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Impact of wind generation uncertainty on power system small disturbance voltage stability: A PCM-based approach

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ABSTRACT

The connection of wind generators with electric power system influences the system stability and nodal voltages. This paper performs uncertainty analysis to investigate the impact of wind generation variation on the small disturbance voltage stability. The probabilistic collocation method (PCM) is presented as a computationally efficient method to conduct the uncertainty analysis. It has been implemented in a simple system to demonstrate its applicability in analyzing wind generation uncertainty. More case studies on a larger system are conducted to obtain a deeper understanding of how the system voltage stability is affected by the integration of DFIG-based wind farms. As compared with the traditional Monte Carlo simulation method, the collocation method could provide a quite accurate approximation for the eigenvalue probabilistic distribution with fewer simulation runs.

1. Introduction

As wind generation continues to expand in size and penetration level, a deeper understanding of its dynamic behavior and impact on system stability becomes necessary. Since the wind farm production is primarily determined by wind speed and thus fluctuating constantly, one of the most important studies is to investigate the dynamic phenomena induced by the variation of wind generation.

Historically power system stability has been associated with the generator rotor angle dynamics. Stimulated by several major voltage collapses, the framework of power system voltage stability as defined in [1] was originated around 1980s [2,3] and had been extensively studied in 1990s [4,5]. Voltage stability can be further classified into small disturbance and large disturbance categories. The small disturbance voltage stability refers to the system's ability to maintain steady voltage levels following small disturbances experienced through continuous changes in load [6–8]. From this view the small disturbance voltage stability is predominantly load stability. With the recent rapid growth of wind generation, operational uncertainty will extend from demand side variability to a significant portion of the supply side variability as well, which will impact system dynamic performance and cause voltage deviations. As a result, it is imperative to take into account the stochastic nature of wind farm output in voltage stability study.

From the end of the last century, the wind generators based on fixed-speed wind turbines have been included in stability studies [9–11]. Later, the grid stability enhancement of the new variable-speed wind generators, especially the Doubly-Fed Induction Generators (DFIG), has been reported in several publications [12–14]. Recently, research efforts to study how further large scale integration of variable-speed wind generators will influence the power system stability and electricity market have been proposed [15].

While such studies are important in their own right, the important issue of how the system small disturbance voltage stability may be influenced by the constantly changing wind generation has not been fully explored yet.

A review of literature reveals that several studies have been reported in the related area. Refs. [16,17] conducted modal and eigenvalue sensitivity analysis on grid-connected DFIGs. The work reported in [18] explored the relationship between uncertain wind generation and system probabilistic small-signal stability analysis via Monte Carlo simulation method.

As very few tools are available to analyze the parameter uncertainties in time-domain simulations, Tatang et al. developed the

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probabilistic collocation method (PCM) to mathematically describe the system response in terms of uncertain parameters [19]. This method has been successfully applied to time-domain simulation studies in the area of global climate change [20]. Later in [21], Hockenberry et al. have introduced the probabilistic collocation method in power system dynamic analysis and discussed its applicability in load uncertainty analysis. More studies have been reported to evaluate the advantage of PCM over other uncertainty analysis techniques in the time-domain analysis of power system load parameter uncertainties [22].

Normally the uncertainty analysis is performed under one of the following situations:

(1) The relationship between the uncertain parameter and the output of interest is known analytically;
(2) The above relationship is unknown. A model of the "black box" needs to be approximated first.

The PCM is designed to address the second situation. This approach allows the use of nonlinear models and evaluation of complicated output functions. It is particularly appealing because it requires a much smaller number of simulations to reach an accurate approximation which may take hours or days for the traditional techniques.

This paper studies how wind generation variation will impact voltage stability under the new energy transfer scenario where traditional generators are supplanted by variable-speed wind generators. Since the relationship between uncertain wind generation and system small disturbance voltage stability is not analytically clear, the PCM is introduced to address the problem. It begins with the mathematical definitions of the collocation method. Then, the wind-connected power system dynamic modeling and small disturbance analysis procedures are provided in Section 3. Sections 4 and 5 constitute the key aspects of the paper. First, a simple system is established to explore the applicability of implementing PCM in the wind generation uncertainty analysis. Next, a more complicated 23-bus power system is presented. Deeper understanding is obtained by monitoring the eigenvalue movement and voltage instability induced by the variation of wind farm output. The computation efficiency of PCM has been demonstrated by comparing it with traditional simulation based approaches.

2. Probabilistic collocation method

The basic idea of PCM is to approximate the relationship between uncertain parameters of the system and the outputs of interest through polynomial models. Based on the probability density function of the uncertain parameters, the concepts of orthogonal polynomials and Gaussian Quadrature Integration are incorporated to solve for polynomial approximation functions. Once the polynomials are obtained, collocation methods are generated to solve for the model coefficients. One major advantage of PCM is that only a handful of simulations are needed to determine the approximation model.

2.1. PCM with multiple inputs

To be general, let $x_1, x_2,\ldots, x_n$ be the uncertain parameters. Suppose a system is represented by a complex, high-ordered, or even "black-box" model. Its response in terms of the uncertain parameters is expressed as:

$$U = P(x_1, x_2, \ldots, x_n) \tag{1}$$

where U is the output of interest (system response). The objective of PCM is to find the following approximation of U:

$$\hat{U} = C_0 + \sum_{i=1}^{n} [C_{i1}p_{i1}(x_i) + C_{i2}p_{i2}(x_i) + \cdots + C_{im}p_{im}(x_i)] + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq i}}^{n} [C_k p_{i1}(x_i) p_{j1}(x_j)] \tag{2}$$

where $\hat{U}$ is an approximation of U, m is the order of this polynomial model, C_0, $C_{i1},\ldots, C_{im}$, C_k are model coefficients, and $p_{i1}(x_i)$, $p_{i2}(x_i),\ldots, p_{im}(x_i)$ are polynomial functions in terms of each uncertain parameter x_i.

2.2. Solving for polynomials

What we need then is to find the set of polynomials and coefficients listed in (2). The polynomials could be derived by deploying the concept of orthogonal polynomials [23]. The definition of orthogonal polynomials is:

$$\int_x P(x)H_i(x)H_j(x)dx = \begin{cases} 1, & \text{if } i=j \\ 0, & \text{if } i\neq j \end{cases} \tag{3}$$

where $P(x)$ is user-defined weighting function of x, $H_i(x)$ and $H_j(x)$ are orthogonal polynomials of x with the order of i and j (i, j = 0, 1,. . .). Eq. (3) suggests that the inner product of any two orthogonal polynomials of different order is always zero.

Assume the probability density function of the ith uncertain parameter is $f(x_i)$. By substituting the weight function $P(x)$ with $f(x_i)$, and using the following definition:

$$H_{-1}(x) = 0, \quad H_0(x) = 1 \tag{4}$$

the remaining higher-order orthogonal polynomials can be derived one by one. Fitting the derived orthogonal polynomials to $p_{i1}(x_i)$, $p_{i2}(x_i),\ldots, p_{im}(x_i)$ of (2), only the coefficients are left to be solved.

2.3. Solving for coefficients

As long as the polynomial functions in (2) are known, the model coefficients can be calculated by feeding different inputs into the system and recording corresponding system response. Suppose the system has n uncertain parameters, and we are using a PCM model with the order of m, the sets of inputs that are needed will be:

$$1 + n \times m + \binom{n}{2} \tag{5}$$

Take the linear PCM model with single uncertain parameter x as an example, Eq. (2) could be rewritten as:

$$\hat{U} = C_0 + C_1 p_1(x) \tag{6}$$

What we need next is to feed the real system with two different values of parameter x, and substitute $\hat{U}$ with the real system response U of each run. Thus the coefficients C_0 and C_1 in (6) could be solved.

In the above linear model example, the two different input values are also called collocation points. It should be noted that the selection of collocation points has significant impact on the accuracy of model approximation. In order to find a good approximation for the PCM model with smallest number of model runs, the Gaussian Quadrature Integration [23] approach is deployed: while selecting the collocation points, the points for the model runs from the roots of the next higher order orthogonal polynomial will