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Risk assessment and risk-cost optimization of distributed power generation systems considering extreme weather conditions

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ABSTRACT

Security and reliability are major concerns for future power systems with distributed generation. A comprehensive evaluation of the risk associated with these systems must consider contingencies under normal environmental conditions and also extreme ones. Environmental conditions can strongly influence the operation and performance of distributed generation systems, not only due to the growing shares of renewable-energy generators installed but also for the environment-related contingencies that can damage or deeply degrade the components of the power grid. In this context, the main novelty of this paper is the development of probabilistic risk assessment and risk-cost optimization framework for distributed power generation systems, that take the effects of extreme weather conditions into account. A Monte Carlo non-sequential algorithm is used for generating both normal and severe weather. The probabilistic risk assessment is embedded within a risk-based, bi-objective optimization to find the optimal size of generators distributed on the power grid that minimize both risks and cost associated with severe weather. An application is shown on a case study adapted from the IEEE 13 nodes test system. By comparing the results considering normal environmental conditions and the results considering the effects of extreme weather, the relevance of the latter clearly emerges.

1. Introduction

Existing power grids have been developed to meet the requirements of conventional single direction power delivery from centralized high-capacity generation units (e.g. thermal plants, nuclear power plants, etc.) to various end-user loads (e.g. industry, commerce, residence, etc.). The energy challenges faced by Europe and the rest of the world are changing the landscape of power systems. Renewable energy resources, often geographically separated from the traditional power sources, are increasingly integrated into the distribution network in the form of distributed generators (DGs), such as photovoltaic panels and wind turbines. Owing to the random nature of these resources, DGs behave quite differently from conventional generators and they inject considerable amounts of uncertainty into power system operation; this uncertainty puts pressure on decision makers to properly assess the risk of the modern distribution networks integrated with DGs.

Unlike power system reliability assessments that focus on the evaluation of quantities such as system average interruption duration index (SAIDI), system average interruption frequency index (SAIFI) and expected energy not supplied (EENS) [1] to reflect the ability to supply adequate electric service over the long term [2], probabilistic risk assessment (PRA) aims to estimate the probability (or frequency) of disturbances to system operation and their consequences [3]: these two elements are the constituents of the risk. Extreme weather conditions (e.g. high wind, thunderstorm, heavy snow, etc.) can significantly affect system risk by increasing the frequency of failures of the power components and/or inducing severe damage [4].

In the past decades, many research works have been devoted to the risk assessment of power systems [3–12,39]. A number of studies have focused on transmission systems [7–9,13,31,32,39]; distribution network risk analysis [6,11] has also been performed to analyze the response of protection devices/systems. Volkanovski et al. [39] have studied power grid reliability by fault tree analysis, considering voltage drop and power flow. Differently, Guikema et al. [10] and Nateghi et al. [12] have focused on the estimation of hurricane damage on distribution networks, using statistical tools to account for historical data. More recently, Gabbar et al. [5] have proposed an integrated framework for risk-based performance analysis of microgrids with DGs installed.

To the authors' knowledge, none of the existing works have considered the impact of extreme weather conditions within the

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framework of the risk assessment of distribution networks or the optimization of the DGs nominal power considering these conditions. Recently, Alvehag and Soder [14] have conducted a reliability assessment for a distribution system considering the influence of extreme weather events (e.g. high wind and lightning). More specifically, in their model the extreme weather events affect the system by causing the overhead lines to fail. Kirschen and Jayaweera also remarked that line performance can be significantly affected by weather conditions [15].

In this paper, we originally develop a simulation-based probabilistic risk assessment framework of DG systems that also considers severe weather. Based on the indications found in literature, we consider high wind and lightning as two major threats that can significantly increase the failure rates of distribution lines.

Furthermore, it we consider the optimal integration of DG within the power grid, which can provide several benefits (e.g. reduced power losses and improved voltage profile) [36]. Optimal integration of DGs needs to consider multiple conflicting objectives on which the decision makers must find satisfactory trade-off solutions. Mena et al. [20] optimize the allocation of DGs in a reliability-cost bi-objective framework of simulation and optimization. Niknam et al. [37] optimize the size and allocation of DGs considering objective like minimizing costs, emissions and losses. In this paper, we propose an innovative risk-cost optimization for DG sizing, with the bi-objective of minimizing risk considering normal and extreme weather events, and the system investment and operative costs.

The rest of the paper is organized as follows. Section 2 presents the risk definition, the severity functions and the distribution line failure probability models, taking into consideration the two environmental threats of high wind and lightning. Section 3 describes the weather modelling and the power component modelling. Section 4 presents the Monte Carlo (MC) simulation procedure for risk estimation and the risk-cost bi-objective framework for optimal DG sizing. Section 5 describes the case study o a relatively complete DG system exposed to extreme weather conditions. Section 6 presents the DG system risk assessment and optimization results, and their analysis. Conclusions are presented in Section 7.

2. Risk concepts

2.1. Definition of risk

We adopt a quantitative definition of risk as the product of the probability of occurrence of the undesired event (i.e. contingency) and the related consequence (i.e. severity) [16,33]. To take into account more than one undesired event [30], the definition is extended by summing all contributions as:

$$R = \sum_i p(E_i) \times Sev(E_i), \tag{1}$$

where $p(E_i)$ is the probability of occurrence of the undesired event E_i and $Sev(E_i)$ is the severity of the related consequences. In probabilistic risk assessment (PRA), contingencies frequencies are used as probabilities and severities functions as consequences [3]. In the context of power systems, contingency is defined as the unexpected loss of one or more elements (e.g. distribution line, transformer or generator) comprising the power system [4]. Over-load, related with the feeders thermal limits, and bus voltage magnitude, related with frequency and system balance, are both indicators of power system stress and are used to represent the consequences for the risk calculation [8]. Thus, the risk index associated with one contingency can be expressed as follows for the whole power network:

$$\begin{aligned} R(C_i|\chi) &= \sum_{k=1}^{L} P(C_i\,|\chi) \times SevOL_k(C_i,\chi) \\ &+ \sum_{b=1}^{B} P(C_i|\chi) \times SevLV_b(C_i,\chi) = P(C_i|\chi) \times [SevLV(C_i,\chi) + SevOL(C_i,\chi)] \\ &= ROL(C_i|\chi) + RLV(C_i|\chi), \end{aligned} \tag{2}$$

where χ is the set of all operational and environmental conditions (e.g. wind speed, ground strike density, solar irradiation, temperature), C_i is the ith contingency, $SevOL_k(C_i,\chi)$ is the overload severity for line k in the conditions of C_i and χ, $SevLV_b(C_i,\chi)$ is the low voltage severity for the node (or bus) b, $ROL(C_i|\chi)$ is the risk associated with overload, $RLV(C_i|\chi)$ is the risk associated with low voltage, L is the total number of lines in the system and B is the total number of nodes in the system. The composite risk due to all contingencies is, then, obtained as:

$$R(\chi) = \sum_{i=1}^{N} R(C_i|\chi), \tag{3}$$

where N is the total number of contingencies. The severity functions and the probability models adopted are illustrated in the subsequent Sections 2.2 and 2.3, respectively.

2.2. Severity functions

The low voltage severity function measures the extent of a violation in terms of voltage magnitude drop at one node. There are three types of severity functions: continuous, percentage and discrete [17]. The one selected for our study is the continuous function, because it measures the extent of the violation by reflecting the realistic sense that a performance close to, but within a performance limit, is, in fact, risky [17].

The continous low voltage severity function adopted is as follows [3]:

$$SevLV_b(V_b) = \begin{cases} a - a \times V_b & V_b \le V_{ref} \\ 0 & V_b > V_{ref} \end{cases}, \tag{4}$$

$$a = \frac{V_{ref}}{(V_{ref} - V_{lim})}, \tag{5}$$

where V_{lim} is the deterministic limit (DL) of the voltage, V_{ref} is the reference voltage and V_b is the voltage magnitude in per-unit (p.u.) in the node or bus b. In this study, we set $V_{lim} = 0.97$ p.u. and $V_{ref} = 1$ p.u., following [27]. Fig. 1 illustrates Eq. (4), where the deterministic violation region (DV) contains the V_b values satisfying $V_b < V_{lim}$ and the near violation region (NV) contains the V_b values satisfying $V_{ref} > V_b > V_{lim}$.

The severity function for overload is specifically defined for each circuit (distribution lines and transformers) and it measures the extent of violation in terms of excessive power flow as the percentage of rating (PR). The mathematical expression for this severity in

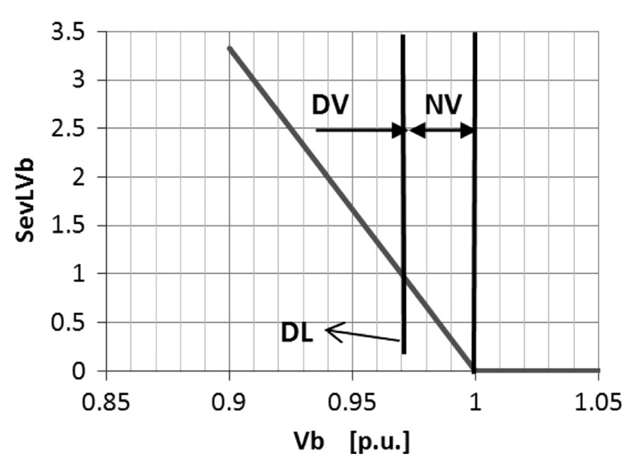

Fig. 1. Severity function for low voltage.