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Study impact of various load models on DG placement and sizing using backtracking search algorithm

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ABSTRACT

In this article, a meta-heuristic technique based on a backtracking search algorithm (BSA) is employed to produce solutions to ascertain distributed generators (DGs). The objective is established to reduce power loss and improve network voltage profile in radial distribution networks by determining optimal locations and sizes of the DGs. Power loss indices and bus voltages are engaged to explore the initial placement of DG installations. The study cares with the DG type injects active and reactive power. The proposed methodology takes into consideration four load models, and their impacts are addressed. The proposed BSA-based methodology is verified on two different test networks with different load models and the simulation results are compared to those reported in the recent literature. The study finds that the constant power load model among various load models is sufficed and viable to allocate DGs for network loss and voltage studies. The simulation results reveal the efficacy and robustness of the BSA in finding the optimal solution of DGs allocation.

1. Introduction

Installations of DGs can be decisively implemented in power systems for grid strengthening, reducing network power losses, peak load shaving, improving voltage profiles, and so on [1]. In a typical distribution system, particularly, in developing countries, network losses are as much as 13–20% of total power generated is wasted in the form of power losses [2,3], which would cost millions of dollars every year. Electrical losses (active or reactive) in distribution utilities are generally of two types: technical and non-technical. The two bus system depicted in Fig. 1 represents a distribution level feeder between buses i and j. The active and reactive power losses in line i–j are given by Eqs. (1) and (2), respectively:

$$P_{ij}^{loss} = R_{ij} \cdot \frac{(P_{eff,j}^2 + Q_{eff,j}^2)}{|V_j|^2} \tag{1}$$

$$Q_{ij}^{loss} = X_{ij} \cdot \frac{(P_{eff,j}^2 + Q_{eff,j}^2)}{|V_j|^2} \tag{2}$$

The feeder power loss is closely related to the reactive and active power flows for a given feeder (see Eqs. (1) and (2)). Therefore, the reductions of these power flows will positively lead to mitigate the network losses. Placement of DGs unit on the system can reduce network losses, similar to placement of capacitors. Studies indicate that poor selection of location and size would lead to higher losses than the losses without DGs [4,5].

Commonly, the DG resources are classified into four categories based on the ability to deliver active and reactive powers [6]. The four different DGs types are considered in literatures [6,7]: (i) DG injects true power (P) only, (ii) DG injects reactive power (Q) only, (iii) DG injects true power (P) but absorbs reactive power, (iv) DG injects both active (P) and reactive (Q) power.

In the last few years various techniques have been developed to find for the optimal location and size of the DG. In common practice, these techniques are categorized to: (i) analytical methods and (ii) evolutionary-based algorithms. Several analytical approaches minimizing line losses are proposed for the DG allocation [5–10] and optimal power flow [11,12]. For the same purpose of DG allocation, an evolutionary algorithm (EA) uses genetic algorithm and an ε-constrained method [13] and other heuristic algorithm methods through harmony search algorithm [14], particle swarm optimization [15,16], artificial bee colony algorithm [17], and differential evolution (DE) [18] and so on have been applied to sit single and/or multi-DGs for various objectives. In addition, the reader can be referred to [19,20], in which very comprehensive reviews covering the available DG placement models and various approaches with satisfactory classifications of researches are covered.

EAs are sufficiently flexible to solve different types of optimization problems without going in depth to the problem. EAs should

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Nomenclatures

P_{Loss}	total network active power loss
Q_{Loss}	total network reactive power loss
P_{ij}^{loss}	active power losses of the line between the nodes i and j
Q_{ij}^{loss}	reactive power losses of the line between the nodes i and j
R_{ij}	resistance of the line between the nodes i and j
X_{ij}	reactance of the line between the nodes i and j
$P_{eff,j}$	total effective real power load fed through bus j
$Q_{eff,j}$	total effective reactive power fed through bus j
θ_{ij}	angle of impedance of line i–j
P_i, Q_i	injected active and reactive power components at bus i
$\|V_i\|$, δ_i, $\|V_i\|$, δ_j	voltage magnitude and angle at bus i and j, respectively
δ_{ij}	difference between δ_i and δ_j
$\|Z_{ij}\|$	impedance magnitude between bus i and j
P_{Gi}	real power generation at bus i
G_{ij}	conductance between bus i and j
B_{ij}	susceptance between bus i and j
Q_{Gi}	reactive power generation at bus i
N_B	number of network buses
nbr	total number of lines
N_{DG}	number of distributed generators (DGs)
$N_{DG}\|_{\max}$	maximum allowable number of DGs units along the network (user defined)
N_L	number of connected loads
$n_{DG,i}$	number of DG units connected to bus i
$P_{DG,i}$	injected active power of ith DG
$Q_{DG,i}$	injected active power of ith DG
$P_{D,i}$	active power demand of load at bus i
$Q_{D,i}$	reactive power demand of load at bus i
W_DG	with DGs installations
WO_DG	without installations of DGs
$P_{DG,\min}$	lower limit of DG active output power
$P_{DG,\max}$	upper limit of DG active output power
$Q_{DG,\min}$	lower limit of DG reactive output power
$Q_{DG,\max}$	upper limit of DG reactive output power
S_i	actual line flow of line i
S_i^{rated}	rated power capacity of line i
λ_{VC}	penalty for the voltage constraints
λ_{LFC}	penalty for the line flow constraint
λ_{PtC}	penalty for the maximum allowable DGs active power
λ_{QtC}	penalty for the maximum allowable DGs reactive power
$PLD(m)$	power loss decline of bus m
$PLI(m)$	power loss index of bus m
$PLD_{\max}$	maximum loss decline
$PLD_{\min}$	minimum loss decline
LF	load flow
CVD	cumulative voltage deviation
α and β	load real and reactive power exponents, respectively
V_{j0}	load bus voltage and load nominal voltage of bus j, respectively
P_j and Q_j	real and reactive power at bus j, respectively
P_{j0} and Q_{j0}	real and reactive operating point at bus j, respectively
N	population size
D	problem dimension
$rand(\ldots)$	uniform distribution [0, 1]
LB_j	lower bound of optimized parameter j
UB_j	upper bound of optimized parameter j
P_i	target individual i in the population P

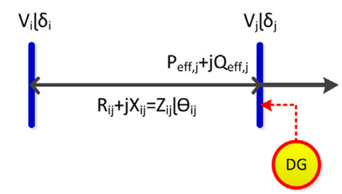

Fig. 1. Portion of a radial distribution network of i–j bus

have global exploration and local exploitation abilities [21,22]. On the other hand, no single algorithm is consistently able to solve all types of optimization problems [23]. Backtracking search algorithm (BSA) is a new meta-heuristic algorithm developed by Civicioglu [24]. The BSA has a unique mechanism for generating a trial individual which enables it to solve numerical optimization problems successfully and quickly. The BSA uses three basic genetic operators: selection, mutation and crossover to generate trial individuals. The BSA has a random mutation scheme that uses only one direction individual for each target individual, in contrast with many genetic algorithms such as DE. The BSA picks the direction (randomly) individual from individuals of a randomly chosen previous generation [24].

The development of an optimization methodology capable of defining DG unit's placement and sizing with the avalanche of DG penetration is a requisite. This study addresses the solution of DG allocation (bus number and size) using the BSA-based approach. One of main interests of the article is to examine the performance of the BSA to define the optimal locations and sizes of DGs. Power loss indices and bus voltages are utilized for the initial identification of DGs locations. DG injects PQ (active–reactive power) is considered to study its effects on network operating performance. The proposed methodology is applied to the 69-bus and the 136-bus radial distribution networks to test its effectiveness.

2. Problem formulation

Mathematically, the DG allocation problem can be formulated as a constrained nonlinear optimization model:

$$\begin{array}{ll} \text{Minimize} & \{F(X,U)+\text{Penalties}\} \\ \text{S.t.} & \begin{cases} g(X,U)=0 \\ h(X,U)\leq 0 \end{cases} \end{array} \tag{3}$$

$F(X,U)$ is the objective function to be minimized (i.e. P_{Loss}); $g(X,U)$ and $h(X,U)$ are the set of equality and inequality constraints, respectively. X is the state variables and U is the vector of control variables. The control variables are DG power outputs (P and Q). The state variables are voltage of buses, and line power flows.

2.1. Objective function and constraints

The objective function is adapted to decrease the system active power losses and inherently reactive power loss as well. Unquestionably, the minimization of network loss yields to enhance the network voltage profile. The CVD should be maintained as small as