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Stochastic reactive power dispatch in hybrid power system with intermittent wind power generation

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ABSTRACT

Environmental concerns besides fuel costs are the predominant reasons for unprecedented escalating integration of wind turbine on power systems. Operation and planning of power systems are affected by this type of energy due to the intermittent nature of wind speed inputs with high uncertainty in the optimization output variables. Consequently, in order to model this high inherent uncertainty, a PRPO (probabilistic reactive power optimization) framework should be devised. Although MC (Monte-Carlo) techniques can solve the PRPO with high precision, PEMs (point estimate methods) can preserve the accuracy to attain reasonable results when diminishing the computational effort. Also, this paper introduces a methodology for optimally dispatching the reactive power in the transmission system, while minimizing the active power losses. The optimization problem is formulated as a LFP (linear fuzzy programing). The core of the problem lay on generation of 2m + 1 point estimates for solving PRPO, where n is the number of input stochastic variables. The proposed methodology is investigated using the IEEE-14 bus test system equipped with HVDC (high voltage direct current), UPFC (unified power flow controller) and DFIG (doubly fed induction generator) devices. The accuracy of the method is demonstrated in the case study.

1. Introduction

Progressively ascending fuel prices accompanied by environmental concerns have induced countries to expand their power system infrastructure to incorporate further renewable energy, notably wind generation [1,2]. Annual statistics show that wind capacity increased by 16% from 2013 to 2014 with 51 GW of new capacity added [3,4]. The unmanageable nature of this category of energy necessitates probabilistic analysis of the power system operation.

MC (Mont-Carlo) technique has been well proven as a trustworthy means to deal with stochastic variables and to attain distribution of the resultant variables with high precision [5–7]. In the view of aforementioned characteristics, MC methods are perceived as the most precise, reliable and robust SAM (stochastic analysis method), which is commonly used as a reference method to inspect the correctness of other probabilistic methods [8–10]. However, the enormous computational effort which is required for this method persuades researchers to use alternative approaches which are capable of quickly acquiring the probabilistic output attributes of the system.

Abundant studies have confirmed that PEMs (point estimate methods) are capable of producing convincing stochastic results while effectively reducing the computational efforts [11–13]. However, the primary version of this method requires the input random variables' PDF (probability density function) to evaluate the 2m + 1 central moments. The aforementioned constraint within the PEM algorithm grew more apparent when stochastic input variables follow no common PDF [13]. This is most assuredly the case when the wind generation sources are integrated into the power grid. Although the stochastic behavior of wind speed is commonly modeled by a Weibull or Rayleigh PDF, the nonlinear relationship between the wind speed and the wind power makes it difficult to match the wind power to any generally known PDF. In order to cope with this issue, a discrete point estimate method is utilized. The core of the discrete point estimate method is that it employs sufficient sample measurement to approximate the (2m−1)th central moment of the input

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Nomenclature

V^{dc}	dc terminal voltage
I^{dc}	dc terminal current
R_c	commutation resistance
a	transformer tap connected to DC terminals
P^{dc}	active power at DC terminals
Q^{dc}	reactive power flowing from the AC to DC
ψ	the voltage angle of AC bus connected to DC
ψ_{dc}	the angle of AC current injected into the DC
V_{cr}	series voltage magnitude of UPFC
V_{vr}	parallel voltage magnitude of UPFC
θ_{cr}	angle of series voltage source
θ_{vr}	angle of parallel voltage source
P_{mk}	transferred active power between bus m and K
Q_{mk}	transferred reactive power between bus m, k
$\tilde{j}$	probabilistic jacobian matrix
t_{ij}	transformer tab between buses i and j
V_g	voltage magnitude of generator bus (PV buses)
Q_z	compensators reactive power
P_{st}	DFIG's stator active power
Q_{st}	DFIG's stator reactive power
I_{ro}	DFIG's rotor current
ξ^{σ}_{out}	the relative error of the standard deviation of the output random variable
$\bar{\xi}^{\mu}_{out}$	the mean error indices of a set of out put
$\bar{\xi}^{\sigma}_{out}$	the standard deviation error indices of a set of out put
$z = f(X)$	the PRPO objective function
X	set of n random variable
X_M	*Mth* sample point of x
K^T	matrix which links objective functions to variables
S	sensitivity matrix
b	dependent parameters matrix
$b_{\max}$, $b_{\min}$	upper and lower boundary of dependent variables
$x_{\max}$	maximum limit of linearized control parameters
$x_{\min}$	minimum limit of linearized control parameters
$\tilde{\leq}$	fuzzy less than or equal to
$\tilde{D}$	fuzzy decision
G, C	fuzzysubsets for objective functions and constraints
$\mu_D(X)$	membership function of D
$\mu_G(X)$, $\mu_C(X)$	membership function of G, C
λ	the degree of satisfaction for fuzzy objective function and fuzzy constraints
$\mu_{f_i}(X)$	fuzzy membership function of $f_i(X)$
ℓ_i	threshold of constraint
$P_L^{(r)}$	active power loss in iteration r
P_{ro}	DFIG's rotor active power
P_{tot}	DFIG's total active power
Q_{ro}	DFIG's rotor reactive power
V_{st}	DFIG's stator voltage
I_{st}	DFIG's stator current
Q_{tot}	DFIG's total reactive power
m_{rj}	*rth* sample central moment of*jth* random variable
$\bar{\mu}_{xj}$	average value of the M observation of *jth* variable
σ_{xj}	the standard deviation of x_j
$\rho_{j,k}$	*kth* concentration points correspond to *jth* input random
$\xi_{j,k}$	*kth* standard location for *jth* input variable
$w_{j,k}$	*kth* weighting factor for *jth* input variable
ξ^{μ}_{out}	the relative error of the mean of the output random variable

Abbreviation

Rec	rectifier
Inv	inverter
MC	Monte Carlo
PDF	probability density function
PEM	point estimate method
MW	Mega Watt
MVAr	Mega VAr
p.u,	Per Unit
PRPO	probabilistic reactive power optimization
RPO	reactive power optimization
LFP	linear fuzzy programming
HVDC	high voltage direct current
FACTS	flexible ac transmission systems
UPFC	unified power flow controller

variables, where m refers to the number of concentration points in PEM approach.

In the other hand, HVDC (high voltage direct current) transmission lines along with FACTS (flexible AC transmission systems) offer an excellent opportunity to support and improve the power supply of sustainable, efficient and reliable future grids [14,15]. FACTS are well known for the fast-response devices that can control the active and reactive power as well as the bus voltage. One of the more comprehensive FACTS devices is UPFC (Unified Power Flow Controller) that helps power systems to share the excessive loads from the lines and leads to the loss decline and high stable operations. To the best of authors' knowledge, only few papers [16–20] have considered PRPO (probabilistic reactive power optimization) in the presence of HVDC and UPFC along with the uncertainties injected by the wind generation source.

Therefore, this paper intended to propose a comprehensive model which consists of HVDC, UPFC and DFIG (double fed induction generator) as one of the most widely used generators in the wind turbine. This model takes the stochasticity under consideration in order to fill this gap. The main idea of this work is to attain the optimal control variables that are appropriate for stochastic situation, meanwhile minimizing the active power loss. Contrary to deterministic RPO (reactive power optimization), the probabilistic nature of input variables results in outputs from the optimization process become probabilistic. In addition, this paper presents a method that takes the uncertainty in optimization process into accounts, while conducting the proposed method in hybrid power system to consider a comprehensive model for investigation the proposed methodology.

The remainder of this paper is arranged as follows: description of system model consisting of DFIG wind turbine, HVDC and UPFC models are introduced in Section 2. Details of discrete PEM are discussed in Section 3. A probabilistic reactive power optimization algorithm is proposed that aims to minimize active power loss in Section 3. The problem is formulated as linear fuzzy programing [21] considering the stochastic effects of the wind generation and loads. In Section 4 the performance of the proposed method is investigated with modified IEEE-14 bus test system and the correctness of the method is evaluated through comparing obtained results with those provided by MC technique.