Coordinated Energy Management of Networked Microgrids in Distribution Systems

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***Abstract*—This paper proposes a novel control strategy for coordinated operation of networked microgrids (MGs) in a distribution system. The distribution network operator (DNO) and each MG are considered as distinct entities with individual objectives to minimize the operation costs. It is assumed that both the dispatchable and nondispatchable distributed generators (DGs) exist in the networked MGs. In order to achieve the equilibrium among all entities and take into account the uncertainties of DG outputs, we formulate the problem as a stochastic bi-level problem with the DNO in the upper level and MGs in the lower level. Each level consists of two stages. The first stage is to determine base generation setpoints based on the load and nondispatchable DG output forecasts and the second stage is to adjust the generation outputs based on the realized scenarios. A scenario reduction method is applied to enhance a tradeoff between the accuracy of the solution and the computational burden. Case studies of a distribution system with multiple MGs of different types demonstrate the effectiveness of the proposed methodology. The centralized control, deterministic formulation, and stochastic formulation are also compared.**

***Index Terms*—Distributed generator (DG), distribution network, mathematical program with complementarity constraints (MPCC), Microgrid (MG).**

Nomenclature

Sets

S	Set of scenarios.
G	Set of types of renewable energy source (RES)-based DGs (wind and solar in this paper) G = $\{WT, PV\}$.
D/M	Set of nodes in DNOs/MGs.

Parameters

$m1$	Point of common coupling (PCC) of mth MG.
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 (MWA).
$p_{i,g}^R$	Predicted active power output of a RES-based DG at node i, $g \in$ G.
$p_i^{\max}$	Maximum allowed active output of the MT at node i.
$q_i^{\max}$	Maximum allowed reactive output of the MT at node i.
ε	Maximum allowed voltage deviation.
γ_s	Probability of sth scenario.
c^G	Generation cost of a MT ($/kW).
$c^{\Delta G}$	Redispatch cost of a MT ($/kW).
p_i^{rd}	Maximum allowable redispatchable generation of the MT at node i.
$c^{S,MG}/c^{B,MG}$	MG price for selling/buying electricity to/from DNO ($/kWh).
$c^{D,MG}/c^{D,DNO}$	MG/DNO price for selling electricity to consumers within the MG/DNO ($/kWh).
$c^{S,DNO}/c^{B,DNO}$	DNO price for selling/buying electricity to/from HV system ($/kWh).
$\Delta p_{i,s,g}^R$	Prediction error of output of type-g DG at node i in scenario s.
α,β	Shape parameters of beta distribution.

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	Base active power output of the MT at node i.
q_i^G	Base reactive output of the MT at node i.
η_1/η_{m1}	Power deficiency of DNO/mth MG.
θ_1/θ_{m1}	Power surplus of DNO/mth MG.
$C_{i,s}^{rd}$	Redispatch cost of a MT at node i in scenario s ($).
$\Delta(\cdot)_s$	Adjustment of $(\cdot)$ in scenario s.

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I. Introduction

MICROGRIDS (MGs) are active clusters of distributed generators (DGs), loads and energy storage, and other onsite electric components. MGs can be considered as intelligent distribution networks with two different modes of operation: islanded mode for the local production of power and grid-connected mode with the capacity available for selling power back to the utility grid or buying power from the utility grid when necessary [1], [2].

A smart distribution system may consist of multiple MGs. The coordinated control in MGs and the distribution system can be considered as a tri-level hierarchical system with the primary droop-control of power electronic interfaces, the secondary control for voltage/frequency restoration and synchronization, and the tertiary control for active and reactive power flow [3], [4]. The third level is in relation to energy management system (EMS) and is the main topic of this paper. A MG can be composed of controllable DGs such as micro turbines (MTs) and renewable energy source (RES)-based DGs such as wind turbines (WTs) and photovoltaic generators (PVs). Meanwhile, a modern smart distribution system may consist of several MGs, in which, the distribution network operator (DNO) and MGs can be run as autonomous entities. The coordination among different MGs and between DNOs and MGs brings new challenges to the power system operation. Moreover, the uncertainties introduced by the intermittent DG outputs make it more difficult to realize optimal energy management of DNOs and MGs.

As an essential element of a smart grid, many studies have been made in the literature on the intelligent energy management of MGs [4]–[15]. Tsikalakis and Hatziargyriou [5] proposed a central controller for a single MG with multiple DGs. The purpose of the coordinated control of DGs was to maximize the profits of the MG. Palma-Behnke *et al*. [6] presented a novel EMS based on a rolling horizon algorithm for a RES-based MG. The optimal dispatch of DGs was formulated as a mixed integer program (MIP) and solved based on forecasting models. Sicong *et al*. [7] combined the MG power dispatch and network reconfiguration to benefit the whole system. The bio-inspired algorithms are adopted to solve the problem. It should be noted that the above work assumes that DGs are dispatchable and controllable, which is not accurate since renewable energy-based DGs are mostly non-dispatchable power sources with intermittent output. Su *et al*. [8] proposed a stochastic energy schedule model for a MG with intermittent renewable energy sources and plug-in electric vehicles (PEVs) so as to minimize the operation cost and power losses. Su and Wang [9] reviewed the EMSs in MG operations. Su *et al*. [10] proposed a model predictive control (MPC)-based power dispatch approach of distribution systems considering the PEV charging uncertainty. But these studies only considered a single MG, and the interactions among different MGs and between MGs and DNOs were not taken into account. Recent studies show that connecting multiple MGs (to make a distribution system with networked MGs) can improve the operation and reliability of the system [10]–[16]. Kumar Nunna and Doolla [11] used multiagent systems (MASs) for the energy management of DGs in networked MGs so that different entities can participate in market. Fathi and Bevrani [12] studied the energy consumption scheduling of connected multiMGs considering demand uncertainty. The online stochastic iterations are applied to capture the randomness of the demand. Asimakopoulou *et al*. [13] studied the energy management of networked MGs by using the bi-level programming. But the stochastic DG outputs were not taken into account. Kargarian *et al*. [14] presented an optimal power flow algorithm to minimize the operation costs, power losses, and voltage deviations of networked MGs. Wu and Guan [15] proposed a decentralized partially-observable Markov decision process to model the optimal control problem of networked MGs. A dynamic programming algorithm is used to minimize the operation cost of each MG. Nunna and Doolla [16] proposed an agent-based EMS to control the operation of networked MGs and allow customers to participate in demand response. Fathi and Bevrani [17] proposed a cooperative power dispatching algorithm of interactions among networked MGs to minimize the network operational cost. It can be seen that the coordinated control of networked MGs and DNOs as well as the stochastic nature of RES-based DGs have not been considered simultaneously in all of the above existing literature. However, RES-based DGs are important components of a MG and a modern active distribution network may consist of several MGs that can run as autonomous entities. The coordinated optimal control of these MGs and the distribution system is an essential problem for the sound operation of a smart grid. The DNO and MG owners can benefit from the lower operation costs and higher profits. The customers can benefit from a more reliable and economical power supply. Therefore, it is necessary to consider them all together.

In this paper, we present a decentralized power dispatch model for the coordinated operation of multiple MGs and a distribution system. The model takes into account uncertainties of RES-based DG outputs. The DNO and MGs are considered as different entities with their individual objectives. Since decisions made by one entity may influence the strategies of the other entities, the equilibriums may exist, where no entity can further optimize its own objective by unilaterally changing its decision. Therefore, we model the problem as a stochastic bi-level problem which can be transformed into a stochastic mathematical program with complementarity constraints (MPCC). The equilibrium theory has been widely applied to power system operation and planning. Jenabi *et al*. [18] proposed a bi-level game approach for coordination between generation and transmission planning in a purely competitive electricity market. Shan and Ryan [19] applied the bi-level program considering fuel supply, social welfare, electricity generation, and transmission to solve the capacity expansion problem. Jalal Kazempour *et al*. [20] proposed a game-theoretic methodology to characterize generation investment equilibria in a pool-based electricity market. Wang *et al*. [21] proposed an incomplete information game model to study the generation capacity expansion problem. The Nash equilibrium is obtained by solving a bi-level optimization problem.

In our model, the main objective of DNO and each MG is to minimize their own operation costs. The costs of a MG include the operation costs of DGs and the cost of purchasing electricity from the DNO: the revenues of a MG result from selling electricity to MG consumers and the utility grid. The costs of a DNO can be classified into operation costs

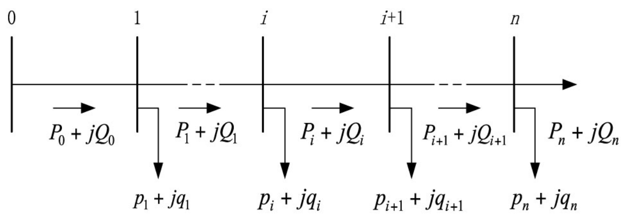

Fig. 1. Diagram of a radial electrical network.

of DNO-owned DGs and the cost of purchasing electricity from MGs and the connected high voltage (HV) system; the revenues include selling electricity to the HV system, DNO consumers, and MGs. The model is formulated as a stochastic bi-level problem with the DNO at the upper level to guarantee the operational constraints such as power flows and voltage levels and MGs at the lower level to minimize the operation costs of individual systems. This bi-level model has been verified in [22] and [23]. Each level is formulated as a stochastic two-stage problem with the first stage to optimize the base generation and power exchanges of all entities based on the forecasted outputs of RES-based DGs and the second stage to adjust generations according to the variations of realized RES-based DG outputs. The uncertain power outputs of wind turbines and PVs are described by scenarios generated from Monte Carlo simulations (MCs). The simultaneous backward scenario reduction method [24] is applied to increase the calculation speed while maintaining the accuracy of the solution.

The major contributions of this paper are summarized as follows.

1) Optimal coordinated control of networked MGs with distinct economic and operational objectives in a distribution system is a new topic with limited existing works.
2) Uncertainty and variability of RES-based DG outputs are fully considered.
3) Stochastic bi-level formulation of the control framework with each level modeled as a two-stage problem.

The remainder of this paper is organized as follows. Section II presents the local optimization problems of the DNO and MGs. Section III introduces the coordinated control scheme of multiple MGs and transforms the coordinated control problem into a stochastic MPCC formulation and proposes the solution methodology. In Section IV, the numerical results are provided. Section V concludes the paper with the major findings.

II. Mathematical Modeling of Individual Systems

This section introduces a widely used electrical network model and provides the local optimization formulation for individual systems, DNO and MGs.

A. Distribution System Model

Consider an electrical network as shown in Fig. 1, there are n buses indexed by $i = 0, 1, \ldots, n$. DistFlow [25] equations can be used to describe the complex power flows at each node i

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

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

$$\begin{aligned} V_{i+1}^2 = {} & V_i^2 - 2(r_iP_i + x_iQ_i) \\ & + (r_i^2 + x_i^2)(P_i^2 + Q_i^2)\Big/V_i^2 \end{aligned} \tag{3}$$

$$p_i = p_i^D - p_i^g, \;\; q_i = q_i^D - q_i^g. \tag{4}$$

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 [26]. 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 [7], [27], [28]

$$P_{i+1} = P_i - p_{i+1} \tag{5}$$

$$Q_{i+1} = Q_i - q_{i+1} \tag{6}$$

$$V_{i+1} = V_i - (r_iP_i + x_iQ_i)\Big/V_1^2 \tag{7}$$

$$p_i = p_i^D - p_i^g, \;\; q_i = q_i^D - q_i^g. \tag{8}$$

B. Optimization Problem for DNO

It is assumed that the DNO also owns both dispatchable DGs (MTs in this paper) and RES-based DGs (WTs in this paper) [29]. The optimization problem of a DNO can be formulated as follows (denote the formulation as $\mathcal{M}$):

$$\begin{aligned} \min \; & \sum_{i\in D} c^G p_i^G + \Big(c^{B,DNO}\eta_1 + \sum_m c^{S,MG}\theta_{m1} \\ & \qquad - c^{S,DNO}\theta_1 - \sum_m c^{B,MG}\eta_{m1}\Big) \\ & + \sum_s \gamma_s \sum_{i\in D}\Big(c^G \Delta p_{i,s}^G + C_{i,s}^{rd}\Big) \\ & + \sum_s \gamma_s \Big(c^{B,DNO}\Delta\eta_{1,s} + \sum_m c^{S,MG}\Delta\theta_{m1,s} \\ & \qquad - c^{S,DNO}\Delta\theta_{1,s} - \sum_m c^{B,MG}\Delta\eta_{m1,s}\Big) \end{aligned} \tag{9}$$

$$\begin{aligned} s.t.\; P_{i+1} = {} & P_i - p_{i+1}^D \\ & + \sum_g p_{i+1,g}^R + p_{i+1}^G, \forall i \in D \bigcup M \end{aligned} \tag{10}$$

$$Q_{i+1} = Q_i - q_{i+1}^D + q_{i+1}^G, \forall i \in D \bigcup M \tag{11}$$

$$V_{i+1} = V_i - (r_iP_i + x_iQ_i)/V_1, \forall i \in D \bigcup M \tag{12}$$

$$1 - \varepsilon \le V_i \le 1 + \varepsilon, \forall i \in D \bigcup M \tag{13}$$

$$0 \le p_i^G \le p_i^{\max}, \forall i \in D \tag{14}$$

$$\begin{aligned} & \sum_{i\in D} p_i^G + \sum_{i\in D, g\in G} p_{i,g}^R + \eta_1 \\ & \quad + \sum_m \theta_{m1} \ge \sum_{i\in D} p_i^D + \theta_1 + \sum_m \eta_{m1} \end{aligned} \tag{15}$$

$$\Delta P_{i+1,s} = \Delta P_{i,s} + \sum_{g} \Delta p^{R}_{i+1,s,g} + \Delta p^{G}_{i+1,s}, \forall i \in D \bigcup M, \forall s \in \mathcal{S} \tag{16}$$

$$\Delta Q_{i+1,s} = \Delta Q_{i,s} + \Delta q^{G}_{i+1,s}, \forall i \in D \bigcup M, \forall s \in \mathcal{S} \tag{17}$$

$$\Delta V_{i+1,s} = \Delta V_{i,s} - \left(r_i \Delta P_{i,s} + x_i \Delta Q_{i,s}\right)/V_1, \forall i \in D \bigcup M, \forall s \in \mathcal{S} \tag{18}$$

$$1 - \varepsilon \le V_i + \Delta V_{i,s} \le 1 + \varepsilon, \forall i \in D \bigcup M, \forall s \in \mathcal{S} \tag{19}$$

$$0 \le p^{G}_{i} + \Delta p^{G}_{i,s} \le p^{\max}_{i}, \forall i \in D, \forall s \in \mathcal{S} \tag{20}$$

$$-p^{rd}_{i} \le \Delta p^{G}_{i,s} \le p^{rd}_{i}, \forall i \in D, \forall s \in \mathcal{S} \tag{21}$$

$$\sum_{i \in D} \Delta p^{G}_{i,s} + \sum_{i \in D, g \in G} \Delta p^{R}_{i,g,s} + \Delta \eta_{1,s} + \sum_{m} \Delta \theta_{m1,s} \ge \sum_{i \in D} \Delta p^{D}_{i,s} + \Delta \theta_{1,s} + \sum_{m} \Delta \eta_{m1,s}, \forall s \in \mathcal{S} \tag{22}$$

$$C^{rd}_{i,s} \ge c^{\Delta G} \Delta p^{G}_{i,s}, \forall i \in D, \forall s \in \mathcal{S} \tag{23}$$

$$C^{rd}_{i,s} \ge -c^{\Delta G} \Delta p^{G}_{i,s}, \forall i \in D, \forall s \in \mathcal{S}. \tag{24}$$

In the objective function (9), 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 five items in (9) represent costs and revenues (C&R) relative to the base generation schedule made based on the forecasts of RES generation. The remaining items in (9) represent the adjustable C&R according to scenarios. The first item in (9) represents the generation costs of all MTs in the DNO. The second to fifth items in (9) represent the costs of power exchange among MGs, DNO, and the HV system. η and θ represent the power flow at the point connecting the distribution network and the HV system. (i.e., if $\eta_1 > 0, \theta_1 = 0$, the DNO is buying electricity from the HV system). Constraints (10)–(12) are linearized DistFlow equations as discussed in the previous subsection. Constraint (13) guarantees that the voltage level of each node is within a predefined range, ε is usually set to be 0.05. Constraint (14) guarantees the active output of a MT is within its maximum allowable value. Constraint (15) describes that the total generation should be equal to or larger than the total load. In the formulation (10)–(15), P_i, Q_i, V_i, p^G_i, q^G_i, η_1, η_{m1}, θ_1 and θ_{m1} are first-stage decision variables determined based on the forecasts. Since WTs and PVs are nondispatchable, 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 wind and solar power prediction errors [30]–[32]. The second-stage variables should be adjustable in order to deal with the variations of loads and RES generation [33], [34].

Constraints (16)–(24) describe the second-stage decision variables $\Delta P_{i,s}$, $\Delta Q_{i,s}$, $\Delta V_{i,s}$, $\Delta p^G_{i,s}$, $\Delta q^G_{i,s}$, $C^{rd}_{i,s}$, $\Delta\eta_{1,s}$, $\Delta\eta_{m1,s}$, $\Delta\theta_{1,s}$, and $\Delta\theta_{m1,s}$, which are adjusted with the realization of scenarios. Constraints (16)–(18) are adjustable linearized DistFlow equations for the sth scenario. Constraint (19) guarantees the voltage level at each node is within the permissible range after the generation is adjusted. In constraint (20), the sum of the base generation schedule and the adjusted outputs should be less than or equal to the rated capacity of a MT. Constraint (21) indicates that the redispatched generation should be within a permissible range. Constraint (22) describes that the total generation should be equal to or larger than the total load. We also consider the redispatch cost which is for the generation adjustment between the base generation and the generation in scenarios. Constraints (23) and (24) guarantee the redispatch cost of a MT is positive (e.g., if $\Delta p^G_{i,s} \ge 0$, which indicates a generation increase, constraint (24) becomes redundant and the redispatch cost $C^{rd}_{i,s}$ becomes equal to $c^{\Delta G} \Delta p^G_{i,s}$ due to the minimization formulation).

C. Optimization Problem for MGs

In this paper, WTs and PVs are considered as RES-based DGs, while MTs are considered as dispatchable DGs. The general optimization problem of a MG can be formulated as follows (Denote the formulation as $\mathcal{M}$):

$$\min \sum_{i \in M} c^G p^G_i + \left(c^{B,MG} \eta_{m1} - c^{S,MG} \theta_{m1}\right) + \sum_{s} \gamma_s \sum_{i \in M} \left(c^G \Delta p^G_{i,s} + C^{rd}_{i,s}\right) + \sum_{s} \gamma_s \left(c^{B,MG} \Delta \eta_{m_1,s} - c^{S,MG} \Delta \theta_{m1,s}\right) \tag{25}$$

$$s.t. 0 \le p^G_i \le p^{\max}_i, \forall i \in M \tag{26}$$

$$\sum_{i \in M} p^G_i + \sum_{i \in M, g \in G} p^R_{i,g} + \eta_{m1} \ge \sum_{i \in M} p^D_i + \theta_{m1} \tag{27}$$

$$\sum_{i \in M} \Delta p^G_{i,s} + \sum_{i \in M, g \in G} \Delta p^R_{i,g,s} + \Delta \eta_{m1,s} \ge \sum_{i \in M} \Delta p^D_{i,s} + \Delta \theta_{m1,s}, \forall s \in \mathcal{S} \tag{28}$$

$$-p^{rd}_i \le \Delta p^G_{i,s} \le p^{rd}_i, \forall i \in M, \forall s \in \mathcal{S} \tag{29}$$

$$0 \le p^G_i + \Delta p^G_{i,s} \le p^{\max}_i, \forall i \in M, \forall s \in \mathcal{S} \tag{30}$$

$$C^{rd}_{i,s} \ge c^{\Delta G} \Delta p^G_{i,s}, \forall i \in M, \forall s \in \mathcal{S} \tag{31}$$

$$C^{rd}_{i,s} \ge -c^{\Delta G} \Delta p^G_{i,s}, \forall i \in M, \forall s \in \mathcal{S}. \tag{32}$$

In the above formulation, the objective function (25) consists of C&R of the MG. The objective function can be divided into two parts: the first three items represent C&R relative to the base generation schedule made based on the forecasts of RES generation. However, RES generation outputs are stochastic in nature. The outputs of dispatchable DGs should be adjusted according to the realized scenario of nondispatchable DG outputs. The last four items in (25) represent the expected adjustments of C&R. In other words, if the RES generations are deterministic and can be accurately forecasted, the last four items should be zero. The costs include the operation cost of dispatchable DGs (MTs in this paper), the costs of buying electricity from the DNO. Since RES-based DGs have zero fuel cost, their operation costs are not included in

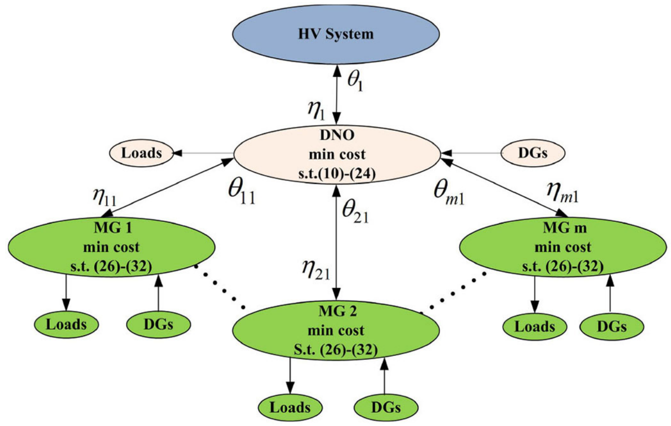

Fig. 2. Interactions between DNO and multiple MGs.

the objective function. The revenues include selling electricity to the DNO and consumers in the MG. The first item in (25) represents the generation costs of all MTs in the MG. The second and third items in (25) 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. η and θ represents the power flow at the point of common coupling (PCC) (i.e., if $\eta_{m1} > 0, \theta_{m1} = 0$, the MG is buying electricity from the utility grid). Constraint (26) guarantees the active output of a MT is within its maximum allowable value. Constraints (27) and (28) describe that the total generation should be equal to or larger than the total load. Constraint (29) guarantees that the redispatched generation should be within a permissible range. In constraint (30), the sum of the base generation schedule and the adjusted outputs should be less than or equal to the rated capacity of a MT. Constraints (31) and (32) represent the redispatch constraints as introduced in the DNO formulation. In the above formulation, the first-stage decision variables are p_i^G, η_{m1} and θ_{m1}, the second-stage decision variables are $\Delta p_{i,s}^G$, $C_{i,s}^{rd}$, $\Delta\eta_{m1,s}$, and $\Delta\theta_{m1,s}$.

III. Transform Stochastic Bi-Level Program Into MPCC

A. Coordinated Operation and MPCC

This paper focuses on modeling interactions among the HV system, DNO, and multiple MGs, as shown in Fig. 2. Due to the close connection of DNO and MGs, the operation of DNO is influenced by the generation and demand of MGs and vice versa. Each entity has its distinct variables and objectives to increase its own benefit. Therefore, the coordinated operations among entities can be modeled as a stochastic bi-level program which can be transformed into mathematical problem with complementarity constraints. In order to deal with the uncertain DG outputs, each level is formulated as a stochastic two-stage problem. In the bi-level model structure, the first level problem is to minimize the DNO costs as shown in (9)–(24), while the second level problem is to minimize the costs of all MGs as shown in (25)–(32).

Since the formulations $\mathcal{M}$ is continuous and convex, its Karush–Kuhn–Tucker (KKT) conditions are necessary and sufficient for optimality. Thus, formulation $\mathcal{M}$ can be replaced by its KKT conditions. Integrating these complementarity constraints in the first-level problem results in a MPCC. The full set of equilibrium constraints of a MG is as follows:

$$0 \le p_i^{\max} - p_i^G \perp \lambda_i^1 \ge 0 \forall i \in M \tag{33}$$

$$0 \le \sum_{i\in M} p_i^G + \eta_{m1} - \theta_{m1} - \sum_{i\in M} p_i^D + \sum_{i\in M,g} p_{i,g}^R \perp \lambda^2 \ge 0 \tag{34}$$

$$0 \le \sum_{i\in M} \Delta p_{i,s}^G + \Delta\eta_{m1,s} - \Delta\theta_{m1,s} + \sum_{i\in M,g} \Delta p_{i,g,s}^R \perp \lambda_s^3 \ge 0 \quad \forall s \in \mathcal{S} \tag{35}$$

$$0 \le -\Delta p_{i,s}^G + p_i^{rd} \perp \lambda_{i,s}^4 \ge 0 \forall i \in M, \forall s \in \mathcal{S} \tag{36}$$

$$0 \le \Delta p_{i,s}^G + p_i^{rd} \perp \lambda_{i,s}^5 \ge 0 \forall i \in M, \forall s \in \mathcal{S} \tag{37}$$

$$0 \le p_i^G + \Delta p_{i,s}^G \perp \lambda_{i,s}^6 \ge 0 \forall i \in M, \forall s \in \mathcal{S} \tag{38}$$

$$0 \le C_{i,s}^{rd} - c^{\Delta G} \Delta p_{i,s}^G \perp \lambda_{i,s}^7 \ge 0 \forall i \in M, \forall s \in \mathcal{S} \tag{39}$$

$$0 \le C_{i,s}^{rd} + c^{\Delta G} \Delta p_{i,s}^G \perp \lambda_{i,s}^8 \ge 0 \forall i \in M, \forall s \in \mathcal{S} \tag{40}$$

$$0 \le p_i^{\max} - p_i^G - \Delta p_i^G \perp \lambda_{i,s}^9 \ge 0 \forall i \in M, \forall s \in \mathcal{S} \tag{41}$$

$$0 \ge c^G - \lambda_i^1 + \lambda^2 + \lambda_{i,s}^6 - \lambda_{i,s}^9 \perp p_i^G \ge 0, \forall i \in M, \quad \forall s \in \mathcal{S} \tag{42}$$

$$0 \ge c^B + \lambda^2 \perp \eta_{m1} \ge 0 \tag{43}$$

$$0 \ge -c^S - \lambda^2 \perp \theta_{m1} \ge 0 \tag{44}$$

$$\gamma_s c^G + \lambda_s^3 - \lambda_{i,s}^4 + \lambda_{i,s}^5 + \lambda_{i,s}^6 - \lambda_{i,s}^9 - \lambda_{i,s}^7 c^{\Delta G} + \lambda_{i,s}^8 c^{\Delta G} = 0 \quad \forall i \in M, \forall s \in \mathcal{S} \tag{45}$$

$$0 \ge c^B \gamma_s + \lambda_s^3 \perp \Delta\eta_{m1,s} \ge 0 \forall s \in \mathcal{S} \tag{46}$$

$$0 \ge -c^S \gamma_s - \lambda_s^3 \perp \Delta\theta_{m1,s} \ge 0 \forall s \in \mathcal{S} \tag{47}$$

$$\gamma_s + \lambda_{i,s}^7 + \lambda_{i,s}^8 = 0 \forall i \in M, \forall s \in \mathcal{S} \tag{48}$$

where λ represents the dual variables of the problem defined in (26)–(32). Specifically, λ_i^1 corresponds to constraint (26), λ_2 corresponds to constraint (27), λ_s^3 corresponds to constraint (28), $\lambda_{i,s}^4$ and $\lambda_{i,s}^5$ correspond to constraint (29), $\lambda_{i,s}^6$ and $\lambda_{i,s}^9$ correspond to constraint (30), $\lambda_{i,s}^7$ and $\lambda_{i,s}^8$ correspond to constraints (31) and (32), respectively. Each MG will have a set of complementarity constraints as shown in (33)–(48). The result of including complementarity constraints of all MGs in the first level problem defined in (9)–(24) is the stochastic MPCC. The formulated MPCC cannot be solved directly using existing linear solvers like CPLEX since the KKT conditions of the second-level problem contain products of variables. Therefore, we apply the Big-M method to linearize the nonlinear terms in the MPCC [35]. For example, constraint (33) can be transformed by the Big-M method as follows:

$$0 \le p_i^{\max} - p_i^G \le M \cdot z_i^1 \tag{49}$$

$$0 \le \lambda_i^1 \le M \cdot (1 - z_i^1) \tag{50}$$

where M is a large value and z_i^1 is a binary variable. We apply the same large value of M to all constraints. All the constraints of (33)–(48) can be linearized in the similar way and are not listed here for brevity. The mixed integer linear programming (MILP) formulation of the proposed MPCC is

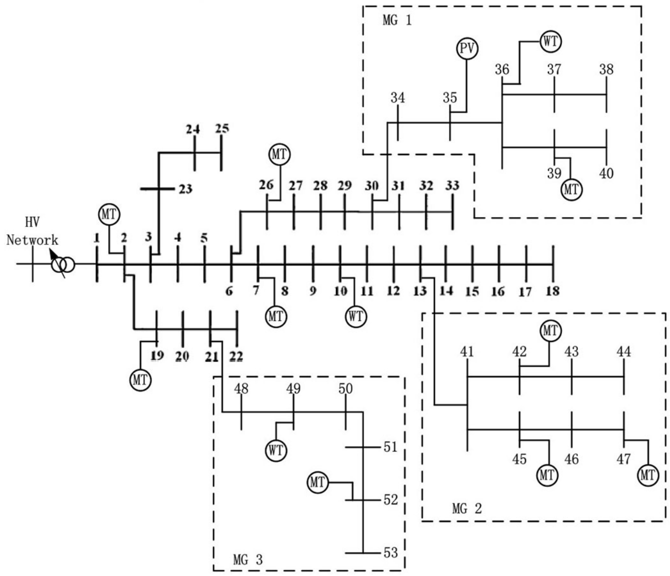

Fig. 3. Test distribution system with networked MGs.

as follows: Minimize (9), subject to (9)–(24), linearized forms of (33)–(48) of all connected MGs.

B. Uncertainties and Scenario Reduction

In this paper, two kinds of RES-based DGs are considered: WTs and 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 distribution to represent prediction errors of wind and solar power [30], [36]. For a predicted power level P_i^{pred} of the DG at node i, the beta function can be defined by two corresponding parameters α and β [36]

$$f_{p_{i,t}^{pred}}(x) = x^{\alpha-1}(1-x)^{\beta-1}. \tag{51}$$

The above beta function models the occurrence of real power values x when a certain prediction value P_i^{pred} has been forecasted. The shape parameters of the corresponding beta function α and β can be calculated as [36]

$$P_i^{\text{pred}} \Big/ S_{\text{base}} = \alpha_i \big/ (\alpha_i + \beta_i) \tag{52}$$

$$\sigma_i^2 = \alpha_i \beta_i \Big/ (\alpha_i + \beta_i)^2 (\alpha_i + \beta_i + 1). \tag{53}$$

The relationship between the predicted power and its error variance can be represented as [32], [36]

$$\sigma_i = 0.2 \times P_i^{\text{pred}} \Big/ P_i^{\max} + 0.21. \tag{54}$$

Using the predicted DG outputs and the equations (51)–(54), the parameters of beta functions for the current prediction data can be calculated. A normal distribution is frequently used to represent the forecasting uncertainty of load consumptions, in which, the mean value of the normal distribution is the forecasted load and the standard deviation is set to be 2% of the expected load [37]. The number of scenarios generated by MCs is reduced by the simultaneous backward reduction method [21]. All of the above distributions and parameter settings can be changed according to the available information of a system.

TABLE I
DESCRIPTION OF NETWORKED MGs

System	Load Bus No.	Total Capacity of DGs (p.u.)	Total Active Load (p.u.)	Total Reactive Load (p.u.)
MG1	34, 35, 37, 38, 39, 40	0.19	0.12	0.072
MG2	42, 43, 44, 45, 46, 47	0.09	0.09	0.06
MG3	48, 49, 50, 51, 52, 53	0.11	0.072	0.048

TABLE II
PARAMETERS FOR CALCULATING CORRESPONDING COSTS

Parameters		Value	
c^G	\$0.1/kWh	$c^{D,MG}$	\$0.2/kWh
$c^{\Delta G}$	\$0.15/kW	$c^{S,DNO}$	\$0.3/kWh
$c^{S,MG}$	\$0.25/kWh	$c^{B,DNO}$	\$0.28/kWh
$c^{B,MG}$	\$0.3/kWh	$c^{D,DNO}$	\$0.3/kWh

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

Type	WT	PV	WT	WT
Bus No.	10	35	36	49
Forecast	0.03	0.06	0.06	0.05

IV. NUMERICAL RESULTS

As shown in Fig. 3, 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 [25].

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. The maximum outputs of a PV and WT are set to be 0.08. The maximum output of a MT is set to be 0.03 p.u. Table I summarizes the system description of MGs. For a MG, it is assumed that the load consumption at each load bus is equal. All buses of MGs are load buses except bus 41 which is connected with two branches in MG2.

Table II shows the parameters used in the case study, which are obtained from [38]. 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-B. 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 MCs 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. The 1000 generated scenarios are reduced to 15 scenarios in this case.

TABLE IV
GENERATION SCHEDULES OF DIFFERENT SOURCES

Entity	Power Source	Centralized Management	Deterministic Game	Stochastic Game
		P (p.u.)	P (p.u.)	P (p.u.)
DNO	HV	0.26	0.251	0.255
	MT2	0.03	0.03	0.03
	MT7	0.001	0.0012	0.003
	MT19	0.03	0.03	0.03
	MT26	0.0205	0.0125	0.01
MG1	MT39	0.02	0.01	0.02
MG2	MT42	0.03	0.03	0.03
	MT45	0.03	0.03	0.03
	MT47	0.03	0.03	0.03
MG3	MT52	0.022	0.03	0.025

Note: The number after MT represents the installation bus, e.g., MT2 represents the MT at bus 2.

TABLE V
ACTIVE POWER EXCHANGE AND TOTAL BENEFIT OF EACH ENTITY

Formulation	From Entity	To Entity	Power Exchange (p.u.)	Profit of 'From' Entity ($)	Total Profits of Entities ($)
Centralized Management	DNO	HV	-0.26	278.71	721.24
		MG1	0.001		
		MG2	0		
		MG3	0		
	MG1	DNO	-0.001	238.35	
	MG2	DNO	0	90	
	MG3	DNO	0	114.18	
Deterministic Game	DNO	HV	-0.251	253.20	717.19
		MG1	-0.01		
		MG2	0		
		MG3	-0.008		
	MG1	DNO	0.01	239.99	
	MG2	DNO	0	90	
	MG3	DNO	0.008	134.00	
Stochastic Game	DNO	HV	-0.255	244.53	698.12
		MG1	-0.018		
		MG2	0		
		MG3	-0.003		
	MG1	DNO	0.018	232.38	
	MG2	DNO	0	90	
	MG3	DNO	0.003	131.21	

To further analyze the performance of the proposed method, three cases are considered: 1) centralized formulation; 2) bi-level deterministic MPCC formulation; and 3) bi-level stochastic MPCC formulation. In the centralized formulation, the objectives of DNO and each MG are the same as (9) and (25), respectively. The objectives of all entities are equally added to formulate a new objective function. The constraints are (10)–(24) and (26)–(32). The deterministic MPCC and stochastic MPCC share the same objective and first-stage constraints. However, since the deterministic MPCC uses the forecasted mean values of the generated scenarios, all second-stage variables and corresponding constraints are removed. In other words, the generation schedules made by the centralized management and the stochastic game consider the uncertainty of DG outputs in the second-stage of the formulations while the deterministic formulation does not.

Table IV shows the generation schedules of different sources and Table V shows the power exchange and profits of all entities based on the schedules. It can be seen that the power generation, exchange, and profits of the three cases are different from each other. The centralized formulation has a higher summation of all profits than the game ones. This is because the objective of the centralized management is to minimize the operation costs of all entities while the benefits of some entities may be sacrificed to achieve the equilibrium in game-theoretic formulations.

In game-theoretic formulations, each entity has its own objective and tries to optimize its own operation. Thus, it can be seen from Table V that there are power exchanges between the DNO and MGs. If we compare the stochastic centralized management and stochastic game, we can find that the profit of the DNO is reduced in the stochastic game from \$278.71 to \$244.53, while the profits of MGs are increased. As indicated before, this is because each entity tries to maximize its own benefits in the game-theoretic formulation. The data listed in the table represents the equilibrium point, which indicates that no one can further optimize its profit by changing its own operation point. It can also be found that there is no power exchange between the DNO and MG2 for all three cases and the generation schedules and profits remain the same. The reason is that the power consumption and generation are equal in MG2 as shown in Table I. There is no power deficiency or surplus. Meanwhile, since all generators in MG2 are MTs which are dispatchable, the results of stochastic and deterministic formulations are the same. It can be seen that the generation schedules, power exchange, and profits of MG1 and MG3 are different. MG1 and MG3 are RES-based MGs whose operations are greatly impacted by the forecasted DG outputs.

It should be noted that the profits of the deterministic game are larger than those of the stochastic game since the forecasted mean values are used in the deterministic game and the stochastic prediction errors are not taken into account. However, prediction errors always exist in reality. If we simply apply the deterministic decisions to a practical system, the performance of the system will be worse than the one with stochastic decisions applied. The quality of a candidate solution of a stochastic programming problem can be evaluated using the expectation of the expected value (EEV) [39]. In order to quantify the quality of the stochastic game solution, we define the expected value problem (EV), which is a deterministic game, as

$$EV = \min f\left(X, \Delta\bar{p}^{R}_{i,s,g}\right) \tag{55}$$

where $f(\cdot)$ represents the objective function, $\Delta\bar{p}^{R}_{i,s,g}$ denotes the expectation of $\Delta p^{R}_{i,s,g}$ and X represents the energy scheduling decisions. The solution of the EV problem can be defined as $\bar{X}$ and is shown in Tables IV and V as the deterministic game results. MCs is used to compare the performances of the deterministic game decision $\bar{X}$ and the stochastic game decision. We generate 1500 scenarios (N'= 1500). The expected performance of using the EV solution can be represented as

$$EEV = \sum_{s=1}^{N'} f\left(\bar{X}, \Delta p^{R}_{i,s,g}\right) \Big/ N'. \tag{56}$$

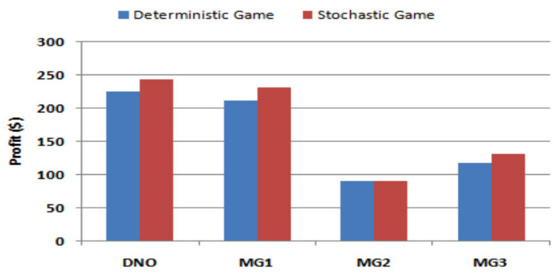

Fig. 4. Performance comparison of stochastic and deterministic games.

EEV measures the performance of $\bar{X}$, allowing second-stage variables to be chosen optimally as functions of $\bar{X}$ and $\Delta p^R_{i,s,g}$. Meanwhile, we define the decisions of the stochastic game as $\hat{X}$. The solution of the stochastic game $\hat{X}$ is used in the same generated scenarios to calculate $f(\hat{X}, \Delta p^R_{i,s,g}),\ s = 1, \ldots, N'$ and then averaged out to compute the expectation. Fig. 4 shows the profits of all entities in the two cases. It is obvious that applying stochastic game decisions can result in more profits for entities with RES-based DGs as its accounts for the DG output uncertainty more accurately.

V. Conclusion

This paper provides a methodology to characterize the interactions between DNO and clusters of MGs. The DNO and MGs are regarded as different entities that are self-managed and operated with distinct objectives to minimize their own operation costs. Both dispatchable and RES-based DGs are considered to be part of MGs. A bi-level stochastic formulation is developed to model the problem taking into account the strategic behaviors of all entities and the intermittent outputs of RES-DGs. The formulation is transformed into a stochastic MPCC. The modified 33-bus test system with three MGs is studied. The results show that significant differences exist in stochastic and deterministic MPCCs. The simulation results also show that the stochastic decisions outperform the deterministic decisions. Compared with previous efforts on MG control, the proposed model considers the coordination of networked MGs and DNO, the probabilistic DG outputs are also taken into account.

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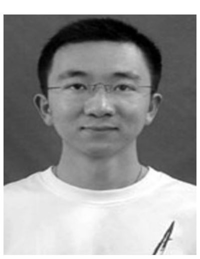

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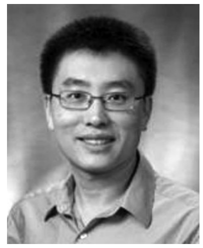

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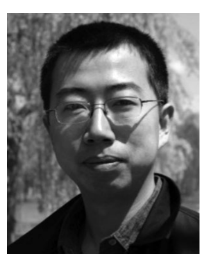

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