Robust Optimization Based Optimal DG Placement in Microgrids

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***Abstract*—This paper proposes a novel Microgrid (MG) planning methodology to decide optimal locations, sizes and mix of dispatchable and intermittent distributed generators (DGs). The long-term costs in the proposed planning model include investment, operation and maintenance (O&M), fuel and emission costs of DGs while the revenue includes payment by MG loads and utility grid. The problem is formulated as a mixed-integer program (MIP) considering the probabilistic nature of DG outputs and load consumption, wherein the costs are minimized and profits are maximized. The model is transformed to be a two-stage robust optimization problem. A column and constraint generation (CCG) framework is used to solve the problem. Compared with conventional MG planning approaches, the proposed model is more practical in that it fully considers the system uncertainties and only requires a deterministic uncertainty set, rather than a probability distribution of uncertain data which is difficult to obtain. Case studies of a MG with wind turbines, photovoltaic generators (PVs) and microturbines (MTs) demonstrate the effectiveness of the proposed methodology.**

***Index Terms*—Distributed Generator (DG), distribution network, microgrid (MG), mixed integer program (MIP), robust optimization.**

NOMENCLATURE

A. Sets

$W_{y,t}^{wt,pv,ld}$	Uncertainty set for wind power, solar power and load consumption.
$\mathrm{N}_w, \mathrm{N}_p, \mathrm{N}_d$	Set of nodes that have WT, PV and LD, respectively.

B. Acronyms

wt	Wind turbine.
pv	Photovoltaic generator.
mt	Micro turbine.
ld	Load consumption.

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C. Parameters

r_i	Line resistance between nodes i and $i+1$.
x_i	Line reactance between nodes i and $i+1$.
$e^{wt,pv,mt}$	Investment cost for a certain type of DG ($).
γ_y	Present worth factor in year y.
d	Annual discount rate.
$H_y^{wt,pv,mt}$	Total operation hours in year y.
$m_y^{wt,pv,mt}$	O&M cost in year y ($).
ϕ	Weight that transforms the hour-based costs to year-based costs.
$s^{wt,pv,mt}$	One discrete increment of DG size (kVA).
σ	Emission factor for MT (kg/kWh).
α_y^{fl}	Fuel price of microturbines in year y.
$\alpha_{y,t}^{emi}$	Emission price of microturbines at time t in year y.
$\beta_{y,t}^{s}/\beta_{y,t}^{b}$	Price for selling/buying electricity to utility grid at time t in year y.
$\beta_{y,t}^{c}$	Price for selling electricity to consumers in MG at time t in year y.
ε	Maximum allowed voltage deviation.
τ	Percentage of excess reserve margin for islanded operation.
Y	Planning horizon.
n_w, n_p, n_d	Total number of nodes that have WT, PV and LD, respectively.
$\omega_{y,t}^{wt,pv}$	Uncertain power output of $s^{wt,pv}$ at time t in year y.
$\omega_{i,y,t}^{ld}$	Uncertain load consumption of node i at time t in year y.
$\overline{\omega}^{wt,pv,ld}\underline{\omega}^{wt,pv,ld}$	Upper and lower bounds of $\omega^{wt,pv,ld}$.
$\hat{\omega}^{wt,pv,ld}$	Mean values of $\omega^{wt,pv,ld}$.
$\overline{\mu}^{wt,pv,ld}\underline{\mu}^{wt,pv,ld}$	Budget of uncertainty of forecasted wind power, solar power and load consumption.

D. Variables

$V_{i,y,t}$	Voltage magnitude of node i at time t in year y.

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$P_{i,y,t}/Q_{i,y,t}$	Active/reactive power flow from node i to $i+1$ at time t in year y.
$p^c_{i,y,t}/q^c_{i,y,t}$	Active/reactive load consumption of node i at time t in year y.
$q^c_{i,y,t}$	Reactive load consumption of node i at time t in year y.
$p^{g,wt,pv,mt}_{i,y,t}$	Active power output of a certain type of DG at node i at time t in year y.
C^{inv}	Investment cost ($).
C^{OM}	Operation and maintenance (O&M) cost ($).
C^{fl}	Fuel cost ($).
C^{emi}	Emission cost ($).
C^{rev}	Revenue of the MG ($).
$a^{wt,pv,mt}_i$	Binary indicator represents whether a certain type of DG exists at node i (1-yes, 0-no).
$b^{wt,pv,mt}_{i,j}$	0 if the jth increment in size is not necessary to compose the DG at node i.
	1 if the jth increment in size is necessary to compose the DG at node i.
$c^{wt,pv,mt}_{i,j}$	$c^{wt,pv,mt}_{i,j} = a^{wt,pv,mt}_i b^{wt,pv,mt}_{i,j}$.
$\eta_{y,t}$	Power deficiency of the MG at time t in year y.
$\theta_{y,t}$	Power surplus of the MG at time t in year y.
Gap	Optimality gap.
ς	Maximum allowable Gap.

I. Introduction

MICROGRIDs (MGs) are active distribution networks integrating distributed generators (DGs), loads and energy storage and other onsite electric components. MGs are usually intended for the local production of power with islanding capabilities (islanded, or autonomous mode) and have capacity available for selling power back to the utility grid (grid-connected mode) [1].

MGs usually consist of various types of DGs such as wind turbines, photovoltaic generators (PVs), biomass, micro turbines and fuel cells. Proper planning of MGs is critical to the operations, return of investments (ROI) and environmental impacts of MGs. As one of the most important aspects of MG planning, the deployment of DGs is to decide the locations, sizes and mix of DGs in a MG. A lot of studies have been made in the deployment of DGs in distribution networks. The study in [2] identified the voltage sensitivity of each bus using continuous power flow analysis, and then deployed DG at the most sensitive bus to improve the voltage security margin and reduce power losses. The study in [3] proposed analytical methods to determine the optimal location to place a DG in radial as well as networked systems to minimize power losses. The study in [4] applied Genetic algorithm (GA) to determine the sizes and locations of DGs considering exponential load models. However, all the above existing works assume that DGs are dispatchable and controllable, which is not accurate since renewable energy-based DGs are mostly non-dispatchable power sources with intermittent output. Only a few papers have considered the uncertain nature of DGs in system planning. The authors in [5] presented a probabilistic planning method to determine the optimal mix of wind, solar, and biomass units to minimize annual energy losses, but the placement of DG units was not considered. The authors in [6] deployed DGs to improve voltage stability. The probabilistic nature of DG output is mentioned but not taken into account in the solution algorithm. In [7], Particle Swarm Optimization (PSO) and ordinal optimization (OO) were combined to obtain optimal deployment of DGs in a distribution system considering the uncertainties of DG outputs and loads. A scenario-aggregation method is proposed to reduce the computational burden.

Although MGs are essential elements in a smart grid, only a few approaches have been reported in the literature in relation to MG planning. Reference [8] presented an algorithm for the MG planning as an alternative to the co-optimization of generation and transmission expansion planning. Reference [9] developed a tool for economic MG planning. It finds the minimum cost of energy and optimal mix of DGs. The uncertainties of DG outputs and load demands were not considered. Reference [10] used PSO to solve the deployment problem of DGs in a MG with the purpose to maximize the benefit-to-cost ratio of MG owners. Only the combined-heat-and-power (CHP)-based DGs were considered, and the environmental impacts were not taken into account. The study in [11] applied GA and PSO to decide the locations and sizes of DGs so as to transform existing distribution networks to MGs. The issues relating to DG types and probabilistic outputs of DGs were not included in the work. The studies in [12]–[14] applied various algorithms such as simulated annealing, PSO and dynamic programming to obtain the optimal sizes and locations of DGs in MGs. However, none of the above papers has considered the stochastic nature of renewable sources (RES)-based DGs and load consumptions in a MG context.

In this paper, we present a two-stage robust optimization-based MG planning model that takes into account uncertainties of DG outputs and load consumptions. The proposed method assumes a centralized decision maker such as the MG owner can make the DG allocation plan in the MG [15]–[17]. The robust optimization (RO) has been applied to solve the unit commitment (UC) problem [18]–[21]. RO has also been used to solve Transmission Network Expansion Planning (TNEP) problem [22]–[24]. Compared with traditional stochastic optimization approaches which rely on a probability distribution of the uncertainty data and sampled scenarios of the uncertainty realizations, RO has several advantages: first, RO only requires limited information of the uncertainty set such as the mean, lower and upper bounds of the uncertain data which are easier to obtain from the historical data or estimated with certain confidence intervals in practice; second, RO calculates an optimal solution that is immune against all realizations of the uncertain data within a predetermined uncertainty set by considering the worst scenario [18], which is also in contrast to stochastic programming that provides probabilistic guarantees for constraint satisfaction [22]. The random parameters are represented by corresponding uncertainty sets in the deterministic formulation [20]. These features make RO highly applicable in solving the MG planning problem where long-term explicit information of uncertain DG outputs and loads is difficult to obtain and a large number of scenarios may be needed for the stochastic program approach to represent the uncertainties during the overall planning period. Meanwhile, RO also has some disadvantages [21]: the solutions of RO are often considered to be conservative; if the exact distribution of the uncertainty data could be known, such information may not be fully used.

In our model, the costs of constructing and operating a MG can be classified into investment costs, operation and maintenance (O&M) costs, fuel and emission costs of DGs; the revenues of a MG result from selling electricity to MG consumers and the utility grid. All these costs and revenues are represented by their net present values (NPV), which are compounded over a period of economic life of DGs [25]. The deployment of DGs in a MG is formulated as a two-stage mixed-integer programming problem with the objective of minimizing the total costs and maximizing the profits by selecting optimal locations, sizes and mix of DGs. The uncertain power outputs of wind turbines and PVs as well as load consumptions in each period are described by corresponding polyhedral uncertainty sets. A column and constraint generation (CCG) framework is developed and applied to solve the problem.

The major contributions of this paper are summarized as follows:

- Multi-objective MG planning model with long-term economic, operational and environmental considerations is a new topic with limited existing works
- Uncertainty and variability of DG outputs and load consumptions are fully considered
- Two-stage robust formulation of the MG planning model and the corresponding solution methodology

The remainder of this paper is organized as follows. Section II introduces the distribution network model and the deterministic formulation of the MG planning problem. Section III transforms the MG planning problem into a two-stage robust formulation and proposes the solution methodology. In Section IV, the computational results are provided. Section V concludes the paper with the major findings.

II. Mathematical Formulation for MG Planning

This section introduces a widely used electrical network model and provides the deterministic formulation of MG planning. The formulation is then transformed to be a bi-level robust optimization model in the next section.

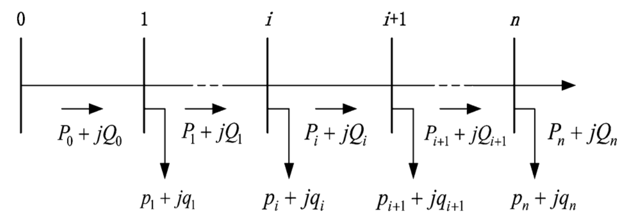

Fig. 1. Diagram of a radial electrical network.

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 [26] equations can be used to describe the complex power flows at each node i:

$$P_{i+1} = P_i - r_i \frac{P_i^2 + Q_i^2}{V_i^2} - p_{i+1} \tag{1}$$

$$Q_{i+1} = Q_i - x_i \frac{P_i^2 + Q_i^2}{V_i^2} - q_{i+1} \tag{2}$$

$$V_{i+1}^2 = V_i^2 - 2(r_i P_i + x_i Q_i) + \left(r_i^2 + x_i^2\right) \frac{P_i^2 + Q_i^2}{V_i^2} \tag{3}$$

$$p_{i+1} = p_{i+1}^c - p_{i+1}^g, q_{i+1} = q_{i+1}^c - q_{i+1}^g \tag{4}$$

In the above equation, p_i^g is generated by DG units which are subject to uncertainties, q_i^g is generated by var compensation devices. 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 [26]–[28].

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

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

$$V_{i+1} = V_i - \frac{r_i P_i + x_i Q_i}{V_0} \tag{7}$$

$$p_{i+1} = p_{i+1}^c - p_{i+1}^g, q_{i+1} = q_{i+1}^c - q_{i+1}^g \tag{8}$$

B. Mathematical Formulation of MG Planning Problem

The optimal integration of DGs into a MG demonstrates various advantages in operational, environmental and economic aspects. This paper assumes that the planned MG consists of three types of DGs: wind turbines (WTs), PVs and microturbines (MTs). The reconfiguration of a MG is not considered in the formulation. This paper focuses on radial networks. For a meshed distribution network, it can be converted to a radial network by breaking the loops through adding dummy nodes [29]. The objective is to determine the optimal locations, sizes and mix of DGs in the MG with the purpose to maximize the long-term economic profits of MG owners. The MG planning problem can be formulated as follows (denote the formulation as $\mathcal{D}$):

$$\min_{a,b,P,Q,V,p^g} C^{inv} + C^{OM} + C^{fl} + C^{emi} - C^{rev} \tag{9}$$

$s.t.$

$$C^{inv} = \sum_i \sum_j e^{wt} a_i^{wt} b_{i,j}^{wt} s^{wt} + \sum_i \sum_j e^{pv} a_i^{pv} b_{i,j}^{pv} s^{pv} + \sum_i \sum_j e^{mt} a_i^{mt} b_{i,j}^{mt} s^{mt} \tag{10}$$

$$C^{OM} = \sum_y \gamma_y \left[\sum_i \sum_j H_y^{wt} m_y^{wt} a_i^{wt} b_{i,j}^{wt} s^{wt} + \sum_i \sum_j H_y^{pv} m_y^{pv} a_i^{pv} b_{i,j}^{pv} s^{pv} + \sum_i \sum_j H_y^{mv} m_y^{mt} a_i^{mt} b_{i,j}^{mt} s^{mt} \right] \quad (11)$$

$$C^{fl} = \sum_y \gamma_y \phi \sum_t \sum_i \alpha_y^{fl} p_{i,y,t}^{g,mt} \quad (12)$$

$$C^{emi} = \sum_y \gamma_y \phi \sum_t \sum_i \alpha_y^{emi} \sigma p_{i,y,t}^{g,mt} \quad (13)$$

$$C^{rev} = \sum_y \gamma_y \phi \sum_t \left[\beta_{y,t}^s \theta_{y,t} - \beta_{y,t}^b \eta_{y,t} + \beta_{y,t}^c \sum_i p_{i,y,t}^c \right] \quad (14)$$

$$\gamma_y = \frac{1}{(1+d)^y}, \quad \forall y \quad (15)$$

$$P_{0,y,t} = \eta_{y,t} - \theta_{y,t}, \eta, \theta \geq 0, \quad \forall y, t \quad (16)$$

$$P_{i+1,y,t} = P_{i,y,t} - p_{i+1,y,t}^c + p_{i+1,y,t}^{g,wt} + p_{i+1,y,t}^{g,pv} + p_{i+1,y,t}^{g,mt}, \quad \forall i, y, t \quad (17)$$

$$Q_{i+1,y,t} = Q_{i,y,t} - q_{i+1,y,t}^c + q_{i+1,y,t}^g, \quad \forall i, y, t \quad (18)$$

$$V_{i+1,y,t} = V_{i,y,t} - \frac{r_i P_{i,y,t} + x_i Q_{i,y,t}}{V_{0,y,t}}, \quad \forall i, y, t \quad (19)$$

$$1 - \varepsilon \leq V_{i,y,t} \leq 1 + \varepsilon, \quad \forall i, y, t \quad (20)$$

$$p_{i,y,t}^{g,wt} = \sum_j a_i^{wt} b_{i,j}^{wt} \omega_{y,t}^{wt}, \quad \forall i, y, t \quad (21)$$

$$p_{i,y,t}^{g,pv} = \sum_j a_i^{pv} b_{i,j}^{pv} \omega_{y,t}^{pv}, \quad \forall i, y, t \quad (22)$$

$$p_{i,y,t}^{g,mt} \leq \sum_j a_i^{mt} b_{i,j}^{mt} s^{mt}, \quad \forall i, y, t \quad (23)$$

$$\tau \sum_y \sum_t \sum_i p_{i,y,t}^c \leq \sum_y \sum_t \left[\sum_i \sum_j a_i^{mt} b_{i,j}^{mt} s^{mt} + \sum_i \sum_j a_i^{wt} b_{i,j}^{wt} s_{i,y,t}^{wt} + \sum_i \sum_j a_i^{pv} b_{i,j}^{pv} s_{i,y,t}^{pv} \right] \quad (24)$$

In the above formulation, the objective function (9) consists of costs and revenues of the planned MG. The costs include investment, O&M costs of DG, emission costs of fossil source-based DG (MT in this paper) and the costs of buying electricity from the utility grid. The revenues include selling electricity to the utility grid and consumers in the MG. Equation (10) represents the total investment cost (purchase and installation) of each type of DGs. All the costs and profits are represented in NPV except for the investment cost since the investment is made only in the reference year. Constraint (11) represents the O&M costs of all DGs during the planning period. The annual O&M cost of a DG can be evaluated based on its size and operation hours. Constraint (12) estimates the total fuel cost of MTs based on the energy generation in a planning horizon. ϕ is the weight to transform hour-based costs to year-based costs, e.g., if we use typical 24-hour system states to represent the overall system behaviors during each year ($t = 1, 2, \ldots, 24$), then $\phi = 365$. Constraint (13) represents the emission cost of MTs, which is associated with the total power generated by MTs during the planning horizon. Equation (14) describes the total revenues of the MG including selling electricity to the utility grid and customers within the MG. Buying electricity from the utility grid is defined as negative revenue. Equation (15) represents the present worth factor for the yth future year. Constraint (16) represents the power flow at the point of common coupling (PCC) (i.e., if $\eta > 0$, $\theta = 0$ MG is buying electricity from the utility grid). Constraints (17)–(19) are linearized DistFlow equations as discussed in the previous subsection. Constraint (20) guarantees that the voltage level of each node is within a predefined range,ε is usually set to be 0.05 pu. DG capacities are discretized at a definite step which is $s^{wt,pv,mt}$ in this paper. Constraints (21) and (22) describe the outputs of WTs and PVs. Since WTs and PVs are non-dispatchable, a forecast is usually used for planning purposes. The uncertain nature of prediction errors will be discussed in the next section. The sizes of a WT and a PV can be represented as $\sum_j b_{i,j}^{wt} s^{wt}$ and $\sum_j b_{i,j}^{pv} s^{pv}$, respectively. In constraint (23), the size of the MT at node i is described as $\sum_j b_{i,j}^{mt} s^{mt}$. Since MTs are dispatchable, the actual power output of a MT can be adjusted to optimize the operation of the MG. Thus, the output of a MT should be equal to or less than the rated size. When an outage happens in the utility grid, the MG should be able to operate in the islanded mode. Currently, there is no standard for the required reserve margin within the island, it is assumed that the island is reliable if the sum of the generated power from all DGs within the MG equals or exceeds a certain percentage of the total load consumption [30], [31]. In this paper, we assume the percentage τ to be 115% as a reserve margin is required due to the variability and uncertainty of RES-based DGs [30]. Equations (21)–(24) include multiplications of two binary variables $a_i$and b_{ij}. In order to reduce the non-linearity of the problem, the bi-linear term $a_i b_{i,j}$ can be replaced by

$$c_{i,j} = a_i b_{i,j}, c_{i,j} \leq a_i, c_{i,j} \leq b_{i,j}, c_{i,j} \geq a_i + b_{i,j} - 1 \quad (25)$$

The formulation $\mathcal{D}$ is a mixed-integer linear program (MILP).

III. Solution Methodology

A. Robust Optimization

Before introducing the detailed RO based formulation, it is necessary to construct uncertainty sets. The probabilistic nature of the formulated MG planning problem results from the intermittent outputs of RES-based DGs (WTs and PVs in this paper) and uncertain load consumptions. The predicted wind power, solar power and loads are normally used in the MG planning problem. However, it is known that errors always exist in prediction models. In stochastic optimization approaches, probabilistic distributions are used to represent prediction errors. For example, the normal distribution and beta distribution are used by previous papers to represent the wind and solar power prediction errors [32]–[34]. In RO, we introduce polyhedral uncertainty sets for wind and solar energy generations as well as load consumptions. We consider the following uncertainty set for the load consumption at each time period t in the planning horizon Y:

$$W_{y,t}^{ld} = \left\{ \omega_{i,y,t}^{ld} \in R^{n_d} : \underline{\mu}_{y,t}^{ld} \leq \frac{\sum_i \omega_{i,y,t}^{ld}}{\sum_i \hat{\omega}_{i,y,t}^{ld}} \leq \overline{\mu}_{y,t}^{ld}, \right. \\ \left. \omega_{i,y,t}^{ld} \in \left[\underline{\omega}_{i,y,t}^{ld}, \overline{\omega}_{i,y,t}^{ld}\right], \quad \forall i \in \mathrm{N}_d \right\} \tag{26a}$$

The range of the load consumption of node i at time t in year y is described by the interval $[\underline{\omega}_{i,y,t}^{ld}, \overline{\omega}_{i,y,t}^{ld}]$. Aggregated load over all nodes at time t in year y is constrained by the "budget of uncertainty" $\underline{\mu}_{y,t}^{ld}$ and $\overline{\mu}_{y,t}^{ld}$. As $\overline{\mu}_{y,t}^{ld}$ increases and $\underline{\mu}_{y,t}^{ld}$ decreases, the size of the uncertainty set enlarges. Thus, the resulting planning solutions are more conservative. The uncertainty set for $\omega_{y,t}^{wt}$ can be defined as

$$W_{y,t}^{wt} = \left\{ \omega_{y,t}^{wt} \in R^{n_w} : \underline{\mu}_{y}^{wt} \leq \frac{\sum_t \omega_{y,t}^{wt}}{\sum_t \hat{\omega}_{y,t}^{wt}} \leq \overline{\mu}_{y}^{wt}, \right. \\ \left. \omega_{y,t}^{wt} \in \left[\underline{\omega}_{y,t}^{wt}, \overline{\omega}_{y,t}^{wt}\right] \right\} \tag{26b}$$

A similar uncertainty set can be defined for the PV.

The formulation $\mathcal{D}$ can be reformulated as a min-max-min robust optimization problem as follows

$$\min_{(a,b,c)\in X} \left\{ C^{inv}(a,b,c) + C^{OM}(a,b,c) \right. \\ \left. + \max_{\omega\in W} \min_{h\in\Omega(a,b,c,\omega)} C^{fl}(h) + C^{emi}(h) - C^{rev}(h) \right\} \tag{27}$$

where $X = \{(a,b,c)|eqn(25)\}$ is the feasible set for the binary variables a, b and c, W represents all uncertainty sets for uncertain quantities ω, and the set $\Omega(a,b,c,\omega) = \{(a,b,c,\omega)|eqns(16) - (24)\}$ is the feasible region for power generation of MTs and power flows. For notational simplicity, we group first-stage binary variables to be f, $f \in F$ with $F = \{0,1\}$. Meanwhile, we group the uncertain variables in the second-stage problem (i.e., ω^{wt}, ω^{pv} and p^c) to be u, $u \in U$ with U as the uncertainty set; other continuous variables such as P, Q, V are grouped to be z, $z \in Z$. The corresponding abstract MG planning model can be shown as follows (let us denote the formulation as $\mathcal{R}$):

$$\min \left\{ A_0^{\mathrm{T}} f + \max_{u\in U} \min_{z\in Z(f,u)} B_0^{\mathrm{T}} u + C_0^{\mathrm{T}} z \right\} \tag{28}$$

$$s.t.\ f \in F \tag{29}$$

where F is defined by constraints (10)–(15); U represents the uncertainty sets of load, wind power and solar power defined as in (26a) and (26b); $Z(f,u)$ is the feasible set for the second-stage decision defined by constraints (16)–(24). Note that Z is parametrized by f and u.

$$Z(f,u) = \left\{ z : A_1^{\mathrm{T}} f + B_1^{\mathrm{T}} u + C_1^{\mathrm{T}} z = q_1\ A_2^{\mathrm{T}} f + B_2^{\mathrm{T}} u + C_2^{\mathrm{T}} z \leq q_2 \right\} \tag{30}$$

where A, B and C are given matrices, and q_1 and q_2 are given vectors of parameters. The optimal solution to $\mathcal{R}$ works well for the worst scenario and is feasible for all possible scenarios due to the min-max-min form of its objective function [19].

B. Solution Algorithm

The proposed min-max-min formulation cannot be solved directly using GAMS or CPLEX. Benders decomposition-type algorithms are one of the most popular ways to solve this kind of problems. Benders decomposition is the one of the most commonly used methods to solve RO optimization problems with a min-max-min structure [18]–[21]. The Benders decomposition method decomposes the problem into a master problem and a subproblem. Optimality cuts based on the dual variables of the subproblem are added to the master problem iteratively. In this paper, we used a Column-and-Constraint Generation (CCG) framework to solve the proposed formulation. CCG was firstly introduced and applied to solve UC problems by [19]. The Benders cuts are usually much less powerful than the primal cuts used in our algorithm and more iterations are needed for the Benders approach to converge [19].

To apply CCG in the MG planning problem, we need to reformulate the formulation $\mathcal{R}$ as a master problem and subproblems. The master problem can be defined as follows:

$$\min_{f\in F} A_0^{\mathrm{T}} f + \xi \tag{31}$$

$$s.t. \xi \geq B_0^{\mathrm{T}} u + C_0^{\mathrm{T}} z \tag{32}$$

$$A_1^{\mathrm{T}} f + B_1^{\mathrm{T}} u + C_1^{\mathrm{T}} z = q_1 \tag{33}$$

$$A_2^{\mathrm{T}} f + B_2^{\mathrm{T}} u + C_2^{\mathrm{T}} z \leq q_2 \tag{34}$$

It can be seen that the master problem is a relaxation of the first-stage problem of $\mathcal{R}$. Thus, it yields a lower bound for $\mathcal{R}$. Denote the solution of the master problem as $\hat{f}$. The subproblem can be defined as:

$$\max_{u\in U} \min_{z\in Z} B_0^{\mathrm{T}} u + C_0^{\mathrm{T}} z \tag{35}$$

$$s.t.\ A_1^{\mathrm{T}} \hat{f} + B_1^{\mathrm{T}} u + C_1^{\mathrm{T}} z = q_1 \tag{36}$$

$$A_2^{\mathrm{T}} \hat{f} + B_2^{\mathrm{T}} u + C_2^{\mathrm{T}} z \leq q_2 \tag{37}$$

For any given solution $\hat{f}$ that is not optimal, the objective value of the subproblem would be larger than the true optimal solution of $\mathcal{R}$. Therefore, the subproblem yields an upper bound for $\mathcal{R}$. However, the subproblem is still a bi-level problem which is difficult to solve. We can reformulate the constraints (35)–(37) into complementary constraints using the KKT optimality conditions [35] as follows:

$$A_1^{\mathrm{T}} \hat{f} + B_1^{\mathrm{T}} u + C_1^{\mathrm{T}} z = q_1 \tag{38}$$

$$C_0^{\mathrm{T}} + \varphi^{\mathrm{T}} C_1 + \lambda^{\mathrm{T}} C_2 = 0 \tag{39}$$

$$0 \leq q_2 - C_2 z - A_2 \hat{f} - B_2 u \perp \lambda \geq 0 \tag{40}$$

where φ and λ are dual variables of the problem defined in (35)–(37). Constraint (40) can be transformed by the Big-M method as follows:

$$0 \leq q_2 - C_2 z - A_2 \hat{f} - B_2 u \leq M \cdot \delta \tag{41}$$

$$0 \leq \lambda \leq M \cdot (1 - \delta) \tag{42}$$

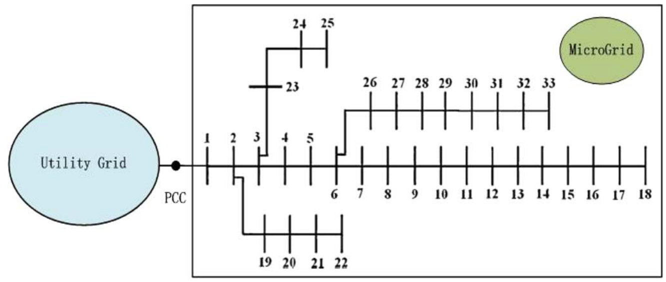

Fig. 2. Test microgrid system.

TABLE I
PARAMETERS FOR CALCULATING CORRESPONDING COSTS

Parameters		Value	
e^{wt}	\$1882/kVA	m_1^{mt}	\$0.012/kWh
e^{pv}	\$4004/kVA	α_1^{fl}	\$0.63/kWh
e^{mt}	\$2293/kVA	α_1^{mt}	\$0.02/kg
m_1^{wt}	\$0.01/kWh	β_1^{s}	\$0.059/kWh
m_1^{pv}	\$0.01/kWh	σ	\$0.003 kg/kWh

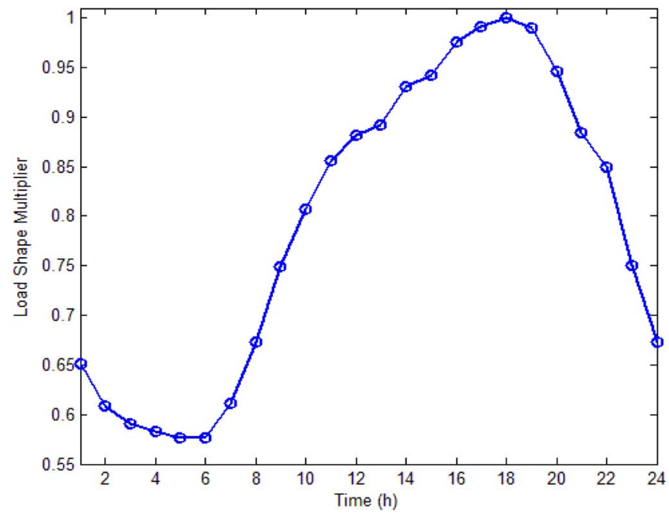

Fig. 3. Load shape multiplier.

where M is a large value and δ is a binary variable. Thus, the constraints of the subproblem become (38), (39) and (41), (42), which is a mixed-integer linear program.

In the lth iteration of CCG algorithm, we add new unknown variables z_l, known variables $\hat{u}^{l-1}$ and corresponding constraints defined as (32)–(34) into the master problem. The basic idea of CCG is to creating a set of new variables and corresponding constraints and add them to the master problem to refine the first stage decisions. The comprehensive procedure of CCG can be summarized as follows (In the l th iteration, denote the master problem as M^l and the subproblem as S^l):

Step 0: Initialization. Set the lower bound $LB = -\infty$, the upper bound $UB = +\infty$, the tolerance $e \geq 0$ and $\hat{u}^0 \in \mathbb{U}$, $l = 1$.

Step 1: Solve the master problem $M^l(\hat{u}^{l-1})$, denote the optimal solution as $(\hat{f}^l, \hat{\xi}^l)$, update the lower bound $LB = \max\{LB, A_0^{\mathrm{T}}\hat{f}^l + \hat{\xi}^l\}$.

Step 2: Solve the subproblem $S^l(\hat{f}^l)$, denote the optimal solution as $\{\hat{u}^l, \hat{z}^l\}$, update the upper bound $UB = \min\{UB, A_0^{\mathrm{T}}\hat{f}^l + B_0^{\mathrm{T}}\hat{u}^l + C_0^{\mathrm{T}}\hat{z}^l\}$; update the formulation of the master problem by adding new variables and corresponding constraints.

Step 3: Denote the optimality gap as $Gap = ((UB - LB)/LB) \times 100\%$, if $Gap \leq \varsigma$, terminate, output the optimal decision $\hat{f}^l$. Else, $l = l + 1$ and go to Step 1.

IV. NUMERICAL RESULTS

An IEEE 33-bus distribution system as shown in Fig. 2 is used in this paper. The system has been used as a MG in solving its planning problem in the literature (e.g., [11], [36]). Details about the test system can be found in [26]. The proposed methodology is applied to transform the 33-bus system into a MG. The power base of the system is set to be 1 MVA and the planning horizon is set to be 20 years. All the experiments are implemented using CPLEX 12.1 at Intel Quad Core 2.40 GHz with 8 GB memory.

Table I shows the parameters used in the case study, which are obtained from [7]. All the costs and electricity prices are presented in U.S. dollars. Only the first-year values of the O&M costs, fuel costs, emission costs and electricity prices are shown. It is assumed that the annual increasing rate for these monetary parameters is 6% during the planning horizon and these parameters remain the same in each year. The annual discount rate d is set to be 5%.

In this case study, one discrete increment of WT, PV and MT ($s^{wt,pv,mt}$) is set to be 30 kVA. $\underline{\omega}_{k,y,t}^{wt,pv,ld}$ and $\overline{\omega}_{k,y,t}^{wt,pv,ld}$ are set to be $0.6 \times \hat{\omega}_{k,y,t}^{wt,pv,ld}$ and $1.4 \times \hat{\omega}_{k,y,t}^{wt,pv,ld}$. Fig. 3 shows the 24-hour profiles of load shape multipliers for all nodes in the first year. The mean load of each node can be calculated by multiplying the multipliers with the load consumptions of the IEEE 33-bus distribution system. It is assumed the annual rate of increase rate of load consumption is 3%.

Figs. 4 and 5 show the 24-hour profiles of mean values of wind and solar power outputs. We also assume the wind speed and solar irradiance do not increase during the planning horizon since a long-term forecasting of wind speed and solar irradiance is beyond the scope of this paper. However, the planner can easily change all the above algorithm settings if enough information is available.

Table II shows the deployment of three types of DGs with different uncertainty budgets. Since it is assumed that the budget remains the same for all corresponding nodes at different times, we use $\underline{\mu}$ and $\overline{\mu}$ to denote budgets for notational brevity. It can be seen that the locations are similar but the DG sizes associated with each location are relatively different. The locations in deployment plans are similar since the topology of the test system remains the same for all instances and DGs should be integrated to certain nodes to meet the system operation requirements such as voltage ranges. However, the demand, wind speed and solar irradiance vary from one instance to another, which result in the relatively different DG sizes.

Table III shows the computational results with different uncertainty budgets. It shows the upper bound and lower bound in each iteration. The data in dark is the final result of the

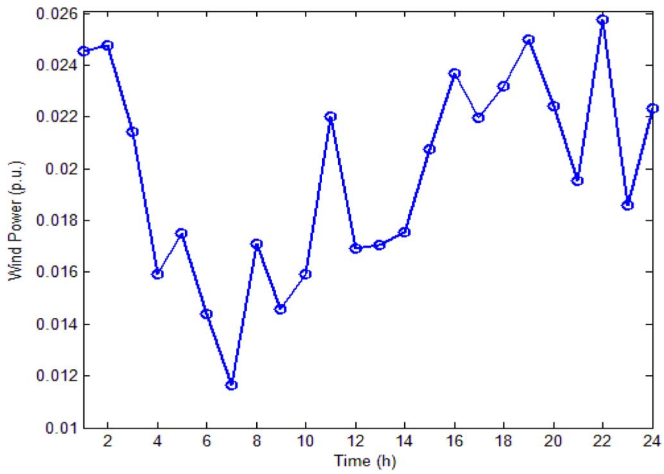

Fig. 4. Wind power output.

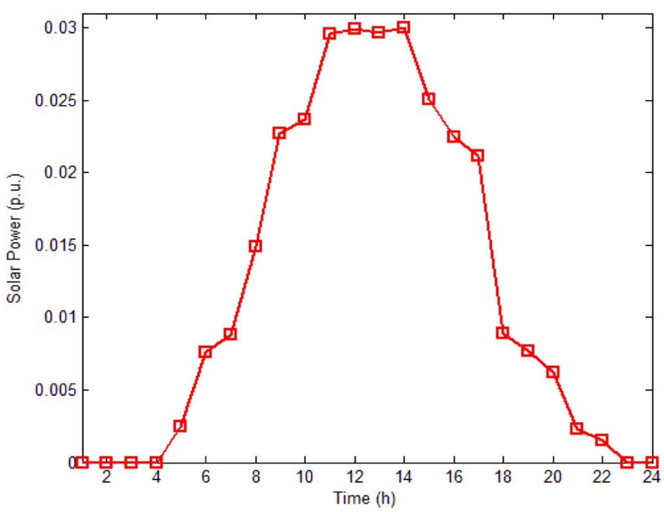

Fig. 5. Solar power output.

corresponding instance. Since the objective of the MG planning problem is to minimize "costs", the calculated objective values are negative. The values shown in this section are absolute values, which represent "profits". It can be seen from the results that the proposed algorithm provides a feasible solution for all instances with the uncertainty budgets. In the five instances, the optimality gap decreases and the profit of the planned MG slightly increases as the degree of uncertainty decreases, which means the decision becomes less conservative. The final optimality gaps of all instances are less than 0.2%. Meanwhile, it takes only a few iterations for the algorithm to converge; the CPU times are less than 10 minutes in all cases. Therefore, the presented methodology can provide a near-optimal solution within reasonable time such as one hour [20], [21], [37].

In order to obtain a better understanding of the proposed robust model, we compare the robust deployment plans with the results of the deterministic method as used in [5]. In the deterministic method the formulation is the same as $\mathcal{D}$, the wind power, solar power and demand are set to be their mean values as shown in Fig. 3–5. Table IV shows the deterministic results. The objective value shown in this table also represents "profits" as in Table III. It can be seen that the deterministic profits are larger than those of the five instances shown in Table III. Meanwhile, the deployment plan is also different from those of the five instances. This shows that although the robust formulation can guarantee the feasibility of the deployment plan with realizations of all scenarios within the uncertainty set, it is more conservative than the deterministic formulation. Table V shows

TABLE II
UNCERTAINTY LEVELS AND DG DEPLOYMENTS

Instance	$\underline{\mu}$	$\overline{\mu}$	Location (node)	Type	Size (kVA)
1	0.70	1.30	2	WT	150
			7	WT	60
			7	PV	30
			8	WT	60
			10	WT	150
			11	WT	60
			19	WT	150
			19	PV	60
			19	MT	90
			20	MT	30
2	0.75	1.25	2	WT	150
			7	WT	60
			8	WT	60
			9	WT	120
			9	PV	30
			10	WT	30
			12	WT	90
			19	WT	150
			19	PV	60
			19	MT	90
			20	WT	90
3	0.80	1.20	2	WT	150
			7	WT	120
			7	PV	30
			8	WT	30
			9	WT	90
			10	WT	30
			12	WT	30
			13	WT	90
			19	WT	150
			19	PV	60
			19	MT	90
			20	WT	120
4	0.85	1.15	2	WT	150
			7	WT	30
			7	PV	30
			8	WT	150
			9	WT	30
			10	WT	90
			12	WT	90
			19	WT	150
			19	PV	60
			19	MT	90
			20	WT	120
5	0.90	1.10	2	WT	150
			7	WT	90
			8	WT	60
			9	WT	120
			9	PV	30
			12	WT	90
			13	WT	30
			19	WT	150
			19	PV	60
			19	MT	90
			20	WT	150

TABLE III
OPTIMAL VALUES (IN MILLION DOLLARS) AND GAPS WITH DIFFERENT UNCERTAINTY LEVELS

$\underline{\mu}$	$\overline{\mu}$	Iteration	UB	LB	Gap
0.70	1.30	1	24.1414	19.0379	26.81%
		2	20.0085	19.8652	0.72%
		3	19.9824	19.9496	0.16%
0.75	1.25	1	24.1414	19.0662	26.64%
		2	20.0477	19.8995	0.74%
		3	20.0460	20.0112	0.17%
0.80	1.20	1	24.1414	19.1051	26.36%
		2	20.0808	19.9415	0.69%
		3	20.0471	19.9561	0.45%
		4	20.0418	20.0197	0.11%
0.85	1.15	1	24.1414	19.1808	25.86%
		2	20.1353	20.1216	0.068%
0.90	1.10	1	24.1414	19.3062	25.04%
		2	20.2504	20.1525	0.048%

TABLE IV
DETERMINISTIC OPTIMAL VALUE AND DEPLOYMENT PLAN

Obj.	Location (node)	Type	Size (kVA)
24.1414	2	WT	150
	6	WT	150
	6	PV	60
	7	WT	30
	9	WT	30
	10	WT	60
	11	WT	30
	12	WT	90
	13	WT	30
	19	WT	150
	19	PV	90
	19	MT	120
	20	WT	60
	21	WT	30

TABLE V
FIRST-STAGE COSTS (IN MILLION DOLLARS) OF ROBUST AND DETERMINISTIC DEPLOYMENT PLANS

Instance	1	2	3	4	5	Deter.
First-stage cost	3.6396	3.9734	4.0930	4.2126	4.3322	4.7237

the first-stage costs of the robust and deterministic deployment plans. It can be observed in Table IV and V that although the profit of the deterministic model is larger than the robust model, the deterministic model deploys more DG capacities and has larger first-stage costs than the robust model. This is because the robust model considers the worst-case scenario and is conservative. When the wind power and solar power are highly uncertain, the algorithm deploys less DGs and buys more electricity from the upstream utility grid. In contrast, when the outputs of renewable energy sources are less stochastic or deterministic, it is better to deploy more DGs.

In (27), all objectives are equally weighted. It is necessary to show the sensitivity of the weights on the robust solutions. Since the O&M cost is associated with the DG size in this paper, the costs in the objective function can be categorized into one-time costs including C^{inv} and C^{OM} as well as potential costs including C^{fl} and C^{emi}. We add a weight factor φ to C^{fl} and C^{emi} as follows:

TABLE VI
ROBUST DEPLOYMENT PLANS WITH DIFFERENT WEIGHT FACTORS

φ	Location (node)	Type	Size (kVA)	φ	Location (node)	Type	Size (kVA)
0.8	2	WT	150	0.9	2	WT	150
	7	WT	150		7	WT	30
	9	PV	30		8	WT	150
	10	WT	90		9	PV	30
	13	WT	60		10	WT	90
	19	WT	150		11	WT	60
	19	PV	30		19	WT	150
	19	MT	120		19	PV	60
	N/A	N/A	N/A		19	MT	90
1.1	2	WT	150	1.2	2	WT	150
	7	WT	120		7	WT	60
	7	PV	60		8	WT	90
	9	WT	30		9	WT	120
	10	WT	120		10	WT	60
	11	WT	30		11	WT	90
	12	WT	90		12	WT	30
	13	WT	30		19	WT	150
	19	WT	150		19	PV	150
	19	PV	30		19	MT	60
	19	MT	90		20	WT	150
	20	WT	150		N/A	N/A	N/A

$$\min_{(a,b,c)\in X} \Big\{ C^{inv}(a,b,c) + C^{OM}(a,b,c) + \max_{\omega \in W} \min_{p\in\Omega(a,b,c,\omega)} \varphi \left(C^{fl}(p) + C^{emi}(p) \right) - C^{rev}(p) \Big\} \tag{43}$$

If the planner is more concerned with C^{fl} and C^{emi} due to the potential large fluctuations of fuel and emission costs in the future, the weight factor φ can be increased. Table VI shows the planning results with different weight factors. $\underline{\mu}$ and $\overline{\mu}$ are set to be 0.8 and 1.2, respectively. It can be seen that the planning results change with different weight factors. For example, the total size of the installed DGs when φ is 0.8 is almost 30% smaller than that of the case with φ equal to 1.2. This is because the formulation concerns more on one-time investment costs when φ is small. Meanwhile, it can be seen that more RES-based DGs are installed for higher values of φ. This is due to the fact that the formulation concerns more on the fuel cost and the emission cost as φ becomes larger, and thus more RES-based DGs are deployed.

V. CONCLUSION

This paper proposed a novel methodology that incorporates Robust Optimization (RO) to solve Microgrid (MG) planning problem. The main objective of the optimization is to minimize the investment, O&M, fuel and emission costs of the MG, while maximizing the MG profits during the planning horizon. Both dispatchable and RES-based DGs are considered to compose the MG. The MG planning problem is subject to system uncertainties associated with the time-varying load consumptions and intermittent outputs of RES-DGs. The proposed method takes into account these uncertainties by defining uncertainty sets in

RO. The degree of uncertainty can be adjusted by the planners to make a tradeoff between the robustness and conservativeness of the solution. Case studies verify the effectiveness of the proposed method and the robustness of the solution under different simulation settings. Compared with previous efforts on DG placement and MG planning, the proposed method considers the probabilistic nature of the planning problem and does not require the hard-to-obtain distributions of random variables. Therefore, the proposed MG planning method is more suitable to be used in practice.

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References

[1] F. Farzan, S. Lahiri, M. Kleinberg, K. Gharieh, F. Farzan, and M. Jafari, "Microgrids for fun and profit: The economics of installation investments and operations," *IEEE Power Energy Mag.*, vol. 11, pp. 52–58, Jul. 2013.

[2] H. Hedayati, S. Nabaviniaki, and A. Akbarimajd, "A method for placement of DG units in distribution networks," *IEEE Trans. Power Del.*, vol. 23, no. 3, pp. 1620–1628, Jul. 2008.

[3] C. Wang and M. H. Nehrir, "Analytical approaches for optimal placement of distributed generation sources in power systems," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2068–2076, Nov. 2004.

[4] D. Singh and K. Verma, "Multiobjective optimization for DG planning with load models," *IEEE Trans. Power Syst.*, vol. 24, no. 1, pp. 427–436, Feb. 2009.

[5] Y. Atwa, E. El-Saadany, M. Salama, and R. Seethapathy, "Optimal renewable resources mix for distribution system energy loss minimization," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 360–370, Feb. 2010.

[6] R. S. Al Abri, E. F. El-Saadany, and Y. M. Atwa, "Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 326–334, Feb. 2013.

[7] K. Zou, A. P. Agalgaonkar, K. M. Muttaqi, and S. Perera, "Distribution system planning with incorporating DG reactive capability and system uncertainties," *IEEE Trans. Sustain. Energy*, vol. 3, no. 1, pp. 112–123, Jan. 2012.

[8] A. Khodaei and M. Shahidehpour, "Microgrid-based co-optimization of generation and transmission planning in power systems," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1582–1590, May 2013.

[9] A. P. Agalgaonkar, C. Dobariya, M. Kanabar, S. Khaparde, and S. Kulkarni, "Optimal sizing of distributed generators in MicroGrid," in *Proc. IEEE Power India Conf.*, 2006, pp. 1–8.

[10] A. K. Basu, S. Chowdhury, and S. P. Chowdhury, "Impact of strategic deployment of CHP-Based DERs on microgrid reliability," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1697–1705, Jul. 2010.

[11] M. V. Kirthiga, S. A. Daniel, and S. Gurunathan, "A methodology for transforming an existing distribution network into a sustainable autonomous micro-grid," *IEEE Trans. Sustain. Energy*, vol. 4, no. 1, pp. 31–41, Jan. 2013.

[12] M. R. Vallem and J. Mitra, "Siting and sizing of distributed generation for optimal microgrid architecture," in *Proc. Power Symp. 37th Annual North Amer.*, 2005, pp. 611–616.

[13] A. Navaeefard, S. M. Tafreshi, M. Barzegari, and A. J. Shahrood, "Optimal sizing of distributed energy resources in microgrid considering wind energy uncertainty with respect to reliability," in *Proc. 2010 IEEE Int. Energy Conf. Exhib.*, 2010, pp. 820–825.

[14] J. Mitra, M. R. Vallem, and S. B. Patra, "A probabilistic search method for optimal resource deployment in a microgrid," in *Proc. PMAPS*, 2006, pp. 1–6.

[15] B. Maurhoff and G. Wood, "Dispersed generation-reduce power costs and improve service reliability," in *Proc. Rural Electric Power Conf.*, 2000, pp. C5/1–C5/7.

[16] D. Zhu, R. P. Broadwater, K.-S. Tam, R. Seguin, and H. Asgeirsson, "Impact of DG placement on reliability and efficiency with time-varying loads," *IEEE Trans. Power Syst.*, vol. 21, pp. 419–427, 2006.

[17] R. Rüther, P. J. Knob, C. da Silva Jardim, and S. H. Rebechi, "Potential of building integrated photovoltaic solar energy generators in assisting daytime peaking feeders in urban areas in Brazil," *Energy Conversion Manag.*, vol. 49, pp. 1074–1079, 2008.

[18] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao, and T. Zheng, "Adaptive robust optimization for the security constrained unit commitment problem," *IEEE Trans. Power Syst.*, vol. 28, pp. 52–63, 2013.

[19] L. Zhao and B. Zeng, "Robust unit commitment problem with demand response and wind energy," in *Proc. Power Energy Soc. General Meeting*, 2012, pp. 1–8.

[20] R. Jiang, J. Wang, and Y. Guan, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Trans. Power Syst.*, vol. 27, pp. 800–810, 2012.

[21] R. Jiang, J. Wang, M. Zhang, and Y. Guan, "Two-stage minimax regret robust unit commitment," *IEEE Trans. Power Syst.*, vol. 28, pp. 2271–2282, 2013.

[22] R. A. Jabr, "Robust transmission network expansion planning with uncertain renewable generation and loads," *IEEE Trans. Power Syst.*, vol. 28, pp. 4558–4567, 2013.

[23] W. Peng, C. Haozhong, and X. Jie, "The interval minimum load cutting problem in the process of transmission network expansion planning considering uncertainty in demand," *IEEE Trans. Power Syst.*, vol. 23, pp. 1497–1506, 2008.

[24] Y. Han, C. Y. Chung, and K. P. Wong, "Robust transmission network expansion planning method with taguchi's orthogonal array testing," *IEEE Trans. Power Syst.*, vol. 26, pp. 1573–1580, 2011.

[25] Z. Wang, Q. Ai, D. Xie, and C. Jiang, "A research on shading and LCOE of building integrated photovoltaic," in *Proc. Power Energy Eng. Conf. APPEEC*, 2011, pp. 1–4.

[26] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

[27] T. Sicong, X. Jian-Xin, and S. K. Panda, "Optimization of distribution network incorporating distributed generators: An integrated approach," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2421–2432, Aug. 2013.

[28] Z. Wang, H. Chen, J. Wang, and M. Begovic, "Hybrid voltage/var control for distribution circuits with photovoltaic generators," *IEEE Trans. Smart Grid*, to be published.

[29] M. Haque, "Efficient load flow method for distribution systems with radial or mesh configuration," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 143, pp. 33–38, 1996.

[30] M. F. Shaaban, Y. M. Atwa, and E. El-Saadany, "DG allocation for benefit maximization in distribution networks," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 639–649, May 2013.

[31] *IEEE Guide for Design, Operation, and Integration of Distributed Resource Island Systems With Electric Power Systems*, IEEE Std 1547.4-2011, 2011, pp. 1–54.

[32] H. Bludszuweit, J. A. Domínguez-Navarro, and A. Llombart, "Statistical analysis of wind power forecast error," *IEEE Trans. Power Syst.*, vol. 23, pp. 983–991, 2008.

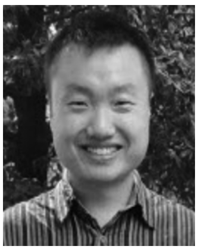
[33] E. D. Castronuovo and J. P. Lopes, "On the optimization of the daily operation of a wind-hydro power plant," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1599–1606, Aug. 2004.

[34] T. Niknam, M. Zare, and J. Aghaei, "Scenario-based multiobjective volt/var control in distribution networks including renewable energy sources," *IEEE Trans. Power Del.*, vol. 27, no. 4, pp. 2004–2019, Oct. 2012.

[35] S. P. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[36] P. Thota and M. Venkata Kirthiga, “Optimal siting & sizing of distributed generators in micro-grids,” in *Proc. Annual IEEE India Conf. (INDICON)*, 2012, pp. 730–735.

[37] B. Chen, J. Wang, L. Wang, Y. He, and Z. Wang, “Robust optimization for transmission expansion planning: Minimax cost vs. minimax regret,” *IEEE Trans. Power Syst.*, to be published.



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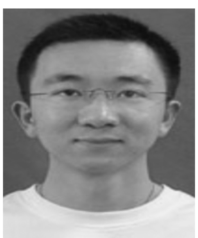

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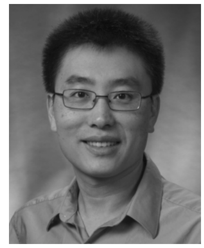

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