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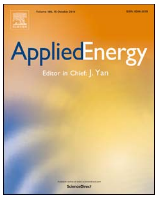

Optimal distributed generation planning in active distribution networks considering integration of energy storage

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HIGHLIGHTS

- A new two-stage optimization method for optimal DGs planning is proposed.
- The maximum output of energy storage is determined by chance-constrained programming.
- Impacts of energy storage integration are analyzed via probabilistic power flow.
- Test results show the proposal is superior to other state-of-the-art approaches.
- Energy storage makes the DGs operate at the rated capacities with high probability.

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ABSTRACT

A two-stage optimization method is proposed for optimal distributed generation (DG) planning considering the integration of energy storage in this paper. The first stage determines the installation locations and the initial capacity of DGs using the well-known loss sensitivity factor (LSF) approach, and the second stage identifies the optimal installation capacities of DGs to maximize the investment benefits and system voltage stability and to minimize line losses. In the second stage, the multi-objective ant lion optimizer (MOALO) is first applied to obtain the Pareto-optimal solutions, and then the 'best' compromise solution is identified by calculating the priority memberships of each solution via grey relation projection (GRP) method, while finally, in order to address the uncertain outputs of DGs, energy storage devices are installed whose maximum outputs are determined with the use of chance-constrained programming. The test results on the PG & E 69-bus distribution system demonstrate that the proposed method is superior to other current state-of-the-art approaches, and that the integration of energy storage makes the DGs operate at their pre-designed rated capacities with the probability of at least 60%.

1. Introduction

Nowadays, with the increasingly high penetration of renewable distributed generation (DG) sources, active distribution networks (ADNs) have been regarded as an important solution to achieve power system sustainability and energy supply security [1,2]. Recently, it is becoming an inevitable trend to make full use of renewable DGs such as wind turbines (WT) and photovoltaic (PV) units, since they have substantial advantages, such as power loss reduction, greenhouse gas emission reduction, flexible voltage regulation, peak-load shaving, higher power quality, supply reliability enhancement [3,4], etc. However, extensive penetration of DGs greatly increases the risks of safe and economic operation of distribution networks since renewable DGs have inherently intermittent nature [5,6], which makes the planning more challenging than ever before. The traditional distribution network planning options, such as the addition or expansion of substations and lines, are unable to meet the needs of modern complex ADNs facing all alternatives together with generation and load uncertainties [6–9]. Therefore, it is necessary to deal with such key challenges in the issue of optimal DG placement.

For this problem, many attempts have been made in the past two decades to solve it using different methodologies, including analytical approach [10–13], mixed integer non-linear programming (MINLP) [14–16], Kalman filter algorithm [17], and computational intelligence

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Nomenclature

α_i	loss sensitivity factor of real power loss at the ith bus
P_L	total system active power losses
Q_L	total system reactive power losses
$U_i\angle\delta_i$	complex voltage at the bus i
R_{ij}	resistance between the buses i and j
P_i	active power injections at the bus i
Q_j	reactive power injections at the bus j
N	number of buses
C_i^{GP}	on-grid price of DGs at the bus i
C_i^{GS}	government subsidy of DGs at the bus i
S_i^{rated}	rated capacity of DGs at the bus i
λ_i^{CF}	capacity factor of DGs at the bus i
C_i^{MC}	maintenance cost of DGs at the bus i
C_i^{FIC}	fixed investment cost of DGs at the bus i
ξ_i^{DG}	annual conversion factor of fixed investment cost of DGs at the bus i
C_P	investment benefit of DGs per year
C_T	annual revenue of investment in DGs
C_I	annual cost of investment in DGs
VSF_{i+1}	voltage stability factor of the $i + 1$ bus
VSF_{total}	voltage stability factor of the total distribution network
R_m	equivalent resistance of the branch m
$P_{\mathrm{loss}}(m)$	active power loss of the branch m
$P_{\mathrm{DG},i+1}$	active power output of DGs at the bus $i + 1$
$Q_{\mathrm{DG},i+1}$	reactive power output of DGs at the bus $i + 1$
$P_{\mathrm{loss,total}}$	total line losses of the distribution system
NB	number of branches in the network
$U_{\min}$	lower bounds of the voltage at the bus i
$U_{\max}$	upper bounds of the voltage at the bus i
P_{Di}	active power of load at the bus i
Q_{Di}	reactive power of load at the bus i
P_{LO}	system active power losses without DGs
Q_{LO}	system reactive power losses without DGs
S_{Lm}	actual complex power in the branch m
$S_{Lm(rated)}$	rated complex power in the branch m
P_{Swing}	active power of the swing bus
Q_{Swing}	reactive power of swing bus
NI	number of indications
γ_{lk}	grey relation coefficient between the kth indication in the lth scheme
w_k	weight of each indication in the scheme
D_l	priority membership of the lth scheme
P_{w}	optimal output of wind power energy
P_{s}	optimal output of solar energy
P_t^{W}	output of wind power at the tth sampling
P_t^{S}	output of solar energy at the tth sampling
ω	given confidence level
v_r	rated wind speed
v_{in}	cut-in wind speed
v_{out}	cut-out wind speed
η	conversion efficiency of PV units
r_{max}	maximum solar-irradiance intensity

Abbreviation

ADNs	active distribution networks
DG	distributed generation
MINLP	mixed integer non-linear programming
CCP	chance-constrained programming
WT	wind turbine
PV	photovoltaic
MT	micro-gas turbine
ALO	ant lion optimizer
MOEAs	multi-objective evolutionary algorithms
MOALO	multi-objective ant lion optimizer
NSGA	non-dominant sorting genetic algorithm
MOPSO	multi-objective particle swarm optimization
MOHS	multi-objective harmony search
LSF	loss sensitivity factor
ESDs	energy storage devices
PPF	probabilistic power flow

approach [18–20]. An analytical method was firstly introduced in [10] to find out the optimal placement of a single DG in both radial and meshed networks to minimize power losses. However, this approach only optimizes siting and considers DG sizing as fixed. In [11], the locating and sizing of DGs are identified instantaneously using an analytical strategy. In [12], an improved analytical approach for multiple DG planning was proposed for reducing energy losses, and the method was examined on three different test systems. A simple analytical type approach was recently presented to optimize the loss related to the active and reactive components of DG branch current. Different from the aforesaid works, a methodology based on based on MINLP was developed in [14] for optimally planning different types of renewable DGs for minimizing annual power loss. In [15], same approach has been implemented for optimal renewable DG placement and sizing to improve the voltage stability margin. Considering the uncertainties of loads and DG outputs, a technique based on multi-objective MINLP was proposed for benefit maximization in distribution systems in [16]. In [17], the optimal DG placement is determined via a Kalman filter algorithm to minimize the losses. More recently, computational intelligence techniques have been successfully adopted to deal with the DG planning issues. In [18], a genetic algorithms-based expansion planning model considering DG integration and conventional alternatives for expansion was presented for ADNs, and two multiple scenarios analysis approaches were employed to tackle uncertainties of DG and load response. In [19], a method for optimum DG siting and sizing of multi-DG units based on maximization of system loadability is proposed with the use of hybrid particle swarm optimization. The work in [20] addressed a multi-objective formulation for simultaneous allocation of distributed energy resources to maximize annual savings by using improved particle swarm optimization.

To sum up, DG planning methodologies for distribution networks have been widely studied, but there is relatively little focus on considering the generation and load uncertainties [6]. Furthermore, due to the high penetration of renewable DG resources, the uncertainties in ADNs are becoming significantly larger than traditional networks [21,22], which causes the actual power outputs of DGs to be barely achieving their pre-designed rated capacities by using the aforesaid methods. In general, it allows obtaining a planning scheme more committed with practical operations to take into account uncertainties during the optimization process in the planning stage, since typical scenarios with their occurrence probabilities are analyzed [18].

Recent research findings have shown that energy storage plays an increasingly important role in optimal DG allocation in distribution networks for the purpose of integrating intermittent renewable generation and loads [21–24], since energy storage devices (ESDs) can effectively shift energy generation and consumption across time spots [25]. After years of research and practice, there are a large set of storage technologies available to support renewable DGs [26], such as battery energy storage [27], supercapacitors [28–31], fuel cells [26,32], etc. In addition, rapid advances recently made in the area of energy storage [32–35] provide more powerful and flexible supports for renewable DG integration.