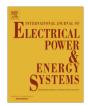
ELSEVIER

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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



Practical application of collocation method in power flow study of South Australia grid



Hang Yin*, Rastko Zivanovic

School of Electrical and Electronic Engineering, University of Adelaide, SA 5005, Australia

ARTICLE INFO

Article history: Received 7 December 2016 Received in revised form 24 March 2017 Accepted 30 June 2017

Keywords: Probabilistic power flow Stochastic collocation method Monte Carlo simulation Sparse grid interpolation Probabilistic collocation method

ABSTRACT

In this paper stochastic collocation method is proposed to solve probabilistic power flow (PPF) model of South Australia (SA). And this model is based upon historical acquisition of power system data of SA. In SA, numbers of wind farms are installed and the variability of wind speed brings more uncertainties into the power system. The traditional deterministic power flow (DPF) computation does not take into account the probabilistic nature of power system uncertainties, so PPF computation is imperative. However, as a commonly used PPF simulation method, Monte Carlo simulation (MCS) has a very high computation cost. Hence, in this paper sparse grid interpolation (SGI) is presented to accomplish PPF analysis with striking high computation efficiency. Meanwhile, instead of using theoretical wind power generation model, probabilistic collocation method (PCM) is used to construct realistic relationship between wind speed and wind power. In addition, fuzzy logic optimization is applied to PCM to improve the accuracy of the model output. The paper concludes with presentation of an aggregated DC power flow model of SA to compare the computation efficiency of the SGI and MC.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Due to the decreasing of natural resources and greenhouse effect, renewable energy is widely used nowadays. In South Australia (SA), there are 19 wind farms with installation capacity about 1472 MW [1]. However, wind source energy cannot be scheduled and dispatched, as with traditional synchronous generators, because its output depends on fluctuating and intermittent wind speed which is highly uncertain. In addition, the power system demand normally varies daily, weekly and seasonally which is deeply associated with human living habit. And those uncertainties cause the power system operation and planning face formidable challenge.

As a conventional power flow analysis method, deterministic power flow (DPF) analysis lacks modeling of the probabilistic nature of power system uncertainties, hence, probabilistic power flow (PPF) analysis was firstly presented in 1974 [2]. The PPF is still based on conventional power flow calculation as DPF. Besides just obtaining the value of system variable such as branch flows, bus voltage, etc., the PPF also has the ability to quantify the probability

E-mail addresses: h.yin@adelaide.edu.au (H. Yin), rastko.zivanovic@adelaide.edu.au (R. Zivanovic).

of the impacting to the power system variable by those uncertain inputs [2].

To obtain the probability density function (PDF) of desired power system variable, the PPF requires the PDF of the system uncertainties to be known, so accurately modeling the system uncertainties is a critical part of PPF analysis. In this paper, system demand, and wind farms generation power are considered as major uncertainties of the power system in SA. Moreover, because some of the market data are not available, so as to simplify the power system model, we just assume two thermal generations have similar pattern with system demand to balance the system, and because the system demands are uncertain, so those balancing data are also represented as a part of system uncertainties. System demand is typically following normal distribution [3]. However, in some realistic cases the PDF of system demand does not follow any known distribution, so Gaussian Mixture Model (GMM) is used which gives an accurate approximation to the non-Gaussian distributions [4], and this method will be applied to build up thermal generation model as well. Based on large measured wind speed data, wind speed can be modelled by two-parameter Weibull distribution [4–7]. Commonly used methods to transfer wind speed to wind power are: using typical wind power curve, in most cases a simplified linear, quadratic or power-law curves are used [5,6]; using theoretical wind power formula [7]. In fact, those methods

^{*} Corresponding author.

are based on empirical analysis or formalized with multi coefficients which may not be suitable or accurate for a real system.

Overcoming the limitation of commonly used wind power model, as one of the contributions in this work, Probabilistic Collocation Method (PCM) is proposed to obtain realistic relationship between wind speed and wind generation power. The PCM was first used in the field of global climate modeling [8,9] which aims to map the uncertain parameters to desired outcomes with a lower order polynomial by properly choosing simulation points. Nowadays PCM is wildly used in power system simulation [10–16,25], such as evaluation of uncertainties in dynamic simulation [10–12], small disturbance studies [13,14], power system damping and voltage collapse studies [15], state estimation [16], and wind farms modeling and power flow computation [25]. And those studies show that PCM can accurately describe the outputs of interest as a polynomial function of the uncertain inputs. In [25], the authors mentioned about using PCM to construct the wind power generation model, but very limited descriptions are given. So here instead of using typical wind power curve or theoretical formula, PCM is used to construct the polynomial mapping from realistic sampled wind speed data to wind generation power data. Meanwhile, fuzzy logic optimization is applied to PCM to improve the accuracy of the model output.

Based on system uncertainties stochastic model, commonly used methodologies to solve PPL are numerical methods, analytical methods and approximate methods. For numerical methods, the wildly used Monte Carlo simulation (MCS) method is a straightforward method with high accuracy [4,17–19]. MCS is just repeatedly running the same model with different input data which is generated by its cumulative density function (CDF), and then those simulation results can depict an accurate stochastic behaviors of the desired outputs. However, MCS method has very high computation cost due to the requiring large number of simulation points. To overcome this, the second method, analytical methods have high computation efficiency, such as Fast Fourier Transformation (FFT) method [20], combination of cumulant and Gram-Charlier expansion series [21] or Cornish-Fisher expansion [22], multilinear simulation method. Although the analytical methods give much lower computation cost, as a tradeoff, due to the complicated mathematical computation and the assumptions during computation the results are not accurate as MCS method. For the third method, approximate methods have similar mechanism of MCS with less simulation points required [23-25], but this method normally just provides the mean and standard deviation of the desired system variable.

To overcome the limitation of those PPF analysis method, sparse grid interpolation (SGI) is demonstrated which combines the advantages of accuracy of MCS and computation efficiency of analytical methods and approximation methods, and technically, the SGI belongs to the approximation methods [29]. SGI was first proposed by Sergey A. Smolyak in 1963 [26] which is used to integrate or interpolate high dimensional functions. And many applications show that SGI is particular suitable for solving high dimension problem with high accuracy and low computation cost [16,27-29]. In [29], with IEEE testing system, the SGI shows similar accuracy as MCS but striking time saving during simulation in PPF analysis. In this paper, as another contribution, SGI method is first applied to realistic power system historical data, and to an aggregated DC load flow model of SA to demonstrate the advantages of SGI comparing with MCS, moreover the simulation results confirm the computational efficiency and accuracy of SGI.

The remainder of this paper is organized as follow. In Section 2, the basic theories of PCM and SGI are described. In Section 3, we present the details of construction power system uncertainties stochastic model. In Section 4, aggregated SA power flow mode is built up for comparing the SGI method with MCS method.

Thereafter, Section 5 illustrates the simulation results and comparison. Section 6 concludes the paper.

2. Collocation methods theory

The collocation method is normally used to numerically solve integral functions or interpolate high dimensional functions. In this section, the basic theory of two types of collocation methods, PCM and SGI, are elaborated. The PCM is a method to map the uncertain inputs to desired outputs with polynomial functions and numerically obtain the stochastic feature of the outputs. The SGI is used to efficiently interpolate high dimension functions.

2.1. PCM

The PCM is based on orthogonal polynomials and Gaussian quadrature integration [10] and developed to model the relationship between uncertain inputs and the interested output with a polynomial function. The coefficients of the polynomial are computed by properly selecting the simulation points.

The Gaussian quadrature integration is a numerical integration technique to solve an integral by selecting certain points, evaluating the output value at those points, multiplying each value by proper weight and applying summation [30] as shown below,

$$\int_{D} f(x)g(x)dx = \sum_{i=1}^{n} f_{i}g(x_{i}), \tag{1}$$

where the f_i are the weights determined by weight function f(x) and x_i are the selected simulation points in region D. The orthogonal polynomials are used to select the simulation points. Two polynomials g(x) and h(x) are said to be orthogonal when their inner product is zero [30], and the inner product is defined by

$$\langle g(x), h(x) \rangle = \int_{D} f(x)g(x)h(x)dx,$$
 (2)

where f(x) is any non-negative weight function defined in the space of D. Based on (2), a set of polynomials H is said to be orthonormal if and only if the following relationship exists for all $h_i(x)$ in H,

$$\langle h_i, h_j \rangle = \begin{cases} 1, & i = j \\ 0, & i \neq j' \end{cases}, \tag{3}$$

where h_i is a polynomial of order i. Each h_i has exactly i roots located in the space of D [30]. Those roots are the collocation points to be used in the PCM.

The formula (1) is exact when g(x) is a polynomial of order less than or equal to (2n-1) [30]. And the g(x) can be expressed by orthonormal polynomials h_i with constant coefficients a_i and b_i ,

$$g(x) = h_n(x) \sum_{i=0}^{n-1} a_i h_i(x) + \sum_{i=0}^{n-1} b_i h_i(x),$$
 (4)

where $h_0(x)$ is a constant. Based on orthogonality, we multiply (4) by $h_n(x)$, the (1) can be rewritten as

$$\int_{R} f(x)g(x)dx = b_0 \int_{R} f(x)h_0(x)dx. \tag{5}$$

If we choose $h_0(x)$ to be 1, then the integration result equals to b_0 .

$$\int_{R} f(x)g(x) = \sum_{i=1}^{n} f_{i}g(x_{i}) = b_{0}.$$
 (6)

In the context of PCM, given an uncertain parameter x as input of the system with its pdf f(x), we intend to construct a polynomial mapping between x and the desired output which is g(x) approximated by [10]

Download English Version:

https://daneshyari.com/en/article/4945584

Download Persian Version:

https://daneshyari.com/article/4945584

<u>Daneshyari.com</u>