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Probabilistic load flow with detailed wind generator models considering correlated wind generation and correlated loads

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ABSTRACT

The enhancement in the penetration of intermittent generation necessitates the need to include uncertain behaviour in the conventional power flow programs. In this paper, four different wind generation models have been incorporated in probabilistic load flow for calculating the probability distribution of the reactive power consumed by the wind generators for three different scenarios; i) uncorrelated wind and uncorrelated loads ii) uncorrelated wind and correlated loads and iii) correlated wind and correlated loads The above mentioned scenarios have been implemented in probabilistic load flow using point estimate method in the IEEE-118 bus test system and accuracy of the results have been validated by comparing these results with those obtained by Monte Carlo simulation studies.

1. Introduction

Presently, to address the twin concerns of global warming and depleting fossil fuels, a lot of importance is being given to generation of power from renewable energy sources (RES). Among various RES, wind generating system (WGS) has already reached a state of mature technology and as a result, significant number of WGS has already been installed around the world. Further, in almost every country of the world, efforts are underway to exploit the full power generation potential of WGS. Now because of random and wide variation of wind velocity, the power output from a WGS is intermittent and of fluctuating nature. When this fluctuating power is injected into the grid, it causes variations in bus voltages and line power flows of transmission system. These variations are going to be quite significant in the future (if not already) because of significant and increasing penetration of WGS in the grid. Therefore, for successful integration of WGS in the grid, these possible variations need to be properly analysed, estimated and quantified. This can be achieved through load flow analysis of the grid in the presence of uncertain power generation from WGS and towards this goal, various probabilistic load flow (PLF) methods have already been suggested in the literature [1–6].

Out of the above works, Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of the quantities of interest have been calculated in Refs. [1–5], while in Ref. [6] only the mean and the standard deviations (of the quantities of interest) have been calculated using an extended Point estimate method (PEM). Further, in all these works the obtained results from PLF have also been compared with the results obtained by Monte-Carlo simulation (MCS) studies. In Refs. [5], Fourier Transform based convolution using DC power flow method has been used to find out the PDF and CDF of the variables of interest. On the other hand, in Refs. [1–4] initially the moments and cummulants of the variables of interest have been calculated using a suitable technique (such as PEM [1,2] and weighted sum of cummulants of input variables [3,4]) and subsequently the PDF and CDF have been computed using an appropriate series expansion (such as Cornish-Fisher [1,2] and Gram-Charlier [3,4]). In Refs. [5–7], different PEM based methods have been proposed for probabilistic analysis of a power system in the presence of WTGs. In Refs. [5], PEM along with Nataf transformation has been used while in Refs. [6] and [7], discrete PEM and extended PEM have been employed respectively.

Although, all the above works have considered load uncertainties, correlation in loads has been considered in Refs. [2] and [6] only. For considering the uncertainties in WGS, basically two approached have been used in the literature. In the first approach, a WGS has been modeled as an uncertain real power injection using Beta distribution [1–3]. In the second approach the uncertainty in the wind speed has been considered using Weibull distribution [4–6] and Rayleigh distribution [8] and subsequently the corresponding injected real power by the WGS has been calculated using the speed-power relationship of the wind generator. Further, in Refs. [1,2,8,7] the correlation among the wind generator has also

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been considered. Also, in some of the works such as [1,5] the uncertainty of the conventional generator has also been taken into account.

From the above discussion it can be seen that in the literature, almost all types of uncertainties have been considered in PLF with WGS. However, in all of the above works, a WGS has been represented as an uncertain injected real power only and no detailed model of the WGS has been considered in these works. As a result it is not possible to calculate the PDF of the reactive power consumed by the WGS by using the approaches described above. Now, it is well known that the reactive power consumed by an individual WGS is quite significant. Therefore, with increasing penetration of WGS in the grid, the aggregate amount of reactive power consumed by all the wind generators is also going to be quite substantial. Thus, sooner or later it will be quite necessary to determine the PDF of this reactive power consumption such that adequate reactive power planning strategy can be adopted for successful integration of WGS into the grid.

To address the above issue, in this paper detailed wind generator models [9] are considered to carry out PLF with wind generators. The basic objective is to calculate the PDF/CDF of the reactive power consumed by WGS in the presence of uncertain loads and uncertain wind power generation. To compute the moments of variables of interest, PEM [10,11] has been used in this work and subsequently the CDF has been determined by using the Cornish–Fisher expansion [1]. Further, the correlation among the loads, as well as among the wind generators has also been considered in this paper. However, it has been assumed in this work that there is no correlation between the loads and the wind generators.

This paper is organized as follows: In Section 2, the basic procedure of PEM based PLF is described. In this section, both three point and five point estimate methods are discussed. In Section 3, the different wind generator models considered in this work are described in detail. In Section 4, the procedure for considering correlation in PLF is discussed. Lastly, in Sections 5 and 6, main results and conclusions of this work are presented, respectively.

2. Point estimate based PLF

The point estimate method can be used to calculate the statistical moments of a random quantity which, in turn, is a function of one or several random variables [10]. In this method, 'h' points on the PDF are first estimated and subsequently, from these estimated points the complete PDF is constructed. The general theory of 'h' point estimation method is given in Ref. [12]. However, in this presented work 3 and 5 point estimate methods have been used and the detailed procedures of PLF using these three methods are given below. For this purpose, it has been assumed that in a power system there are total 'n' number of random input variables. For instance, if there are 'L' load buses in a power system, each having both real and reactive power loads which are randomly fluctuating, then n = 2L. The objective of PLF is to calculate the PDFs of bus voltage magnitudes and angles from the PDFs of these 'n' variables.

Let the l^{th} random variable x_l ($l = 1,2,\ldots n$) having PDF f_l be considered [11]. The PEM uses two, three or 'h' estimated points of x_l i.e. $x_{l,1}$, $x_{l,2}$ or $x_{l,h}$ as defined in Eq. (1) to replace f_l by matching the first $h+1$ moments of f_l.

$$x_{l,k} = \mu_l + \xi_{l,k}\sigma_l \quad \text{for } k = 1,2\ldots h \tag{1}$$

In eq. (1), μ_l and σ_l are mean and standard deviation of x_l respectively and $\xi_{l,k}$ can be obtained as explained in the following two sub-sections for three, five and seven point estimate methods.

The procedure for estimating the points of each variable x_l with their corresponding weights are described below.

2.1. Three point estimate Method (3PEM)

1. Find the coefficients of skewness and kurtosis of x_l using eq. (2) and (3) respectively [11];

$$\lambda_{l,3} = \frac{E\left[(x_l - \mu_l)^3\right]}{\sigma_l^3} \tag{2}$$

$$\lambda_{l,4} = \frac{E\left[(x_l - \mu_l)^4\right]}{\sigma_l^4} \tag{3}$$

where $E[(x_l - \mu_l)^p] = \sum_{t=1}^{N}(x_l(t) - \mu_l)^p \times P_r(x_l(t))$; $p = 3,4$; N is the number of observations for x_l; $x_l(t)$ is the t^{th} observation of x_l and $P_r(x_l(t))$ is the probability of $x_l(t)$.

2. Calculate $\xi_{l,1}$ and $\xi_{l,2}$ by using eq. (4). Also set $\xi_{l,3} = 0$

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k} \times \sqrt{\lambda_{l,4} - \frac{3}{4}\lambda_{l,3}^2}, \quad k = 1,2. \tag{4}$$

3. Obtain the three point estimates of PDF (denoted as $x_{l,1}$, $x_{l,2}$ and $x_{l,3}$ respectively) from eq. (1). Further obtain the corresponding weighting factors $w_{l,1}$, $w_{l,2}$ and $w_{l,3}$ from eqns. (5) and (6) below.

$$w_{l.k} = \frac{(-1)^{3-k}}{\xi_{l,k}(\xi_{l,1} - \xi_{l,2})}, \quad k = 1,2 \tag{5}$$

$$w_{l.3} = \frac{1}{n} - \frac{1}{\lambda_{l,4} - \lambda_{l,3}^2} \tag{6}$$

2.2. Five point estimate Method

1. Find the standard central moments as [10]:

$$\lambda_{l,i} = \frac{E\left[(x_l - \mu_l)^i\right]}{\sigma_l^i}, \quad i = 3,\ldots,2m. \tag{7}$$

where, $m = 4$, for five point estimate method (5PEM).

2. Find the standard locations $\xi_{l,q}$, where $q = 1,\ldots m$, by obtaining the roots of the polynomial given in eq. (8).

$$p(\xi) = C_0 + \sum_{j=1}^{m} C_j\xi^j \tag{8}$$

In eq. (8), $C_m = 1$ and the coefficients C_0,C_1,…,C_{m-1} are the solutions of the system of equations shown below:

$$\begin{bmatrix} 0 & 1 & \lambda_{l,3} & \cdots & \lambda_{l,m} \\ 1 & \lambda_{l,3} & \lambda_{l,4} & \cdots & \lambda_{l,m+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \lambda_{l,m} & \lambda_{l,m+1} & \cdots & \cdots & \lambda_{l,2m-1} \end{bmatrix} \begin{bmatrix} C_0 \\ C_1 \\ \vdots \\ C_{m-1} \end{bmatrix} = -\begin{bmatrix} \lambda_{l,m+1} \\ \lambda_{l,m+1} \\ \vdots \\ \lambda_{l,2m} \end{bmatrix} \tag{9}$$