Energy 134 (2017) 349–359

Contents lists available at ScienceDirect

Energy

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

A new optimal power flow approach for wind energy integrated power systems

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ARTICLE INFO

Article history:
Received 1 December 2016
Received in revised form
26 May 2017
Accepted 8 June 2017

Keywords:
Wind power (WP)
Optimal power flow (OPF)
Scenario
Probability density function (PDF)

ABSTRACT

Penetration of wind generation into power systems in recent years has greatly affected optimal power flow (OPF) because of the uncertain behavior of this new energy resource. In this research work, at first, a novel scenario generation approach is proposed to model wind power (WP) uncertainty. The proposed scenario generation approach includes construction of probability density function (PDF) pertaining to WP forecast error, segmentation of the PDF by an efficient clustering approach to obtain both the optimal number and the optimal arrangement of the clusters, and the generation of WP scenarios using the optimized clusters through roulette wheel mechanism. Secondly, this paper presents a new OPF framework based on DC network modeling for wind generation integrated power systems. Thirdly, a new out-of-sample analysis is presented to evaluate the long-run performance of the proposed OPF approach encountering various realizations of uncertain WPs. Finally, the performance of the proposed method for solving WP-integrated OPF problem is extensively illustrated on the IEEE 30-bus and the IEEE 118-bus test systems and compared with the performance of the deterministic method and the Weibull PDF method. These comparisons illustrate better performance of the proposed method, while it has reasonable computation times.

1. Introduction

Wind energy penetration into electric power systems has been continuously increased in recent years due to the environmental benefits and low operation cost of wind generators [1]. Wind energy also protects utilities and energy consumers from the economic risks associated with changing fuel prices. However, there are some problems and challenges for developing wind energy, both in the short-term and long-term. For short-term, optimizing the operating state of a WP-integrated power system, while balancing the generation and demand in each node, i.e. power flow problem, is a major concern for the system operators due to the volatility of WP.

The power system is the most complicated man-made system due to its large size and complex interactions. To operate this sophisticated system efficiently, OPF has been widely used, e.g., in the dispatch centers of power systems. The main application of an OPF tool is optimizing the operating state of the power system, i.e. determining the optimum settings of its control variables such as generation set-points of units [2]. In the recent years, increasing penetration of WP into power systems has greatly affected the operating state of these systems due to the uncertainty of wind generation. The operating point determined by conventional deterministic OPF, which simply ignores the uncertainty of WP, may not be optimal or even feasible in practice, due to deviations of realized wind generations from their forecast values. The proposed method of this paper has been designed to overcome this problem. In other words, the real application of the proposed method is solving OPF, i.e. optimizing the operating state, for a WP-integrated power system considering the uncertainty of wind generation. The volatile nature of WP has recently led to developing stochastic OPF models. A review of these works is given in the following.

In Ref. [3], a self-adaptive evolutionary programming method is employed to solve OPF incorporating WP generators. In this reference, WP uncertainty is modeled by means of Monte-Carlo simulation (MCS) based on the probability density function (PDF) of Weibull for wind speed. In Ref. [4], an OPF model, considering WP forecast error, includes the expected cost of deploying reserves to compensate the deviations of WP generators from their scheduled generations. Additionally, the penalty

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http://dx.doi.org/10.1016/j.energy.2017.06.046
0360-5442/

Nomenclature

Sets and indices

n,m	Bus indices
NB	Set of buses
s	Index of sample scenarios used to construct WIOPF model
s'	Index of trial scenarios used to evaluate WIOPF model
G	Set of buses including conventional units (other than wind farms)
NS	Number of scenarios generated by the proposed scenario generation method
NSr	Number of sample scenarios, i.e. the scenarios obtained from the scenario reduction method ($NSr < NS$)
NS^t	Number of trial scenario
SW	Set of buses including wind farm.
SR^U	Set of generators providing up reserve
SR^D	Set of generators providing down reserve

Parameters

B_{nm}	Element located in row n and column m of the susceptance matrix of power system
C_n	Generation cost of conventional unit of bus n ($/MWh)
P_n^{dem}	Active power demand at bus n
P_n^{max}	Maximum active power generation of conventional unit of bus n
P_n^{min}	Minimum active power generation of conventional unit of bus n
$VOLL_n$	Value of lost load for bus n ($/MWh)
R_n^{Dmax}	Maximum down spinning reserve capacity of conventional unit of bus n
R_n^{Umax}	Maximum up spinning reserve capacity of conventional unit of bus n
C_n^U	Up spinning reserve cost of conventional unit of bus n ($/MWh)
C_n^D	Down spinning reserve cost of conventional unit of bus n ($/MWh)
P_{nm}^{max}	Maximum flow limit of the branch connecting bus n and bus m

Variables

CF_s	Objective function (cost function) of the WIOPF in the sample scenario s
$CF_{s'}^t$	Objective function (cost function) of the WIOPF in the trial scenario s'
CF_{sample}^{agrt}	Aggregated cost of the sample scenarios
CF_{trial}^{agrt}	Aggregated cost of the trial scenarios
$P_{n,s}$	Active power generation of conventional unit of bus n (MW) in the scenario s
$P_{n,e}$	Expected value for the active power generation of conventional unit of bus n, obtained from aggregating $P_{n,s}$, $\forall s \in NSr$, values
$P_{nm,s}$	Active power flow from bus n to bus m in the sample scenario s
$P_{nm,s'}$	Active power flow from bus n to bus m in the trial scenario s'
$\delta_{n,s}$	Voltage angle at bus n in the sample scenario s
$\delta_{n,s'}$	Voltage angle at bus n in the trial scenario s'
$Pw_{n,s}$	Wind power generation of the wind farm connected to bus n in the sample scenario s
$Pw_{n,s'}$	Wind power generation of the wind farm connected to bus n in the trial scenario s'
$LS_{n,s'}$	Load shed at bus n in trial scenario s'
$R_{n,s'}^U$	Up spinning reserve deployment of bus n in trial scenario s'
$R_{n,s'}^D$	Down spinning reserve deployment of bus n in trial scenario s'
$prob_s$	Probability for scenario s of the set of generated scenarios by the proposed scenario generation method
$prob_s^u$	Updated probability for scenario s of the set of reduced scenarios; $prob_s^u$ is obtained from $prob_s$ by the scenario reduction technique considering merged scenarios
β	Convergence coefficient
$\delta_{NS^t}^{CF}$	Standard deviation of the objective function values over the trial scenarios

cost for not using all available WP is modeled in Ref. [4]. In Ref. [5], an artificial bee colony algorithm is used to solve the stochastic OPF problem incorporating HVDC linked wind farms. This reference models the stochastic nature of WP as well as the uncertainties in electric vehicles (EV) via statistical models. The work of [6] uses a scenario-based approach for solving the stochastic multi-period OPF problem considering WP uncertainty. In Ref. [7], an adjustable robust optimization approach to incorporate WP uncertainty into OPF is presented. The robust OPF formulation has been solved using quadratic programming with successive constraint enforcement. The work of [8] introduces an OPF model in which the stochastic nature of wind speed is represented using two-parameter Weibull PDF. The optimization problem of [8] is solved using artificial bee colony algorithm. In order to represent normal PDF for the uncertainty source of wind speed forecast, the work of [9] proposes a triangular approximate distribution (TAD) model. In Ref. [10], the variations of WP have been considered in an OPF problem. The problem has been solved by modified bacteria foraging algorithm. In Ref. [11], an OPF problem in the presence of WP generation has been solved with three evolutionary algorithms in Algeria's Adrar power system. The work of [12] proposes a dynamic economic dispatch problem that is solved by chaotic quantum genetic algorithm in a power system with WP generation at a period. An economic emission dispatch problem for a power system with WP penetration is solved by hybrid firefly algorithm in Ref. [13]. In Ref. [14], a multi-objective economic dispatch model is presented, which considers the profit and risk of a particular dispatch simultaneously under WP uncertainty. This multi-objective problem is solved by multiple-group search optimizer with multiple producers. In Ref. [15], the generator availability and uncertainty of WP have been considered in an economic dispatch problem. The uncertainty of WP is modeled by a discrete Beta PDF in Ref. [15]. In Ref. [16], a hydro-thermal-wind economic emission dispatch has been solved by modified gravitational search algorithm based on a non-dominated sorting genetic approach. The uncertainty of WP is modeled by Weibull PDF in Ref. [16]. With considering the risk and profit brought by WP uncertainty, an OPF problem is solved by group search optimizer with intra-specific competition and levy walk method in Ref. [17]. Gaussian distribution is used for modeling the uncertainty of WP in Ref. [17]. The uncertainty of WP is modeled by Weibull PDF and considered as constraints of an