Electric Power Systems Research 166 (2019) 73–82

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Reliability assessment method of composite power system with wind farms and its application in capacity credit evaluation of wind farms

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ARTICLE INFO

Keywords:
Composite power system reliability
Wind farms
Non-sequential Monte Carlo Simulation
State merging
Parallel computing
Capacity credit

ABSTRACT

This paper presents a non-sequential Monte Carlo Simulation (MCS)-based method for the reliability assessment of composite power system with wind farms (WFs). A multistate probability table and its corresponding Spearman's rank correlation coefficient (SRCC) are combined to represent the power outputs of WFs, which makes the multistate model of WFs compatible with the non-sequential MCS while considering the dependence among power outputs of WFs. By constructing a system state array with encoding conversion, a state merging technique is proposed, which significantly reduces the number of system states to be evaluated. In addition, the parallel computing technique is employed to accelerate the contingency analysis for the merged system states. Furthermore, the capacity credit (CC) of WFs considering both wind power correlation and transmission network constraints is evaluated based on the proposed reliability assessment method. Finally, the effectiveness of the proposed reliability assessment method and its application in the CC evaluation are demonstrated using extensive numerical studies on several modified test systems.

1. Introduction

Composite power system reliability is concerned with the problem of assessing the ability of generation and transmission system to supply adequate electrical energy to the major load points [1]. It has been successfully applied in many areas, such as generation source planning, transmission development planning, transmission operation planning and operating reserve assessment [2,3]. Meanwhile, in recent years, wind power generation has been rapidly and widely developed worldwide for tackling the problems of environmental pollution and energy supply sustainability. Due to the intermittent and variable nature of wind speed, output power of wind farms is stochastic and quite different from those of conventional units. Thus, there is a pressing need for studying the reliability evaluation of composite power system with wind power integration.

The composite power system reliability evaluation generally involves three basic steps: selecting system states, evaluating the consequences of selected system states and calculating risk indices [2]. Analytical enumeration and Monte Carlo Simulation (MCS) are two primary approaches that have been proposed to select system states. Though the analytical method can obtain the exact reliability indices by explicitly or implicitly identifying all possible system states, it is rarely used in reliability assessment of composite power system with wind farms (WFs). The reason is that analytical method has difficulty in assessing reliability for practical-size systems due to the curse of dimensionality [3], as well as difficulty in building analytical models of WFs considering wind power correlation. Naturally, it is sensible to use MCS for reliability assessment of composite power system with WFs. The MCS can be further categorized into sequential and non-sequential simulation. The sequential simulation moves chronologically through the system states, while the non-sequential simulation selects the system states randomly [4]. In the past few decades, researchers have conducted considerable studies on the improvement of MCS for power system reliability. To take advantages of the computational efficiency of non-sequential MCS and the accuracy of sequential/chronological simulation, pseudo-sequential and pseudo-chronological MCS were proposed in Refs. [5,6] for calculating the loss of load cost (LOLC), respectively. In Ref. [4], quasi-sequential MCS was proposed in order to deal with time-dependent aspects such as load variation, generating capacity fluctuation from renewable sources, and maintenance. Aiming at improving the computational efficiency of MCS, kinds of variance reduction techniques, such as importance sampling [7], Latin hypercube sampling (LHS) [8], cross-entropy methods [9] and subset simulation [10] were proposed in recent years. From the perspective of

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https://doi.org/10.1016/j.epsr.2018.09.023
Received 15 April 2018; Received in revised form 12 August 2018; Accepted 30 September 2018

evaluation process of power system reliability, these variance reduction techniques can be summarized as accelerating computation at the first stage of system reliability assessment, i.e., selecting system states. Based on this perception, we were inspired to accelerate computation of composite power system reliability at another stage of evaluation process. In this paper, an accelerating method based on non-sequential MCS is proposed to deal with the sampled system states. The proposed method is based on the observation that a large number of system states sampled by non-sequential MCS are repetitive. Thus, if we can avoid conducting contingency analysis for the repeating system states, the computation effort will be greatly reduced. In this paper, we skillfully merge all of the sampled system states by constructing system state arrays with encoding conversion technique. The main contributions of this paper can be summarized as follows:

(1) A multistate probability table and its corresponding Spearman's rank correlation coefficient (SRCC) are combined to represent the probabilistic characteristics of WFs power outputs, allowing the consideration of wind power correlation under the framework of non-sequential MCS.
(2) Several innovative techniques are utilized to speed up the analysis for thousands of simulated system states. First, the binary array with respect to a system state is constructed and represented by a decimal number. This makes it convenient to identify and merge system states obtained by non-sequential MCS, and thus greatly reduces the number of system states under analysis. Second, the parallel computing technique is used for contingency analysis of the merged system states, which accelerates the process of state evaluation significantly.
(3) On the basis of the proposed reliability evaluation method of composite power system with WFs, capacity credit (CC) evaluation of WFs considering both wind power correlation and transmission constraints is implemented. This is different from existing literatures which only consider wind power outputs correlation or transmission constraints [11–13].

The remainder of this paper is organized as follows. Section 2 presents the non-sequential MCS-based reliability evaluation method of composite power system with dependent WFs. Section 3 shows the application of the proposed reliability evaluation method in the CC evaluation of WFs considering both wind power correlation and transmission constraints. The effectiveness of the proposed reliability evaluation method and the necessity of incorporating both wind power correlation and transmission constraints in the CC evaluation are verified by a number of numerical tests in Section 4. Finally, conclusions are made in Section 5.

2. Fast reliability evaluation method of composite power system with WFs based on non-sequential MCS

Three aspects of the work have been completed to develop an efficient non-sequential MCS-based method for evaluating the reliability of composite power system with WFs in this section: the state sampling of independent conventional generation units, lines and dependent WFs outputs, the reduction of number of system states to be evaluated and the parallel computing of merged system states. The implementation of these three contributions is demonstrated as follows.

2.1. Components state sampling of composite power system with WFs

The non-sequential MCS method is also called the state sampling approach, and it is based on the fact that a system state is a combination of all component states. In order to evaluate reliability of the composite power system with WFs using a non-sequential MCS, the states of conventional generating units, transmission lines and WFs have to be determined first. Generally, the conventional generating units and transmission lines are assumed to have two states of failure and success. Their failures are independent of each other [2]. In this context, each component state of generating units and transmission lines can be modeled by producing random numbers distributed uniformly between [0,1]. Let PF_i denote the ith component failure probability and U_i denote a random number distributed uniformly between [0,1]. Then the state of the ith component S_i can be determined by:

$$S_i = \begin{cases} 1\,(failure), & 0 \le U_i < PF_i \\ 0\,(success), & PF_i \le U_i \le 1 \end{cases} \tag{1}$$

In order to adapt to the non-sequential MCS, a wind farm is supposed to be represented as a generating unit with multistate output power [14]. The multistate probability table [15,16] of a wind farm is generally constructed and used to sample the output power state of a wind farm. In Ref. [17], the sequential output power series of a WF considering both wind speed correlation and wind turbine generator (WTG) outage was developed by using a Copula function. Subsequently, the multistate model of the total wind power generation system was built by using an apportioning technique. Additionally, this multistate output power model has been used for reliability evaluation of generating system with WFs. However, when it comes to the reliability evaluation of composite power system with farms, there are two issues needing to be addressed. First, the multistate probability table of each wind farm, instead of the probability table of wind power of all WFs, has to be modeled for composite system reliability, as WFs are generally integrated into power system at different buses. Fortunately, similar to modeling the multistate probability table of all of the WFs [17], this issue is easy to be solved by applying an apportioning technique to the simulated output power series of each WF. Second, it should be noted that there exists correlation between power outputs of WFs in adjacent areas [18], and thus the state sampling of each WF cannot be determined by using independent random numbers, which is quite different from the state sampling of conventional system components. Pearson correlation and rank correlation are two coefficients used to measure the dependence among random variables in power system analysis. Compared with rank correlation coefficient, Pearson correlation coefficient is not invariant under non-linear strictly increasing transformations in cases of non-normally distributed variables [19,20]. And on the other hand, it is pointed out in Refs. [19,21] that the WF power output does not follow the Normal distribution, thus it is wise to choose rank correlation to measure the dependence among WFs power outputs. Rank correlation coefficients, including Spearman's rank correlation coefficient, Kendall's rank correlation coefficient and Gini correlation coefficient, are mainly used to measure the degree of monotonic dependence between random variables [18,22]. Considering that the Spearman correlation between two variables is equal to the Pearson correlation between the rank values of those two variables [23], we are inspired to use correlated random variables following uniform distribution between [0,1] to simulate dependent WFs outputs. In this paper, the procedure of sampling correlated WFs outputs compatible with a non-sequential MCS is proposed as follows:

(1) Simulate sequential output power series of WFs considering wind speed correlation, WTG outage, and dependency between WTG outage and wind speed. The detailed process was shown in [17].
(2) Calculate the Spearman correlation coefficient R_p between WFs power outputs based on the sequential wind power series generated in Step (1).
(3) Use apportioning technique to create multistate probability table of WFs from sequential wind power series generated in Step (1).
(4) Produce random numbers distributed uniformly between [0,1] with specified linear correlation coefficient R_p. This step is convenient to implement by Copula method.
(5) Determine WF output states according to the random numbers generated in Step (4). Assume that X_i is a random number generated