \min \quad & \omega_i p_i^D (1 - y_i) + \sum_s \gamma_s \sum_i \left| V_i + \Delta V_{i,s} - V_n \right| \\ \text{s.t.} \quad & (13)\text{–}(17) \text{ and } (19)\text{–}(24). \end{aligned} \tag{27}$$

In the objective function (27), the first item represents the voltage deviations from the nominal voltage. The second item is the penalty function for load shedding according to their importance. The first and second items are based on the forecasted load consumptions and DG outputs. The third item represents adjusted voltage deviations. The details of constraints can be found in the previous section. p_i^D and q_i^D in constraints (13), (14), and (18)–(20) need to be updated by $y_i p_i^D$ and $y_i q_i^D$, respectively.

D. Optimization Problem for DNO

It is assumed that the DNO also owns both dispatchable DGs and RES-based DGs [27]. The optimization problem of a DNO can be formulated as follows (denote the formulation as $\mathcal{D}$):

$$\begin{aligned} \min & \sum_i c^G p_i^{G,\mathrm{MT}} - \sum_i c^D p_i^D \\ & + \left(c^E \phi + \sum_m c^E \theta^m - c^E \mu - \sum_m c^E \eta^m \right) \\ & + \sum_m \pi^m + \sum_s \gamma_s \sum_i \left(c^D \Delta p_{i,s}^D + C_{i,s}^{\Delta G} \right) \\ & + \sum_s \gamma_s \left(c^E \Delta\phi_s + \sum_m c^E \Delta\theta_s^m - c^E \Delta\mu_s - \sum_m c^E \Delta\eta_s^m \right) \\ & + \sum_s \gamma_s \sum_m \Delta\pi_s^m \end{aligned} \tag{28}$$

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$$\text{s.t. (13)–(17), (19)–(24), and (26),} \qquad \forall i \in D, \forall s \in S$$

$$\sum_i p_i^{G,\mathrm{MT}} + \sum_{i,g} p_{i,g}^R + \sum_m \eta^m + \phi \geq \sum_i p_i^D + \sum_m \theta^m + \mu \tag{29}$$

$$\sum_i \Delta p_{i,s}^{G,\mathrm{MT}} + \sum_{i,g} \Delta p_{i,g,s}^R + \sum_m \Delta\eta_s^m + \Delta\phi_s \geq \sum_i \Delta p_{i,s}^D + \sum_m \Delta\theta_s^m + \Delta\mu_s, \quad \forall s \in S. \tag{30}$$

In the objective function (28), costs of DG operation and buying electricity from the HV system and MGs are positive, while selling electricity to the HV system, DNO customers and MGs is considered as the negative costs. The first six items in (28) represent C&R relative to the base generation schedule made based on the forecasts of loads and RES generation. The seventh item represents the penalty functions between DNO and MGs. The remaining items in (28) represent the adjustable C&R and penalties according to scenarios. Constraints (29) and (30) represent the generation-load balance.

As discussed in Section I, the only information exchanged between DNO and the networked MGs in the decentralized EMS is the power exchange at the point of common coupling. In order to model the mutual impacts of operational conditions among all entities, we need to introduce penalty functions in the negotiation process

$$\pi_{k,j}^m = \lambda_k\left(\left|\theta_{k,j}^m - \theta_{k,j}^{m*}\right| + \left|\eta_{k,j}^m - \eta_{k,j}^{m*}\right|\right). \tag{31}$$

The above penalty function is for the mth MG with base generation. It represents the penalty for the MG related to the shared variables with the DNO. The index j represents the jth iteration in the first level. The index k represents the kth iteration in the second level. $\theta_{k,j}^{m*}$ and $\eta_{k,j}^{m*}$ are the power exchange requested by the mth MG in the jth first-level iteration and kth second-level iteration. $\theta_{k,j}^m$ and $\eta_{k,j}^m$ are the power exchange requested by the DNO. λ_k is a penalty factor and updated according to the following rule in each iteration:

$$\lambda_k = \psi\lambda_{k-1}, \forall k. \tag{32}$$

Larger ψ represents more aggressive penalty and may lead to suboptimal solutions; smaller ψ indicates that more iterations are needed for the algorithm to converge. In this paper, we set $\psi = 2$. The operator can change the settings according to a specific system. It can be seen the penalty is increasing until the power exchanges requested by the two entities become equal. Similarly, the penalty function for the mth MG with adjusted generation in the sth scenario can be designed as follows:

$$\Delta\pi_{k,j,s}^m = \lambda_k\left(\left|\Delta\theta_{k,j,s}^m - \Delta\theta_{k,j,s}^{m*}\right| + \left|\Delta\eta_{k,j,s}^m - \Delta\eta_{k,j,s}^{m*}\right|\right). \tag{33}$$

E. Uncertainty and Scenario Reduction

In this paper, two kinds of RES-based DGs are considered: 1) WTs; and 2) PVs. The predicted wind and solar power will be used. It is known that errors always exist in prediction models. The beta function is shown to be an appropriate

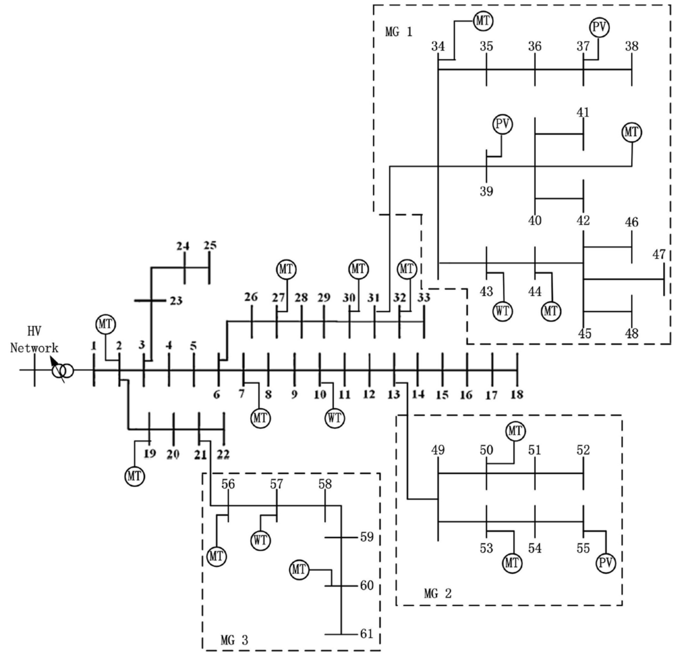

Fig. 4. Test distribution system with networked MGs.

distribution to represent prediction errors of wind and solar power [22], [28]. For a predicted power level P_i^R of the DG at node i, the beta function can be defined by two corresponding parameters α and β [28]

$$f(x) = x^{\alpha-1}(1-x)^{\beta-1}. \tag{34}$$

The above beta function models the occurrence of real power values x when a certain prediction value P_i^R has been forecasted. The shape parameters of the corresponding beta function α and β can be calculated as [28]

$$P_i^R / S_{\mathrm{base}} = \alpha_i / (\alpha_i + \beta_i) \tag{35}$$

$$\sigma_i^2 = \alpha_i\beta_i / (\alpha_i + \beta_i)^2(\alpha_i + \beta_i + 1). \tag{36}$$

The relationship between the predicted power and its error variance can be represented as [24] and [28]

$$\sigma_i = 0.2 \times P_i^R / P_i^{\max} + 0.21. \tag{37}$$

Using the predicted DG outputs and (34)–(37), the parameters of beta functions for the current prediction data can be calculated. The number of scenarios generated by Monte Carlo simulations is reduced by the simultaneous backward reduction method [21].

IV. Numerical Results

As shown in Fig. 4, a modified IEEE 33-bus distribution system with three MGs is used in this paper. Details about the IEEE 33-bus test system can be found in [19]. The power base of the system is set to be 10 MVA. The line resistance and reactance of all MGs are set to be 0.006 and 0.01 p.u., respectively. Table I summarizes the system description of MGs. For an MG, it is assumed that the load consumption at each load bus is equal. Table II shows the parameters used in the

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TABLE I
DESCRIPTION OF NETWORKED MGS

System	Load Bus No.	Total Active Load (p.u.)	Total Reactive Load (p.u.)
MG1	34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48	0.21	0.12
MG2	49, 50, 51, 52, 53, 54, 55	0.105	0.07
MG3	56, 57, 58, 59, 60, 61	0.072	0.048

TABLE II
PARAMETERS FOR CALCULATING CORRESPONDING COSTS

Parameter	Value	Parameter	Value
c^G	\$0.05/kWh	c^D	\$0.3/kWh
$c^{\Delta G}$	\$0.1/kW	c^E	\$0.1/kWh

TABLE III
FORECASTED OUTPUTS OF RES-BASED DGS FOR ONE TIME PERIOD

Bus No.	10	37	39	43	55	57
Type	WT	PV	PV	WT	PV	WT
Forecast	0.04	0.03	0.03	0.04	0.03	0.04

TABLE IV
MT DISPATCHES IN ITERATIONS

MT (Node)	Iteration No.						
	1	2	3	4	5	6	7
	Active Power Generation (p.u.)						
MT2	0.1505	0.1422	0.1410	0.0987	0.0901	0.0901	0.0901
MT7	0.1508	0.1510	0.1507	0.1503	0.1500	0.1500	0.1500
MT19	0.1500	0.1488	0.1412	0.1005	0.0901	0.0901	0.0901
MT27	0.1500	0.1514	0.1427	0.0725	0.0106	0.0106	0.0106
MT30	0.1509	0.1515	0.1508	0.1505	0.1500	0.1500	0.1500
MT32	0.1500	0.1500	0.1452	0.0210	0.0011	0.0011	0.0011
MT34	0.1506	0.1509	0.1504	0.1503	0.1500	0.1500	0.1500
MT39	0.0650	0.0678	0.0674	0.0669	0.0663	0.0663	0.0663
MT44	0.0003	0.0002	0.0004	0.0005	0.0017	0.0017	0.0017
MT50	0.0566	0.0532	0.0529	0.0527	0.0525	0.0525	0.0525
MT53	0.0547	0.0536	0.0532	0.0526	0.0525	0.0525	0.0525
MT56	0.1500	0.1485	0.1441	0.0821	0.0639	0.0639	0.0639
MT60	0.0128	0.0158	0.0149	0.0146	0.0140	0.0140	0.0140

TABLE V
TOTAL PROFIT OF EACH ENTITY IN STOCHASTIC PROGRAMMING

Entity	DNO	MG1	MG2	MG3
Profits (\$)	302	2423	1599	327
Bus No.	1	31	13	21
Power Exchange (p.u.)	0.0080	0.0579	0.1380	-0.0075

TABLE VI
POWER EXCHANGES IN DETERMINISTIC PROGRAMMING

Entity	Bus. No.	Exchange in Iteration 1	Exchange in Iteration 2	Exchange in Iteration 3
DNO	1	0.0080	0.0480	0.0480
MG1	31	0.1960	0.0690	0.0690
MG2	13	0.1200	0.1501	0.1501
MG3	21	-0.0240	-0.0142	-0.0142

TABLE VII
MT DISPATCHES IN ISLANDED MODE

MG	MT (Node No.)	Dispatch (p.u.)	Load shed
MG1	MT34	0.0802	No
	MT39	0.0503	
	MT44	0.0195	
MG2	MT50	0.0371	No
	MT53	0.0382	
MG3	MT56	0.0242	No
	MT60	0.0081	

case study, which are obtained from [29]. All the costs and electricity prices are presented in U.S. dollars.

Table III shows the forecasted outputs of RES-based DGs for one time period. The probabilistic distributions of forecast errors can be estimated using the method described in Section III-E. It is of note that the proposed method is not limited to the energy management of a single period. It can be straightforwardly extended to consider multiple periods without loss of generality.

One thousand scenarios are generated using Monte Carlo simulation to represent the prediction errors in the prediction horizon. As discussed in the previous section, scenario reduction is applied to reduce the computation efforts while maintaining the solution accuracy.

In the grid-connected mode, earning economic profit is a major objective for all entities. Table IV shows the stochastic dispatch results of MTs. It can be seen that the results change with the iterations and remain the same after five iterations, which indicates that the negotiation among all entities ends. Fig. 5 shows the power exchanges among all entities in the iterations, which clearly describes the process of the negotiation. For the DNO, positive values indicate that the DNO would like to buy electricity from other entities, while negative values indicate selling electricity. For the MGs, positive values represent selling electricity to the DNO, while negative values represent buying electricity from the DNO. It can be seen from Fig. 5 that all entities want to sell electricity to others at the beginning. After five iterations, the agreements among all entities are achieved. The DNO is buying electricity from the HV system, MG1 and MG2, while selling electricity to MG3. The power exchanges and total profits of all entities can be found in Table V. Table VI shows the power exchanges if uncertainties of DG outputs are not taken into account. Compared to the stochastic programming, the deterministic problem takes less iteration (only two iterations) to converge. The power exchange results without considering uncertainties are also different from Table V. Since the outputs of RES-based DGs are stochastic in nature, it is more practical to apply the proposed stochastic bi-level optimization algorithm to coordinate the operations.

In the islanded mode, it is assumed that the outputs of RES-based DGs are the same as shown in Table III. The objective is to maintain the technical operation of all MGs. Table VII shows the dispatch and load shedding results. Since we have enough generation capacity in the current situation, no load shedding is necessary. Fig. 6 shows the lowest and highest voltages in all MGs. It can be seen that the lowest and highest voltage levels are always within the safe range ($\pm 5\%$) [30].

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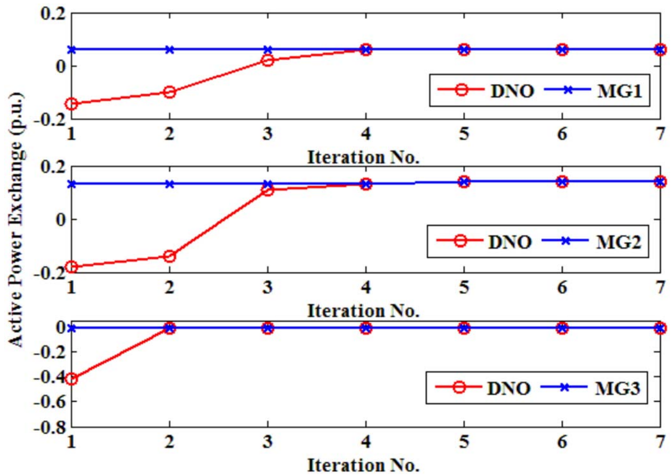

Fig. 5. Power exchange between DNO and MGs in iterations.

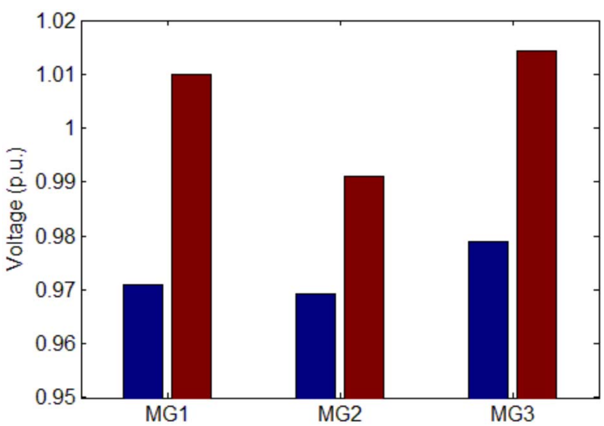

Fig. 6. Highest and lowest voltage levels in each MG in islanded mode.

V. Conclusion

This paper proposes a decentralized EMS for a distribution system with networked MGs. Both dispatchable and RES-based DGs are considered to be part of MGs. In the grid-connected mode, the DNO and MGs are considered as self-managed entities with distinct objectives to minimize their own operation costs. A stochastic decentralized bi-level algorithm is applied to solve the problem taking into account the intermittent outputs of RES-based DGs, the uncertain load consumption and the coordinated operating points of all interdependent systems. In the islanded mode, the operational objectives are to maintain the voltage stability and the reliable power supply to customers in an MG. A modified 33-bus test system with three MGs is studied. The simulation results show that the negotiation among all entities converges in a few iterations in the grid-connected mode and all MGs maintain stable operations in the islanded-mode. Compared to previous efforts on MG operation, the proposed model considers the interactions between the networked MGs and DNO while the stochastic DG outputs are also taken into account.

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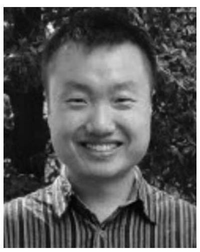

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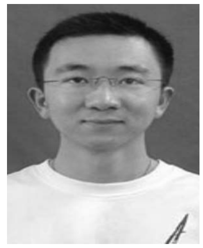

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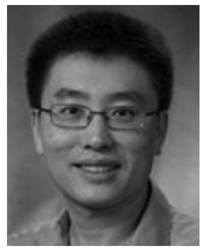

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