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An importance sampling technique for probabilistic security assessment in power systems with large amounts of wind power

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ABSTRACT

Larger amounts of variable renewable energy sources bring about larger amounts of uncertainty in the form of forecast errors. When taking operational and planning decisions under uncertainty, a trade-off between risk and costs must be made. Today's deterministic operational tools, such as N-1-based methods, cannot directly account for the underlying risk due to uncertainties. Instead, several definitions of operating risks, which are probabilistic indicators, have been proposed in the literature. Estimating these risks require estimating very low probabilities of violations of operating constraints. Crude Monte-Carlo simulations are very computationally demanding for estimating very low probabilities. In this paper, an importance sampling technique from mathematical finance is adapted to estimate very low operating risks in power systems given probabilistic forecasts for the wind power and the load. Case studies in the IEEE 39 and 118 bus systems show a decrease in computational demand of two to three orders of magnitude.

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1. Introduction

Large-scale integration of wind power brings about an increase in the uncertainty on operating conditions faced by system operators. Managing this uncertainty requires tools that can trade off costs and risk entailed by the wind power forecast errors. Today's operational tools such as N-1-based methods are mostly deterministic. They traditionally combine a predefined contingency list with a predefined operating condition. This means that they do not directly consider the probabilities of either the different contingencies or the different operating conditions. Consequently, a shift to new risk-based operational frameworks that consider the underlying uncertainty due to large amounts of wind power and other renewables has been advocated [1–9].

The cornerstone of the proposed risk-based operational frameworks is probabilistic security assessment [10], in which a probabilistic description of the uncertainty in terms of outage rates (for transmission lines and generation units) and forecast error distribution functions (for load and wind power) is used to compute risk measures related to power system security. Proposed risk measures are probabilities of violation of operational and stability constraints [4,5,9] or expected values of the severity of these violations [6,8]. In both cases, assessment tools must efficiently carry out the following two tasks [11]. First, *contingency selection* identifies critical contingencies out of a large set of possible contingencies [11–14]. Second, in *contingency evaluation*, the contribution of the post-contingency systems to the risk measures is assessed. In this paper, an efficient method for contingency evaluation is developed for computing the pre- and post-contingency probabilities of violations of the operating constraints, given probabilistic forecasts for the load and wind power and a list of contingencies selected by the system operator.

For operational purposes, the probabilistic security assessment described above differs from the body of work studying generation and composite system adequacy for planning studies [15–18] in that the time horizon of interest is very short, up to an hour. The operational perspective taken in this paper follows the one described in [8,10], where power system operators need to assess the short-term risk of violating operating constraints due to the short-term wind and load forecast errors. In particular, stability

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issues such as voltage instability, which were not taken into account in the adequacy studies in [15–18], are considered in the operating constraints in the present paper.

Monte-Carlo simulations (MCS) can be used to estimate the probability of violations of operating constraints. These probabilities, however, will typically be very low since power systems are operated securely, which makes their estimation by crude Monte-Carlo (CMC) simulations computationally demanding [17]. Therefore, speed-up methods such as variance reduction techniques (VRTs) are necessary to reduce the computational burden of MCS [19,20].

Importance sampling (IS) is one VRT that can lead to a significant decrease in computation time by carefully choosing a sampling distribution that more often produces interesting samples for the quantity to be computed. Designing efficient importance sampling schemes is a problem-specific procedure [19,21].

For generation and composite system adequacy, much research has been done for using importance sampling to change the outage rates of components [14,17,22–24].

For power system security, importance sampling has been used for changing the sampling distribution of operating conditions (load levels and wind power productions) to train decision trees to identify critical operating conditions close or beyond the stability boundary in [25,26] and, in the context of probabilistic security assessment, to speed up the computation of probabilities of violation of operating constraints in [27,28].

In this paper, we present a new importance sampling (IS) scheme for estimating the probabilities of violation of operating constraints due to short-term load and wind power forecast errors. The IS scheme is a two-stage approach that, first, computes quadratic approximations of the stability boundaries developed in [5] and, second, uses these quadratic approximations to design efficient importance sampling schemes by using the method presented in [29,30] in the context of mathematical finance. The contribution of the present paper is to use the second-order approximations previously developed by the authors in [5] to adapt the method in [29,30], which proposed an efficient IS estimator for estimating the risk of high losses in portfolios, to probabilistic security assessment.

The proposed approach is similar to [27,28]. Compared to [27], the proposed approach is more efficient as shown in the case studies. In particular, the Monte-Carlo simulations using the proposed approach do not suffer from convergence issues that arose in some case studies in [27]. In [28], the problem of interest was the probability of violation of operating constraints during a certain period, given a description of the operating conditions during this period as stochastic processes. In contrast, in this paper, a specific point in time is considered for probabilistic security assessment, given a description of the operating conditions as random variables.

The rest of the paper is organized as follows. Section 2 presents the challenges in estimating the probabilities of violation of operating constraints. Section 3 describes the proposed two-stage method to construct efficient importance sampling distributions. Section 4 presents case studies in which the proposed importance sampling distribution is compared to crude Monte-Carlo simulations and to the importance sampling scheme proposed in [27].

2. Problem formulation

2.1. Power system security

System operators seek at maintaining a secure operation of power systems by keeping the operating point $\lambda = [u \quad \zeta] \in \mathbb{R}^l$ in the stable operation domain $D \subset \mathbb{R}^l$. This stable operation domain is the set of operating points satisfying operating constraints, such as stability and operating limits. Here, $u \in \mathbb{R}^{n_u}$ represents n_u controllable parameters such as the active power generation at the controllable generators and $\zeta \in \mathbb{R}^{n_s}$ n_s stochastic system parameters such as load and wind power production.

Typically, system operators operate the system according to the N-1 criterion. According to this criterion, system operators consider a list of critical contingencies. They operate the system so that the operating point remains in the stable operation domain even after any single contingency from this list occurs. If a contingency occurs in the power system, the stable operation domain changes. In the following, D^i, $i>0$, denotes the stable operation domain for the system after contingency i has occured, and D^0 that of the pre-contingency system. By taking preventive or corrective actions through changing u, different regions of D^i can be reached, which enables system operators to improve or recover system stability if needed.

Given forecasts on the uncertain parameters ζ, deterministic N-1 based approaches try to identify worst-case scenarios and to ensure that the system fulfills all operating constraints in the considered pre- and post-contingency systems for these worst-case scenarios. In contrast, the use of probabilistic methods which consider the joint probability distribution of ζ will enable system operators to not only consider a few scenarios but the whole set of information available through forecasts on ζ. In probabilistic approaches, operating constraints can be violated but the controllable parameters such as generators' active production are set so that the probability of violation is kept very low. It leads to a more flexible and less conservative use of the system's resources [31,32].

The operating risk as defined from [33] measures the probability of the system to be outside one of the stable domains $D^i(u)$ at time T, given the forecast of ζ for that time. It can be written as:

$$R^{\zeta}(u) = \sum_{i=0}^{n_c} q_i \mathrm{Prob}\left(\zeta \notin D^i(u)\right) \tag{1}$$

where index $i=0$ is for the pre-contingency system, $i \in \{1, \ldots, n_c\}$ is for one of the n_c post-contingency systems of interest, q_i is the rate of contingency $i>0$ and $q_0 = 1 - \sum_{i=1}^{n_c} q_i$.

In the following, we consider the problem of efficiently estimating the pre- and post-contingency probabilities of violations $\mathrm{Prob}\left(\zeta \notin D^i(u)\right)$ for some i, and drop the index i corresponding to the pre- or post-contingency systems for simplicity of notation.

2.2. Wind power and load forecast error distributions

Let $\boldsymbol{W}$, $\boldsymbol{P}$ be the set of nodes where a wind farm, respectively a load, is connected. Let w_i be the wind power production at node $i \in \boldsymbol{W}$, and p_i the load at node $i \in \boldsymbol{P}$. The stochastic system parameters are $\zeta = [w^T \quad p^T]^T$, where w is the vector of all wind power productions and p the vector of all loads.

It is assumed that probabilistic forecasts give the marginal forecast error distributions of all stochastic system parameters, as well as a measure of the correlation between them. The loads p are modelled by a Gaussian distribution $\mathcal{N}(m_p, \Sigma_p)$ representing a point forecast m_p and the load forecast error distribution $\mathcal{N}(0, \Sigma_p)$ around it. Wind power forecast errors are typically not Gaussian distributed [34,35]. The marginal distribution functions F_{w_i}, $i \in \boldsymbol{W}$, of the wind power forecast errors can be either defined as the empirical cumulative distribution functions (CDF) from historical data or as parametric functions such as beta distributions or other recently proposed distributions in the literature [36–39].

The joint distribution function of ζ which is required to draw samples of ζ for performing probabilistic security assessment is not known. To overcome this issue, the joint Normal transform in [40–42] that builds on Gaussian copulas is used in the present paper. By using the joint Normal transform, the wind power productions in w can be expressed as a function of a

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