Electrical Power and Energy Systems 105 (2019) 814–822

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A bi-level robust planning model for active distribution networks considering uncertainties of renewable energies

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ARTICLE INFO

Keywords:
Active distribution system
Second-order cone programming (SOCP)
Column and constraint generation (CCG)
Renewable uncertainties
Robust optimization

ABSTRACT

The distribution companies will face huge challenges in upgrading the existing network due to the uncertain integration of distributed renewable generations. In this paper, we propose a bi-level robust planning model for active management elements (AMEs) including on-load tap changer (OLTC), electrical storage system (ESS), capacitor bank (CB), and static VAR compensation (SVC) in order to accommodate uncertain development of wind power and photovoltaic power. The planning problem is constructed in two levels which are investment level and operation level. To overcome the poor convergence of the bi-level model, variables in both investment level and operation level are associated together. After equivalent transformation for non-linear terms the planning model can be formulated as a mixed integer second order conic programming (MISOCP) problem by some special means such as second order conic relaxation (SOCR) and big-M approach. We address the renewable uncertainties in four different seasons by a typical budget uncertainty set with adjustable budget. Then a two-stage robust mathematical model is proposed to decide a robust AME deployment scheme and solved by column and constraint generation (CCG) algorithm.

1. Introduction

The shortage of fossil fuels and the increasing environmental pollution have caused a rapid development of renewable energy around the world [1]. The high penetration of distributed generation (DG) may result in the bi-directional power flow and voltage violation in the system, which promote the emergence of active distribution network (ADN) with various distributed and controllable resources [2]. Also, the random characteristic of intermittent DGs such as wind turbine generation (WTG) and photovoltaic generation (PVG) is a key issue in the active distribution network planning. Therefore, how to construct an effective planning scheme with uncertainties of renewable energies considered is currently a great challenge for the distribution companies.

To cope with abovementioned challenge, active network management (ANM) is usually regarded as an indispensable part in the ADN planning to maximize the hosting capacity of DG [3] or promote maximal utilization of clean DG power [4]. In the early time periods, ANM is introduced to coordinate the voltage control, which mainly includes secondary voltage regulation of on-load tap changer (OLTC) and reactive power compensation by discrete capacitor banks (CBs) and continuous static Var compensations (SVCs). Besides OLTC, CB and SVC, electrical storage system (ESS) is first explored as an ANM means in [5] and [6]. The optimal installment position and capacity of ESSs are decided in [7], where the reactive power regulation of ESSs is also taken into account. A two-layer configuration model for capacity of storage system is established in [8] to decrease to power fluctuation in the distribution feeder line. Therefore, an appropriate deployment scheme for OLTCs, CBs, SVCs, and ESSs is of significance to maximize the utilization of renewable DG and guarantee the system security [9]. Generally, this paper defines all active management elements (AMEs) as network topology management means and carries out a corresponding plan for those management means to accommodating integration of renewable energies.

At the same time, the distribution companies would hardly predict the exact power injection of DGs in the future since many end-users and generation companies can make their own DG investment decisions independently [10]. Besides, the maximum renewable DG power is anticipated to be consumed in the low carbon policy environment. Thus, the uncertainty nature of those renewable DGs is indispensable in the distribution network planning when large amounts of renewable energy resources integrated into the systems [11,12]. In this regard, the distribution network planners need to take full consideration of the

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https://doi.org/10.1016/j.ijepes.2018.09.032
Received 1 July 2018; Received in revised form 6 September 2018; Accepted 17 September 2018

Nomenclature

Indices

i, j	index of buses
ij	index of lines
t/s	index of time periods/season
n	index of iteration for MP of CCG
l	index of investment type
$\delta(j)/\psi(j)$	set of buses whose parent/child is bus j
$B/B^{\mathrm{P}}/B^{\mathrm{W}}/B^{\mathrm{Load}}/B^{\mathrm{TR}}/B^{\mathrm{ESS}}/B^{\mathrm{OLTC}}/B^{\mathrm{CB}}/B^{\mathrm{SVC}}$	set of network buses/PVG/WTG/Load buses/main-grid/ESS/OLTC/CB/SVC
$\Omega^{\mathrm{ESS}}/\Omega^{\mathrm{OLTC}}/\Omega^{\mathrm{CB}}/\Omega^{\mathrm{SVC}}$	set of investment candidate buses of ESS/OLTC/CB/SVC
$K^{\mathrm{ESS}}/K^{\mathrm{SVC}}$	set of investment type available for ESS/SVC
E	set of branches
r_{ij}/x_{ij}	resistance/reactance of line
$C^{\mathrm{inv}}/C^{\mathrm{ope}}$	investment cost/operation cost
$c_l^{\mathrm{ESS}}/c^{\mathrm{CB}}/c_l^{\mathrm{SVC}}/c^{\mathrm{OLTC}}$	installation price for ESS/CB/SVC/OLTC
$x_{j,l}^{\mathrm{ESS}}/x_j^{\mathrm{CB}}/x_{j,l}^{\mathrm{SVC}}/x_j^{\mathrm{OLTC}}$	installation decision for ESS/CB/SVC/OLTC
$c^{\mathrm{Loss}}/c_{s,t}^{\mathrm{TR}}/c^{\mathrm{W}}/c^{\mathrm{P}}/c^{\mathrm{ENS}}$	operation price for power loss/main grid power/WTG/PVG power curtailment/ENS
$C^{\mathrm{W}}/C^{\mathrm{P}}/C^{\mathrm{ENS}}/C^{\mathrm{TR}}/C^{\mathrm{Loss}}$	cost for WTG/PVG power curtailment/ENS/main grid power/power loss
$P_{j,s,t}^{\mathrm{W0}}/P_{j,s,t}^{\mathrm{P0}}$	forecast power of WTG/PVG

$P_{j,s,t}^{\mathrm{TR}}/P_{j,s,t}^{\mathrm{W}}/P_{j,s,t}^{\mathrm{P}}/P_{j,s,t}^{\mathrm{ENS}}$	power of main grid/WTG/PVG/ENS
$P_{ij,s,t}/Q_{ij,s,t}$	active/reactive power flow from bus i to bus j
$I_{ij,s,t}/V_{j,s,t}$	current of branch ij and voltage of bus j
$P_{j,s,t}^{\mathrm{d}}/P_{j,s,t}^{\mathrm{c}}$	discharge/charge power of ESS
$P_{j,s,t}^{\mathrm{Load}}/P_{j,s,t}^{\mathrm{ENS}}$	active power of load/ENS
$Q_{j,s,t}^{\mathrm{TR}}/Q_{j,s,t}^{\mathrm{CB}}/Q_{j,s,t}^{\mathrm{SVC}}/Q_{j,s,t}^{\mathrm{Load}}/Q_{j,s,t}^{\mathrm{ENS}}$	reactive power of main grid/CB/SVC/load/ENS
ω	coordination factor between the investment cost and operation cost
D_s	duration of season s
M^{CB}	maximum installation number of CB
$\underline{V}_j/\bar{V}_j/\bar{I}_{ij}$	lower/upper bound of voltage magnitude/current limit of branch
$\underline{P}_j^{\mathrm{TR}}/\bar{P}_j^{\mathrm{TR}}$	lower/upper bound of main grid active power
$\underline{Q}_j^{\mathrm{TR}}/\bar{Q}_j^{\mathrm{TR}}$	lower/upper bound of main grid reactive power
$u_{j,s,t}^{\mathrm{d}}/u_{j,s,t}^{\mathrm{c}}$	charge/discharge status of ESS
$\underline{P}_j^{\mathrm{d}}/\bar{P}_j^{\mathrm{d}}$	lower/upper bound of discharge power of ESS
$\underline{P}_j^{c}/\bar{P}_j^{c}$	lower/upper bound of charge power of ESS
$E_{j,s,t}^{\mathrm{ESS}}$	capacity for ESS
$\underline{E}_j^{ESS}/\bar{E}_j^{ESS}$	lower/upper bound of capacity for ESS
$\alpha_j^{\mathrm{c}}/\alpha_j^{\mathrm{d}}$	charge/discharge efficiency of ESS
$\lambda_{j,s,t}^{\mathrm{OLTC}}$	tap ratio (secondary to primary) for OLTC

uncertainties of renewable DGs. The stochastic programming is widely used to deal with these uncertainties [13,14]. In [15,16], the available PVG or WTG power outputs were studied by the probability simulation. In the stochastic approach, Monte Carlo method is a common-used means to generate large-scale scenarios for PVG, WTG, load demand, electricity price or electric vehicle based on the given probabilities [17–19]. It is noteworthy the known probability density function is necessary in the stochastic method [20]. However, it is hard to get the accurate probabilities of those uncertain sources such as wind power or solar power in the real-world application. Compared to the stochastic programming method, robust optimization becomes a promising approach in the past few years because of its briefness [21,22]. In the robust optimization structure, only uncertainty set or bound instead of the probability distribution is applied to describe the volatility range of uncertain parameters [23,24]. Generally, robust approaches have lots of advantages: (a) an exact hard-to-obtain probability distribution is not required [25]; (b) the optimal solution obtained can immunize against all the realizations within the uncertainty set [26]. A two-stage robust investment scheme involved price-elastic demand response is proposed in [27] to get optimal investment decisions. An information-gap decision theory based robust method to solve the multiyear reinforcement planning model of distribution network is established in [28], which considers several kinds of uncertainty sources such as loads and electricity prices. The location and sizing of both dispatchable and intermittent distributed generators in microgrid are decided in [29] by a two-stage robust fashion, which is solved by the constraint generation framework. All above existing researches indicate that robust optimization is an efficient method to solve the uncertainties in the distribution network planning. A transmission expansion planning model is proposed in [30] considering the uncertainty of load demand and renewable energy generation described by budget set. The budget based uncertainty set attracts extensive attention worldwide due to the adjustable budget by conservativeness purpose. Besides, the uncertainty sets in different seasons should separately be modeled because there may exist large difference among DG power curves in different seasons. Thus, we adopt budget based adjustable polyhedral uncertainty set to describe the joint uncertainties of WTG and PVG in this paper.

From [31], we know that the distribution system planning problem can be divided into two levels including investment level and operation level, and separately solved in investment and operation level. In the investment level, the intelligent algorithms such as genetic algorithm [32], particle swarm optimization [33] are usually used due to the discrete variables involved [34]. The optimization model in the operation level is considered as an AC optimal power flow problem because of nonlinear power flow constraints [35], which is commonly solved by the original dual interior point method [36,37]. However, this nonlinear characteristic cannot guarantee the global optimal solution [38]. Luckily, via the second order conic relaxation (SOCR) the branch flow model constraint can be illustrated as a convex and conic form. This non-linear model in operation level can thus be transformed as a second order conic programming (SOCP) problem for quickly and efficiently solving [39]. Also, above respective manner would cause poor convergence in upper (investment) level and much long computation time in the whole programming [40]. As we can see in [41] it takes 20,000 iterations before the solution of the expansion model meets the convergence requirement. Therefore, integrated solving method by associating investment level and operation level is indispensable to more quickly obtain an optimal solution.

Based on the aforementioned discussions, we propose a bi-level robust planning model for active management elements including On-load tap changers, electrical storage systems, capacitor banks, and static VAR compensations. The variables in both investment level and operation level are associated together to pursuit a better convergence performance. Several equivalent transformations for non-linear terms are then applied to express the planning model as a mixed integer second order conic programming problem. Moreover, by introducing an adjustable polyhedral uncertainty set in four different seasons to address the uncertainties of renewable energies, a two-stage robust mathematical model is formulated and solved by column and constraint generation (CCG) algorithm.

The rest of the paper is organized as follows: In Section 2, a general description of bi-level planning model for distribution systems is presented. Section 3 formulates the mathematical modelling of robust model. The variable association, equivalent transformation for non-linear terms and column-and-constraint generation algorithm are presented in Section 4. Numerical computational results and analysis on a