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Optimal allocation and adaptive VAR control of PV-DG in distribution networks

Xueqian Fu [a], Haoyong Chen [a,b,*], Runqing Cai [c], Ping Yang [a]

[a] School of Electric Power, South China University of Technology, China
[b] Asia-Pacific Research Institute of Smart Grid and Renewable Energy, Hong Kong
[c] Guangzhou Power Supply Co. Ltd., China

HIGHLIGHTS

- A methodology for optimal PV-DG allocation based on a combination of algorithms.
- Dealing with the randomicity of solar power energy using CCSP.
- Presenting a VAR control strategy to balance the technical demands.
- Finding the Pareto solutions using MOPSO and SVM.
- Evaluating the Pareto solutions using WRSR.

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ABSTRACT

The development of distributed generation (DG) has brought new challenges to power networks. One of them that catches extensive attention is the voltage regulation problem of distribution networks caused by DG. Optimal allocation of DG in distribution networks is another well-known problem being widely investigated. This paper proposes a new method for the optimal allocation of photovoltaic distributed generation (PV-DG) considering the non-dispatchable characteristics of PV units. An adaptive reactive power control model is introduced in PV-DG allocation as to balance the trade-off between the improvement of voltage quality and the minimization of power loss in a distribution network integrated with PV-DG units. The optimal allocation problem is formulated as a chance-constrained stochastic programming (CCSP) model for dealing with the randomness of solar power energy. A novel algorithm combining the multi-objective particle swarm optimization (MOPSO) with support vector machines (SVM) is proposed to find the Pareto front consisting of a set of possible solutions. The Pareto solutions are further evaluated using the weighted rank sum ratio (WRSR) method to help the decision-maker obtain the desired solution. Simulation results on a 33-bus radial distribution system show that the optimal allocation method can fully take into account the time-variant characteristics and probability distribution of PV-DG, and obtain the best allocation scheme.

1. Introduction

Distributed generation (DG) is increasingly being embedded in electric power systems, which offers technical, economic and environmental advantages [1]. DG allocation for loss reduction is one of the most important concerns for distribution network operators [2]. The impacts of DG units are often evaluated by multiple criteria such as costs, voltage profile, emission and real power losses of the distributed networks [3]. It is important to find an effective way to determine the optimal sizes and locations of multiple DG units in a distribution network. There have been a number of optimization techniques used to obtain the optimal sizes and locations of multiple DG units with various objective functions, such as a dual-index analytical approach [4], particle swarm optimization (PSO) [5], a three-stage procedure [6], hybrid evolutionary algorithms [7], binary particle swarm optimization [8], the dynamic programming search method [9], and a benefit-cost analysis [10]. In Ref. [11], a hybrid intelligent algorithm consisting of the multi-objective particle swarm optimization (MOPSO) and support vector machines (SVM) is presented for optimal allocation of DG in

* Corresponding author at: School of Electric Power, South China University of Technology, China. Tel.: +86 13826100525.

E-mail address: eehychen@scut.edu.cn (H. Chen).

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Nomenclature

WRSR	weighted rank sum ratio
PLR	power loss reduction index
VPI	voltage profile index
Probit	probability unit
Γ	gamma function
$a,\ b$	shape parameters
$H(f)$	Hessian matrix
N	number of transmission lines
N_b	number of buses
p_{ij}	proportion of the *ij*th element
η_i	inverter conversion efficiency
γ_p	temperature coefficient of power
w_j	entropy weight of the *j*th index
N_l	number of PV-DG locations
e_j	entropy of the *j*th index
k_i	weighting factor of bus *i*
L_i	active load at bus *i*
ξ	stochastic number vector
g_j	difference coefficient of the *j*th index
S_l	transmission line loading
$V_i,\ \delta_i$	voltage magnitude and angle, respectively at bus *i*
r_{ij}	real part of the *ij*th element of the bus impedance matrix
SF_i	sensitivity factor with respect to reactive power injection at node *i*
P_{nomG}	rated capacity of the PV array, referred at standard test conditions
$P_i,\ Q_i$	active and reactive power injections at node *i*, respectively
$Q_{i\max}$	maximum limit of the VAR installed at node *i*
P_{loss}	total loss in the system with PV-DG
P^b_{loss}	total loss in the system without PV-DG
δ_{ij}	voltage angle difference at bus *i* and bus *j*
AVD	absolute voltage deviations
ε	bound on voltage
V_0	nominal voltage magnitude
T_c	PV temperature in the current time step
$T_{c,\mathrm{STC}}$	PV temperature under standard conditions
P_g	actual active power of the PV
G	solar irradiance in the current time step
$G_{\max}$	maximum solar irradiance
G_{STC}	solar irradiance at standard conditions
$\boldsymbol{L}$	candidates for the number of PV-DG
$N_{l\max}$	maximum number of PV-DG locations
m	number of the Pareto solutions
n	number of the objective functions
$\boldsymbol{\alpha},\ \boldsymbol{\beta},\ \boldsymbol{\gamma}$	vectors of confidence levels
$\boldsymbol{X}$	control variable vector
$S_{l\max}$	maximum capacity of lines
$S_\Sigma,\ S_{\Sigma\max}$	a total capacity of inverters and maximum limit
$VP_w,\ VP_{wo}$	voltage profile of the system with PV-DG and without PV-DG, respectively
$G_{ij},\ B_{ij}$	real and imaginary parts of the *ij*th element of the admittance matrix
$P_{gci},\ Q_{gci}$	active and reactive power capacities of the inverter installed at node *i*, respectively
$P_{Di},\ Q_{Di}$	active and reactive power demands at node *i*, respectively
$S_{gi},\ P_{gi}, Q_{gi}$	apparent, active and reactive power outputs of the inverter installed at node *i*, respectively
$P_{i\max},\ P_{i\min}$	maximum and minimum limits of the PV-DG installed at node *i*, respectively

distribution networks. Classical multi-objective optimization techniques, such as evolutionary algorithms, the ε-constraints method and the weighted-sum approach [12–16], are commonly used for optimal allocation of multiple DG units. The methods and algorithms in optimal allocation of DG and shunt capacitors in distribution networks are introduced in [17], which shows the importance of reactive power. Approaches employed to reduce power loss and improve voltage profile have been adopted to dispatch the active and reactive power of the DG units [18,19].

A lot of work has been done in the last decade on the impacts of PV-DG on electricity distribution networks [20–27]. The integration of PV-DG in distribution networks can cause reduction of losses but voltage fluctuations [20]. The technologies for evaluating the reliability of PV power systems and quantifying the effects of PV interconnection on the reliability have been reported in [21]. Ref. [22] presents new multiobjective index (IMO)-based analytical expressions and a self-correction algorithm to specify the size and power factor of PV and battery energy storage units for loss minimization and voltage stability enhancement. A study in [23] presents an analysis of the main active techniques for islanding detection in single phase photovoltaic microinverters. In order to minimize costs and CO_2 emissions, authors in [24] model PV and other distributed energy resources in commercial buildings in California as a mixed integer linear program. Taher Niknam et al. provide a method to solve the stochastic multi-objective optimal micro-grid operation problem with PV and other clean sources by considering power output, load demand and market price [25]. A method using GIS is proposed to find the optimal sizes and locations of PV-DG units for long-term planning considering both the net profit and voltage profile [26]. Ref. [27] presents an adaptive reactive power control algorithm to improve voltage profile and reduce system loss in a radial distribution circuit with photovoltaic cells.

In this paper, We develop a new model for PV-DG optimal allocation considering the randomness of solar energy based on chance-constrained programming theory, in which takes the minimum losses and voltage profiles as the objectives. The optimal active and reactive power dispatch for multiple PV-DG units is determined by random sampling solar radiation over one year based on an adaptive reactive power (VAR) control strategy. A support vector machine (SVM) combined with stochastic simulation is used to fit the network models. A multi-objective particle swarm optimization algorithm is applied to efficiently and effectively obtain the Pareto frontier. After the Pareto non-inferior decision set is found, the optimal allocation scheme is selected by WRSR. The IEEE-33 bus system is used to verify the performance of the proposed method.

2. Planning model

2.1. PV-DG model

There are two approaches used to model the behavior of solar radiation: physical modeling and statistical solar climatology [28]. The probability density functions of solar radiation have been modeled in several different ways, depending on the geographical area and time resolution [29–31]. In [29], surface solar radiation is assumed to be Beta-distributed random variables. The geographical location and time resolution can affect the suitability of a distribution as a probability density function of solar radiation. In Algeria, the hourly solar radiation data is modeled by a single Beta