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A computational framework for risk-based power systems operations under uncertainty. Part I: Theory

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ABSTRACT

With larger penetrations of wind power, the uncertainty increases in power systems operations. The wind power forecast errors must be accounted for by adapting existing operating tools or designing new ones. A switch from the deterministic framework used today to a probabilistic one has been advocated. This two-part paper presents a framework for risk-based operations of power systems. This framework builds on the operating risk defined as the probability of the system to be outside the stable operation domain, given probabilistic forecasts for the uncertainty (load and wind power generation levels) and outage rates of chosen elements of the system (generators and transmission lines). This operating risk can be seen as a probabilistic formulation of the $N-1$ criterion. The stable operation domain is defined by voltage-stability limits, small-signal stability limits, thermal stability limits and other operating limits. In Part I of the paper, a previous method for estimating the operating risk is extended by using a new model for the joint distribution of the uncertainty. This new model allows for a decrease in computation time of the method, which allows for the use of later and more up-to-date forecasts. In Part II, the accuracy and the computation requirements of the method using this new model will be analyzed and compared to the previously used model for the uncertainty. The method developed in this paper is able to tackle the two challenges associated with risk-based real-time operations: accurately estimating very low operating risks and doing so in a very limited amount of time.

1. Introduction

Wind power penetration levels have been increasing steadily and are expected to continue doing so in the coming decades [1]. Larger wind power penetrations bring about new challenges in power system operations because the assumed values of the wind power production are not known but given by forecasts. The production forecast errors must be accounted for and accommodated in today's operating tools, or new tools must be designed. Traditional, deterministic tools rely on what is called in [2] a few "snapshots" of the power system, reflecting the expected future operating conditions. While this has been possible when most of the uncertainty was due to the load, relying on analyses based on a few snapshots is not deemed appropriate anymore in power systems with large penetrations of wind power. Consequently, a shift from deterministic to probabilistic tools has been advocated [2,3]. Probabilistic tools use probabilistic forecasts giving the joint probability distribution of the forecast errors of all uncertain parameters (load, wind power production), while deterministic tools only use a few possible values, "snapshots", from the forecasts.

In deterministic approaches, the system is made ready to meet the studied snapshots, identified as critical, in the sense that the system must fulfil operating constraints for the given snapshots. This is no longer possible when considering the joint probability distribution because of two reasons [4,5]. First, fulfilling these operating constraints for all possible outcomes of the probability distributions would result in large costs. Second, ensuring that no operating constraints are violated given the probability distributions modeling the uncertainty can be impossible. For these reasons, probabilistic tools look at the probability of violations of the operating constraints. This probability of violation defines an operating risk, in the terminology of [6]. Different definitions for the operating risk can be considered depending on the task at hand. The challenge with the probabilistic approach is the computation of the operating risk, since the studied operating constraints typically are nonlinear functions of the uncertain parameters (load, wind power production) whose joint probability distribution is assumed to be known through forecasts.

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$u \in \mathbb{R}^{n_u}$ controllable parameters
$W = [W_1, \ldots, W_{n_w}]^T \in \mathbb{R}^{n_w}$ random vector representing the probabilistic forecast for all wind power injections W_k
F_{W_k} cumulative distribution function of W_k
f_{W_k} probability distribution function of W_k
$p = [p_1, \ldots, p_{n_l}]^T \in \mathbb{R}^{n_l}$ random vector representing the probabilistic forecast for all loads p_k
$\zeta = [W^T\, p^T]^T \in \mathbb{R}^l$ stochastic system parameters
$\lambda = [u^T\, \zeta^T]^T$ system parameters
$X = [X_1, \ldots, X_{n_w}]^T$ multivariate Gaussian random vector, with all X_i standard normal variables $\mathcal{N}(0, 1)$
$\hat{\zeta} = [X^T\, p^T]^T$ stochastic system parameters in a new space
$\hat{\lambda} = [u^T\, \hat{\zeta}^T]$ system parameters in a new space
$q_i, i = 1, \ldots, n_c$ outage rate for contingency i
$q_0 = 1 - \sum_{i=1}^{n_c} q_i$ probability of no outage
$F^i, i = 0, \ldots, n_c$ vector of state and power flow equations for the pre- or post-contingency system i
$h^i, i = 0, \ldots, n_c$ vector of operating limits for the pre- or post-contingency system i
$D_i(u) \subset \mathbb{R}^l, i = 0, \ldots, n_c$ stable operating domain for the pre- or post contingency i
$\Sigma_i(u) \subset \mathbb{R}^l, i = 0, \ldots, n_c$ Stability boundary of the pre- or post-contingency system i (bounds $D_i(u)$)
$\Sigma_{ij}(u)$ jth smooth part of $\Sigma_i(u)$
$\Sigma_{ij}^a(u)$ second-order approximation of $\Sigma_{ij}(u)$
d_{ij} function defining the signed distance to $\Sigma_{ij}^a(u)$
$R^{\zeta}(u), R^{\hat{\zeta}}(u)$, operating risk given probabilistic forecast for ζ or $\hat{\zeta}$, and a given value u of the controllable parameters
$\hat{R}_1, \hat{R}_2$ approximations of the operating risk

In [7], operating risks are defined as the probabilities of violation of transfer limits across specified bottlenecks and are estimated using Cornish-Fisher expansions of the linearized power transfers. In [5], the operating risks are also defined as the probabilities that the flows on certain lines exceed the transfer limits. The power transfers are linearized to become linear functions of the uncertain parameters, and the probabilistic constraints are back-mapped to the uncertain parameter space using these linear functions. In [8,9], operating risks are defined as the probabilities of violation of transfer limits and of violation of the generators' limits. The corresponding constraints are recast as second-order conic inequalities to make them tractable, under the assumption that the uncertain parameters – wind power productions – are independent and Gaussian distributed. In [8], a data-robust algorithm is proposed to account for non-Gaussian cases. In [10,11], the operating risk is defined as the probability of operating the system outside the stable operation domain. The stable operation domain is bounded by voltage stability limits, small-signal stability limits and thermal limits. Cornish-Fisher expansions are used to estimate the operating risk. The formulation in [11] was extended in [12,13] in order to account for both non-Gaussian distributions of the uncertain parameters and the correlation between them. While the previously cited works consider only thermal stability limits, the significant contribution of the formulation in [10–13] is that it also considers voltage and small-signal stability limits. Additionally, one single joint operating risk is defined, while other works consider several operating risks, one per line or generator. In all previously cited work, the operating risks were used as constraints in chance-constrained optimal power flows (CCOPF) to find the most cost-efficient re-dispatch of participating generators while ensuring low operating risks. In some work, CCOPF is called stochastic optimal power flow [7,11] or risk limiting dispatch [6].

Two challenges arise when using an operating risk in power system operations:

1. Secure power systems operations require a very low operating risk, i.e. the events corresponding to not satisfying the operating constraints are rare events. Estimating the probability of such rare events is computationally challenging.
2. The time available for computation or estimation of the operating risk is constrained when dealing with real-time operations. Efficient and fast methods must therefore be developed.

The operating risk as defined in [13] is estimated using approximations which have been shown to be accurate in different power systems in [10–12,14]. The computational aspects, however, have not been studied.

In this two-part paper, the computational aspects of the method in [13] are studied, and a new model for the joint distribution of the forecast for wind power injections is used. This model aims at reducing the computational time of the method to be able to use it in real-time operations in large power systems. This model relies on further approximations compared to [13]. The accuracy of these approximations is investigated. The main contributions of this two-part paper are: (1) a new computationally efficient model for the joint distribution of the forecast for wind power injections and (2) a study of the computational aspects of the method.

The remainder of part I is organized as follows. Section 2 introduces the concept of operating risk and the definition of operating risk used in this paper. Section 3 reviews the method used in [13] that estimates this operating risk, and discusses its computational requirements. Section 4 introduces a new model for the joint probability distribution of the uncertain parameters, and explains how to integrate it in the method reviewed in Section 3. Section 5 summarizes the method, and discusses the difference between the old and the new models for the joint distribution of the uncertain parameters.

2. Power systems operations under uncertainty

2.1. Operating risk

Power systems operations have relied on the $N-1$ criterion which states that the considered power systems must remain stable after the loss of one large component (transmission line or generator). The uncertainty faced when planning and operating power systems has typically come from the loads, whose patterns can be forecast well [15]. For the expected load, power systems are operated to fulfil the $N-1$ criterion. The $N-1$ criterion takes the form of operating constraints which must be fulfilled for the system to remain stable. These operating constraints are differential-algebraic equations and inequalities which at steady state can be written

$$\begin{cases} F^i(x^i, y^i, \lambda) = 0, & i = 0, \ldots, n_c \\ h^i(x^i, y^i, \lambda) \geq 0, & i = 0, \ldots, n_c \end{cases} \tag{1}$$

$$\Leftrightarrow \quad G^i(x^i, y^i, u, \zeta) \geq 0, \quad i = 0, \ldots, n_c, \tag{2}$$

where the superscript i is for the base case $i=0$ or any of the n_c studied post-contingency cases included in the $N-1$ criterion, $i = 1, \ldots, n_c$. $x^i \in \mathbb{R}^{n_s}$ are state variables (generators' internal variables for example), $y^i \in \mathbb{R}^{n_y}$ are algebraic variables (typically voltage magnitudes and angles) and $\lambda \in \mathbb{R}^m$ are system parameters. The parameters λ can be divided into controllable parameters