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RESEARCH ARTICLE

Sensitivity of Voltage Sags Estimation to Uncertainties

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ABSTRACT Voltage sags are power quality disturbances mainly caused by faults with a highly random nature. For this reason, the severity and frequency of occurrence of voltage sags is typically analyzed by means of probabilistic methods, such as Monte Carlo simulations, where different probability distributions are selected to model the uncertain inputs (e.g., fault impedance, fault location, fault rate, etc.). The selection and parameterization of the appropriate probability functions involves many difficulties to ensure that they represent the distribution of input variables in a realistic way and so, many different approaches can be found in literature. This paper studies the sensitivity of voltage sags severity to the uncertainty in the input models in order to focus modeling effort on the input variables that are more critical and effectively have an influence on voltage sags levels, whereas non-influential parameters can be neglected or modeled by means of simplified hypothesis. The method proposed is based on Design of Experiments and Analysis of Variance (ANOVA) and is able to discriminate with a statistic confidence level whether the uncertainty in the input significantly affects voltage sags severity indices or not. The effect of uncertainty on voltage sags indices SARFI90 and SARFI70 has been evaluated in realistic scenarios for IEEE test networks of 24 and 118 buses and in the power system of Ecuador with 357 nodes. General trends have been also established that help to understand the effect of the modeling of input parameters on the estimated number of sags.

INDEX TERMS Analysis of variance, design of experiments, sensitivity analysis, power quality, uncertainty, voltage sag.

I. INTRODUCTION

Voltage sags are short duration reductions in voltage magnitude which are typically caused by short-circuit currents and last from a few cycles to a few seconds [1], [2], [3]. These disturbances affect the normal operation of sensitive equipment and cause interruptions in the industrial production process [4], [5], [6], [7], [8], [9].

To evaluate and decide the mitigation scheme against these disruptions both the frequency of occurrence and the vulnerability of equipment to voltage sags must be investigated [1]. This approach implies a double-sided analysis including the estimation and characterization of voltage sags levels in the power system. Ideally the monitoring of all sensitive sites would be required during very long monitoring periods [10], [11] (e.g., if voltage sags occur once a week, it would take at least 7 years of monitoring to obtain a 10% accuracy in the estimation of annual indices [10]). In addition, very often there is a limitation in the number of available monitors which prevents from using this source of information or requires using advanced voltage sags state estimation methods [12], [13], [14], [15].

As an alternative, since the index values extracted from a single year data are insufficient to make a correct

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assessment [16], voltage sag simulation studies based on the probabilistic analysis of faults are frequently used [10], [17], [18], [19], [20], [21], [22], [23], [24] to characterize a site's performance. However, the modeling assumptions used for the uncertain input parameters have a considerable impact on how reliable the voltage sag simulation results are and, as this work has demonstrated, there is significant inconsistency in the literature when it comes to modeling the input characteristics, particularly fault impedance and fault rate [10], [17], [18], [19], [20], [21], [22], [24]. In order to properly assess to which extent the accuracy of voltage sags simulations is influenced by the inputs used, further research work is still required. The work presented in this paper contributes to improving knowledge in this unresolved topic. Its first contribution is to perform a comprehensive review of the different and divergent assumptions considered in the literature covering voltage sag simulations. Following this, and as a main and novel contribution, a method based on statistical techniques is proposed for the sensitivity analysis of voltage sags severity to uncertain fault parameters. This method has been applied in a systematized way to three different size networks. In this sense, the method proposed and the results obtained, represent an advance in the understanding of simulation studies of voltage sags and in the identification of parameters whose uncertainty significantly influence the results, and their discrimination from those with the least impact. As a result, simulation studies can focus modelling efforts on the key simulation parameters while the rest are disregarded.

Sensitivity methods enable the analysis of the impact of input variables on the variation of a system output. The applications of sensitivity techniques in power systems research have been applied to different problems such as generator ranking [25], load classification [26], voltage stability assessment [27], [28], [29], transient response prediction [30], small-disturbance stability [31], power system stabilizer design and frequency support from storage devices and system dynamics [32], [33], or uncertainties in power system models [34], [35]. However, very little work has been done regarding the sensitivity of power quality disturbances to uncertain parameters. In [36] the influence of measurement errors on the solution to the fault location problem is analyzed. A sensitivity analysis technique based on design of experiments is applied to [37], but the results are not systematically analyzed across the whole network and a single study network is considered. This, together with the fact that the levels of the input variables are arbitrarily selected, makes the results neither generalizable nor extensible to other systems.

In this work, a sensitivity method is proposed that may determine, with a certain degree of confidence, whether or not input uncertainty influences the main voltage sag indices in simulation studies. This method is based on Design of Experiments (DoE) and Analysis of Variance (ANOVA) [38]. This paper estimates the voltage sags severity indices at all nodes of three different power system networks and conducts a thorough examination of the input values and common assumptions used in the literature, as well as of their discrepancies. As a result of the systematized sensitivity methodology applied, general trends are obtained that can aid in understanding the sensitivity of the input parameter models on the estimation of the number of sags in simulation studies.

This paper is organized as follows. In section II a general overview of the proposed method is provided. In section III, the main uncertain inputs are described and a bibliographical revision of their modeling is included, the output variables SARFI90 and SARFI70 as representative severity indices are also defined. Sections IV and V describe the methodology employed and, finally, different sensitivity studies are presented in section VI that allows us to drive general conclusions about the sensitivity of voltage sags indices to different uncertain parameters.

II. SENSITIVITY ANALYSIS APPLIED TO VOLTAGE SAGS ESTIMATION

The main cause of voltage sags are short-circuit faults occurring in the system [1]. Due to the highly stochastic nature of faults, severity indices of voltage sags are typically estimated through probabilistic approaches which require modeling faults uncertainty by means of appropriated probability distributions.

The aim of this work is improving the understanding about factors which determine voltage sags levels and determining to which extent voltage sag indices are significantly influenced by the model selected for the input variables considered in the analysis.

Sensitivity analysis is a mathematical tool which allows studying the behavior of the output of a model or system considering the stochastic nature or uncertainties in its inputs. In this work, in a set of experiments previously established by means of the Design of Experiments method, Monte Carlo method is applied to probabilistically estimate voltage sags indices by applying short-circuit analysis to uncertain input variables associated to the stochastic behavior of faults. In this way, the effect of these uncertainties on the output variables of the proposed model (voltage sags indices) can be evaluated and interpreted by means of sensitivity analysis.

There are several well-established techniques for the sensitivity analysis; the one used in the paper is Analysis of Variance. Design of Experiments and ANOVA methods are statistical procedures which determine, with statistical rigor, if a response variable can be considered affected by a determined set of input variables for a given confidence level (usually 95%) [38].

The process followed in this work is schematically shown in Fig. 1. In the following sections, each component of this process will be described in detail.

III. MODELING OF INPUT UNCERTAINTIES

Monte Carlo method is a widely-applied technique to estimate voltage sags [16], [17], [18], [39]. However, the validity of the results simulated by means of Monte Carlo

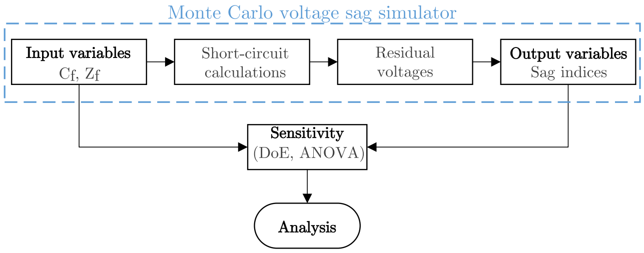

FIGURE 1. Process scheme.

relies on the accuracy of the considered probabilistic models of stochastic inputs which, typically, can be fault rate, fault impedance, fault location and fault type. Different probability models adopted for these input variables are discussed below.

A. FAULT RATE

The fault rate of a power system line or bus, C_f, represents the number of faults occurred in that element over a certain period, typically, one year. Since voltage sags are caused by faults, element fault rates and the number of sags in a system are variables with a direct relation between them.

Usually, the specific number of short-circuit faults occurred in an element can experience wide variations from one year to another. Approaches found in literature to model the number of faults in an element and in a year differ significantly from each other due to the difficulty and uncertainty in estimating fault rates values. A very common approach is considering a constant fault rate C_f for the whole system and for all the analyzed years [10], [17], [19], [40], [41]. In [18], [21], [42], [43], and [44] a constant fault rate is applied for each voltage level. However, the number of faults varies widely from one year to another and the assumption of constant fault rate is not very realistic. One of the approaches that comes closest to reality is the modeling of the number of faults in buses and lines over a year by means of a Poisson distribution [39], [45], [46].

Poisson is a well-known discrete distribution that models the number of events occurred in a fixed time interval, provided that the events occur at random, independently in time and at a constant rate. Poisson distribution can be modeled by means of:

$$f(k, \lambda) = \Pr(C_f{=}k) = \frac{\lambda^k e^{-\lambda}}{k!} \qquad k = 0, 1, 2 \ldots \tag{1}$$

where $f(k, \lambda)$ represents the probability distribution function of the yearly number of faults C_f, k represents the number of occurrences, and λ is the average fault rate in the element.

The main practical difficulty to apply (1) lies in estimating parameter λ. Usually, the average fault rate λ of a line or bus in the system can be estimated from historical records obtained from the operation data of the protection system. However, this value is very often subject to an error due to the lack of a sufficiently long historical data series or because it is referred to a new network (or a test network) for which no historical failure data record exists.

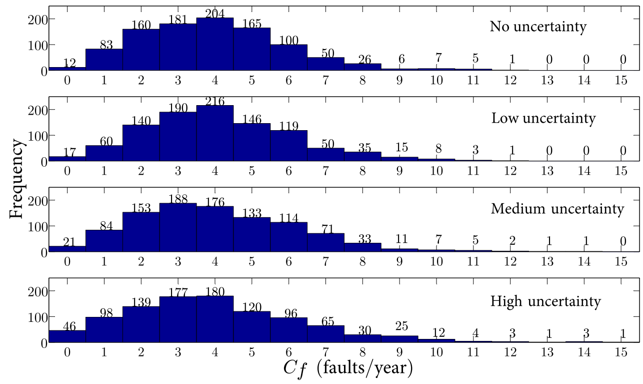

FIGURE 2. Frequency distribution of the fault rate coefficient C_f by means of a Poisson distribution in the scenarios of low, medium, and high uncertainty.

In this work, in order to consider the uncertainty associated to the average elements fault rates λ a non-biased Gaussian-distributed noise proportional to the average rate in the Poisson distribution is added to the model. Therefore, the number of faults C_f in an element in a specific year is obtained as a Poisson distribution with average value λ' as:

$$C_f \sim \text{Poi}(\lambda') \tag{2}$$

where λ' follows a normal distribution with mean λ and deviation σ, with $\sigma = n \cdot \lambda$ and $n \in \{1/9, 2/9, 1/3\}$ to model three different scenarios with different uncertainty:

- low uncertainty $\sigma = \lambda/9$
- medium uncertainty $\sigma = 2\lambda/9$
- high uncertainty $\sigma = \lambda/3$

Therefore, λ' will be with 99.6% probability between $\lambda \pm 3\sigma$ to account for the uncertainty in the λ value. For instance, in the scenario of high uncertainty, λ' will be with 99.6% probability between 0 and 2λ.

The effect of the modeled uncertainty in the frequency distribution is shown by means of an example in Fig. 2. This figure shows the frequency distribution of the fault rate coefficient in a 1000 year simulation by means of the proposed model with $\lambda = 4$ faults/year for low, medium, and high uncertainty. In these three frequency distributions, the fault rate λ is the same, however, extreme values C_f of number of faults per year are reached more frequently in the distribution with higher uncertainty. In the analysis shown later in this work, it is verified whether the uncertainty in the fault rate has a significant impact on voltage sags severity or not.

In this work, the average fault rates considered have been 0.027 faults/year at buses with voltage level higher or equal to 138 kV and 0.021 faults/year at lower voltage levels. For lines, 3.28 faults per year and per 100 km have been considered at voltage levels equal or higher to 138 kV and 1.53 faults/(year x 100 km) for lower voltage levels.

B. FAULT IMPEDANCE

Fault impedance Z_f is one of the most relevant parameters which influence the values of short-circuit currents and,

TABLE 1. Fault impedance values in bibliography.

References	Z_f (Ω) assumed
[10], [18], [19], [27], [40]–[42], [44], [47], [48]	0
[17], [20], [43]	$\mathcal{N}(5,1), \mathcal{N}(10,1)$
[39]	$0, 5, 25, 40$
[50]	Unif(0,10), Unif(0,20), Unif(0,30)
[21]	$5, 40$

consequently, the severity of voltage sags. However, due to the lack of reliable information about the value of this variable, very often studies disregard its effect. There is neither a unified value nor a standard model for this parameter and great discrepancies can be found for the modeling of Z_f among different voltage sags studies. Approaches found in the literature to model fault impedance are summarized in Table 1. From Table 1 it can be observed that the majority of voltage sags studies assume that fault impedance is zero [10], [18], [19], [27], [40], [41], [42], [44], [47], [48]. This represents a non-realistic assumption that is usually justified under the premise that this leads to severe conditions, since it causes lower fault voltages and, consequently, an overestimation of sags. However, this restrictive character of the hypothesis is not always desirable, nor is it always correct. For example, when solving the problem of voltage sags monitors location, the assumption of low or null fault impedances eases observability and, consequently, leads to monitoring programs with lower monitoring requirements that can be incomplete for higher fault impedance scenarios [49].

In some other works, the fault impedance is modeled by using a Gaussian-distributed random variable [17], [20], [43] with different characteristics summarized in Table 1. Other authors use two equiprobable values [21], four equiprobable values [39] or uniform distribution of fault impedances with different maximum resistance values [50].

All these different approaches demonstrate the difficulty and lack of consensus in fault impedance modeling in voltage sags studies as shown in Table 1.

Line to ground faults on lines, the most common short-circuits in power systems, usually result as flashover of the insulators caused by lightning induction or failure of the insulators. In this case, the current path for ground faults typically includes the arc resistance R_{arc} and the grounding impedance (tower footing resistance R_{ft}).

The value of R_{arc} depends mainly on the distance between the line and the tower (which increases with the voltage level) and also on the current flowing through the arc [51], [52]. Typical values of R_{arc} are between 0.2 Ω and 14.4 Ω [53]. The tower footing resistance R_{ft} has usually a maximum value standardized according the regulations of each region. For example, in Spain, this value is limited to 20 Ω for high voltage lines [54]. In the case of a line with ground wire, the equivalent R_{ft} magnitude is considerably lower, this value is usually less than 6 Ω [53].

Another common cause of faults is the accidental contact between lines and other elements (e.g., vegetation, fauna, etc.). In this case, the estimation of the fault impedance Z_f has to include a contact resistance of the element with a wide range of values adding additional difficulty to the estimation of Z_f.

From all this, it follows that fault impedance is a parameter with high uncertainty in its estimation and, the occurrence of a null fault impedance value (which is a common assumption in voltage sags studies) is very unlikely.

As stated above, there is neither a unified value nor a standard model for the modeling of Z_f applied to voltage sags studies. In this work, it is studied if the statistic model and/or the values employed make a significant impact over the voltage sag indexes. Specifically, the sensitivity to three features (or factors) regarding the fault impedance are considered:

1) *Distribution of Z_f.* In this work, two random distributions are considered to model the stochastic impedance value. Due to the lack of data and the stochastic nature of the impedance, Gaussian distribution (as in [17], [20], [43]) or equiprobable Z_f values between the extreme values are assumed. In the case study section, these two models are compared, in order to check whether or not the probability model employed affects the results of the voltage sags analysis.
2) *Average fault impedance.* In the developed simulator and considering the realistic values previously described and the considerations made, two different levels have been considered for the average fault impedance: low impedance $\mu_{Z_f} = 6\,\Omega$ and high impedance $\mu_{Z_f} = 30\,\Omega$.
3) *Fault impedance uncertainty.*
To determine the effect of Z_f dispersion on voltage sags, an associated variability has been implemented. Three levels are studied: low uncertainty (i.e., dispersion is small referred to the average μ_{Z_f}), medium, and high uncertainty (i.e., large variability). Concretely, for the uniform distribution, the random value for the simulated fault impedance is comprised between: $\mu_{Z_f}(1-k)$, $\mu_{Z_f}(1+k)$, where $k = 1/3$, $2/3$ and 1, for the low, medium, and high uncertainty cases, respectively.
In the Gaussian distribution, the fault impedance is modeled using a normal $N(\mu_{Z_f}, (k\mu_{Z_f})^2)$ where $k =$ 0.11, 0.22 and 0.33, for the low, medium, and high uncertainty cases, respectively. Considering that in a Gaussian distribution 99% of the observations are in the range $\mu \pm 3 \cdot \sigma$ the variability range of observations in the normal distribution is closed to the variability range proposed in the uniform probability distribution.

C. FAULT TYPE

Faults can be line to ground (LG), double line to ground (LLG), double line (LL), and three phase (LLL). Usually, LLL faults are more severe for end-user equipment but far more improbable than LG faults. The probability of occurrence of each of these fault types is determined by historical operation data. In general, there is a broad agreement among different authors regarding the fault type probability.

In this work 80% of faults have been considered LG, 5% are LL, 10% are LLG and, finally, 5% are LLL as proposed in [40] and [55].

D. FAULT LOCATION

In order to compute voltage sags, the faulty components and the physical location of faults along the length of lines have to be taken into account in the short-circuit analysis. First, to select the faulty network elements, the average fault rates of each element (line or bus) are considered as described in section III-A. According to these average fault rates, the specific number of faults in buses and lines is determined considering the Poisson distribution of (1) for each simulated year. Faults at buses directly provide the faulted location, so that it is sufficient to apply short-circuit theory to calculate the fault currents and voltage sags at remote nodes. However, when the faulted element is a line, it is necessary to establish the fault location along the length of the line. The widely accepted approach in literature is random selection of the fault position along the line length, assuming that the fault location is equally probable throughout the line [17], [18], [19], [20], [39], [41]. In practice, this is the only possible approach unless that very precise data regarding fault probability along the length line is known. On the other hand, this is a quite realistic assumption in most scenarios and so, this is the adopted approach in this study.

E. INPUT VARIABLES ANALYZED

The input variables to be analyzed in the sensitivity study and their chosen values are described below:

- Fault rate uncertainty (σ_{C_f}). This parameter quantifies the uncertainty associated with the fault rate employed. Three levels of uncertainty are considered: low, medium or high in accordance with the values indicated in (2). Note that the average number of faults is not considered as a factor in the sensitivity study in order to not to increase the number of experiments and because it can be directly deduced that there is a linear relation between the number of faults and the number of sags from analytical equations. Therefore, the dependency of the number of sags with the average number of faults is direct.
- Average fault impedance (μ_{Z_f}). As stated in subsection III-B, two values for the average fault impedance are considered: low impedance (6 Ω) or high impedance (30 Ω).
- Fault impedance uncertainty (σ_{Z_f}). This parameter quantifies the uncertainty associated with the fault impedance employed. Three values are considered: low, medium or high in accordance with the explanation in subsection III-B.
- Distribution model for fault impedance ($\mathcal{P}(Z_f)$). This parameter characterizes the random-number generation process employed in the fault simulation. Two most common distributions are considered: uniformly distributed or Gaussian distributed.

Hereinafter, these four input variables are called factors, and the values (levels) for these factors are summarized in Table 2.

TABLE 2. Considered factors and their levels.

Factors	Levels
C_f uncertainty (σ_{C_f})	• Low uncertainty • Medium uncertainty • High uncertainty
Average Z_f (μ_{Z_f})	• Low impedance • High impedance
Z_f uncertainty (σ_{Z_f})	• Low uncertainty • Medium uncertainty • High uncertainty
Z_f model ($\mathcal{P}(Z_f)$)	• Uniformly distributed • Gaussian distributed

F. SENSITIVITY ANALYSIS: RESPONSE VARIABLES

Traditionally, the most common indices considered in voltage sag analysis are SARFI90 and SARFI70 which are defined as the number of voltage sags in a certain bus with residual voltage below a threshold 0.9 p.u. and 0.7 p.u., respectively [56], [3]. SARFI90 is the most significant index to evaluate voltage sags severity in a site, while SARFI70 is a good indicator of intolerable sags for most final-users of the network.

Indices SARFI90 and SARFI70 are calculated for each bus and for each simulated year. By using the yearly values obtained for SARFI90 and SARFI70, the mean and standard deviation of these indices can be computed for any given bus and will be considered as the response variables in the sensitivity analysis:

- The average number of sags for the considered time period and for a selected bus: $\mu_{SARFI90}$ and $\mu_{SARFI70}$.
- The observed metric $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$ quantify the inter-annual variability of the estimated number of voltage sags in each site, that is, the standard deviation of the yearly values of SARFI90 and SARFI70.

Parameters $\mu_{SARFI90}$, $\mu_{SARFI70}$, $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$ are estimated using the SARFI90 and SARFI70 values for the whole simulated time horizon. If the number of considered years is increased, the two aforementioned values are more accurately computed, but requiring a higher CPU time. Thus, there is a trade-off between computational efficiency and numerical accuracy. In the paper, a simulation period of 500 years has been considered.

IV. MONTE CARLO VOLTAGE SAGS SIMULATOR

Monte Carlo methods are computational algorithms which are commonly used to analyze complex models whose analytic approach is cumbersome or even unfeasible [16]. These procedures rely on repeated random sampling in order to obtain numerical results that allow the characterization of the distribution of the output variables.

Broadly speaking, the Monte Carlo algorithm is composed by the iterative repetition of the following three main parts:

(i) Stochastic generation of random samples from the probability distributions which model each input variable.
(ii) Solving the analytical equations of the model by considering the input values sampled in i). In voltage sags studies, equations of the model are the classical short-circuit calculations well known in power systems to obtain the residual voltage at distant buses during the fault [41].
(iii) Finally, obtaining the statistics of the outputs and aggregating or characterizing their parameters. In this case, the parameters detailed in section III-F.

As for the number of iterations to be considered, 500 years have been simulated as a compromise between the CPU time needed and the accuracy of the results.

In order to obtain general conclusions, three different networks have been studied:

1) The IEEE test network of 24 buses, pictured in Fig. 3, with 33 lines and 5 power transformer. This network operates at 138 kV and 230 kV [57].
2) The IEEE test network of 118 buses generation plants. This network mainly operates at 138 kV, 161 kV, and 345 kV. Its one-line diagram is shown in Fig. 4. Additional information can be found in [58].
3) The Ecuadorian power system network. It comprises 357 nodes, 216 lines, 162 power transformers, and 105 generation plants. The transmission system mainly operates at 69 kV, 138 kV, and 230 kV. Its one-line diagram is presented in Fig. 5. More details can be found in [60].

In the simulations performed, the type of winding connection provided in the data system of each network has been assumed. In unbalance voltage sags, the usual assumption of considering the residual voltage of the sag as the lowest voltage of the three phases has been taken into account.

Figure 6 shows the results of the application of this method to the IEEE test network of 24 buses. As aforementioned, 500 simulated years have been considered. In this figure, the average number of sags obtained at each bus along all the simulated years is shown for different residual voltage levels (i.e. average number of sags with voltage below 90%, with voltage below 80%, etc.). It can be observed that buses 8, 9 and 10 are the most problematic in terms of number of voltage sags, reaching a value between 10 and 11 voltage sags with voltage below 90% per year, while buses 7, 18 and 22 experience the least number of voltage sags.

Figure 7 shows a similar graph referred to the IEEE 118 buses network. Since the size of the network is larger in this case and so it is the number of possible faulted elements, the resulting average number of voltage sags increases and some buses experience a value close to 30 voltage sags per year with residual voltage of less than 90%.

Finally, Figure 8 shows the results referred to the Ecuadorian 357 buses network.

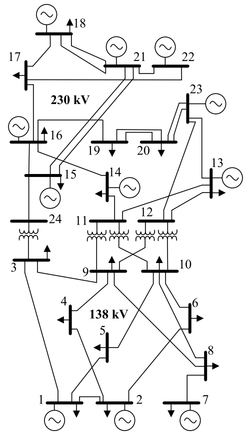

FIGURE 3. One-line diagram of IEEE-24 test network.

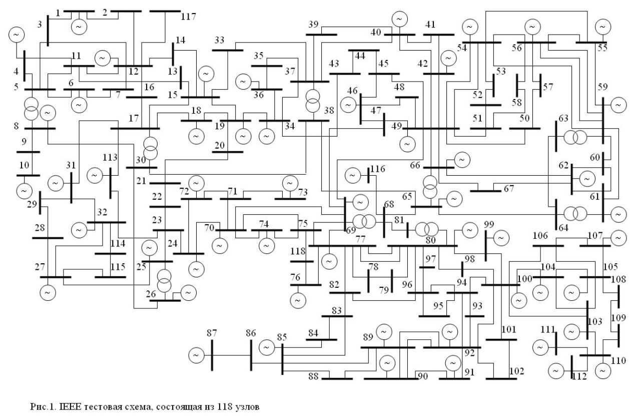

FIGURE 4. One-line diagram of IEEE 118 buses test network.

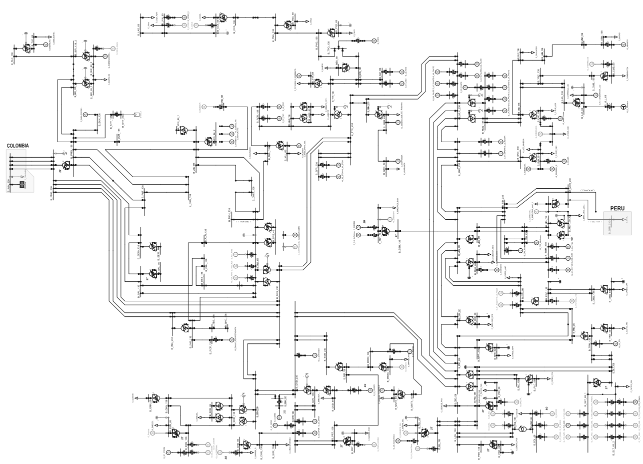

FIGURE 5. One-line diagram of Ecuadorian power system network.

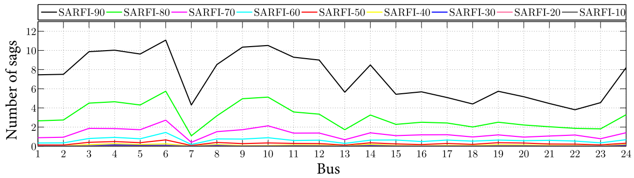

FIGURE 6. Number of sags (SARFI indices) at IEEE 24-bus test system.

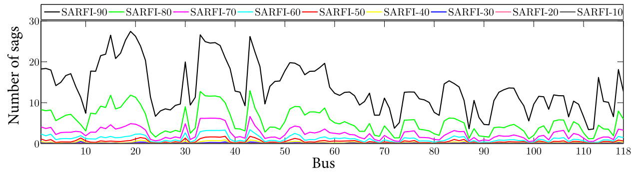

FIGURE 7. Number of sags (SARFI indices) at IEEE 118-bus test system.

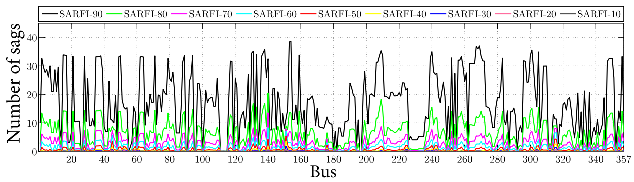

FIGURE 8. Number of sags (SARFI indices) at Ecuadorian 357-buses network.

V. SENSITIVITY ANALYSIS

As described in section III-F, a sensitivity analysis is performed to study the influence of the most uncertain input variables over the sag indices $\mu_{SARFI90}$, $\mu_{SARFI70}$, $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$.

Specifically, the statistical analysis allows checking if the (i) distribution model for Z_f, (ii) the mean value of Z_f, (iii) the uncertainty associated with Z_f and (iv) the uncertainty associated with C_f significantly affect the mean and standard deviation of SARFI indices.

A. DESIGN OF EXPERIMENTS

The Design of Experiments is a statistical tool for analysing the effect of one or more variables, which are called "factors" in the model. These factors can take different values that are called levels.

In our study, from Table 2, it can be observed that there are 2 factors with 2 levels each, and two factors with 3 levels, therefore, $2 \cdot 2 \cdot 3 \cdot 3 = 36$ different combinations of the considered factors values. Table 3 shows the values in each scenario for the four considered factors.

For each combination of factor levels, three different simulations (using different random seeds) are performed,. Thus, 108 different 500-year Monte Carlo simulations have been analyzed for each considered network.

B. ANOVA TECHNIQUE

Once the set of DoE tests has been developed, the obtained responses must be evaluated. The technique used in this paper for sensitivity analysis is Analysis of Variance. The ANOVA test relates the variance of the residuals of each factor to the variance of the model and establishes for the required confidence level (usually 95%) the influence of a given factor [38], [59].

ANOVA provides a mathematical criteria either to reject or to accept the null hypothesis or the alternative hypothesis related to each test. The null hypothesis corresponds to no statistically significant influence of the factors shown in Table 2 on the average or deviation of the SARFI90 and SARFI70. The alternative hypothesis establishes that input factors provide statistically dissimilar outputs and, therefore, they have a significant influence over the voltage sag indices SARFI90 and SARFI70.

The ANOVA model is described below:

$$y_{\omega,k} = \mu + \alpha_\omega + \beta_\omega + \gamma_\omega + \delta_\omega + u_{\omega,k} \quad (3)$$

where $y_{\omega,k}$ corresponds with the value of the response variable for each analysis performed (described in section III-F) for the ω-th scenario and the k-th replication, μ is the global effect (i.e., the average value of the considered output variable), parameter α_ω is the main effect of the uncertainty of C_f for the ω-th scenario, parameter β_ω is the main effect of the average of Z_f for the ω-th scenario, parameter γ_ω is the main effect of the uncertainty of Z_f for the ω-th scenario, and parameter δ_ω is the main effect of the Z_f model for the ω-th scenario. Finally, $u_{\omega,k}$ corresponds with the non-biased Gaussian-distributed random error for the ω-th scenario and the k-th replication. The values for each factor are detailed in Table 3.

Since the aim of this study is to identify if each factor has a significant influence over the response variable, the following four sets of inference tests are performed:

$$\begin{cases} H_0 : \alpha_\omega = 0 \\ H_1 : \exists\omega|\alpha_\omega \neq 0 \end{cases} \quad \begin{cases} H_0 : \beta_\omega = 0 \\ H_1 : \exists\omega|\beta_\omega \neq 0 \end{cases}$$
$$\begin{cases} H_0 : \gamma_\omega = 0 \\ H_1 : \exists\omega|\gamma_\omega \neq 0 \end{cases} \quad \begin{cases} H_0 : \delta_\omega = 0 \\ H_1 : \exists\omega|\delta_\omega \neq 0 \end{cases} \quad (4)$$

where the null hypothesis for the first test corresponds to the non statistically-significant influence of the factor on

TABLE 3. Values employed for each scenario.

Scenario	C_f uncert.	Z_f avg.	Z_f uncert.	Z_f model	Scenario	C_f uncert.	Z_f avg.	Z_f uncert.	Z_f model
1	Low	Low	Low	Unif	19	Med	High	Low	Unif
2	Low	Low	Low	Norm	20	Med	High	Low	Norm
3	Low	Low	Med	Unif	21	Med	High	Med	Unif
4	Low	Low	Med	Norm	22	Med	High	Med	Norm
5	Low	Low	High	Unif	23	Med	High	High	Unif
6	Low	Low	High	Norm	24	Med	High	High	Norm
7	Low	High	Low	Unif	25	High	Low	Low	Unif
8	Low	High	Low	Norm	26	High	Low	Low	Norm
9	Low	High	Med	Unif	27	High	Low	Med	Unif
10	Low	High	Med	Norm	28	High	Low	Med	Norm
11	Low	High	High	Unif	29	High	Low	High	Unif
12	Low	High	High	Norm	30	High	Low	High	Norm
13	Med	Low	Low	Unif	31	High	High	Low	Unif
14	Med	Low	Low	Norm	32	High	High	Low	Norm
15	Med	Low	Med	Unif	33	High	High	Med	Unif
16	Med	Low	Med	Norm	34	High	High	Med	Norm
17	Med	Low	High	Unif	35	High	High	High	Unif
18	Med	Low	High	Norm	36	High	High	High	Norm

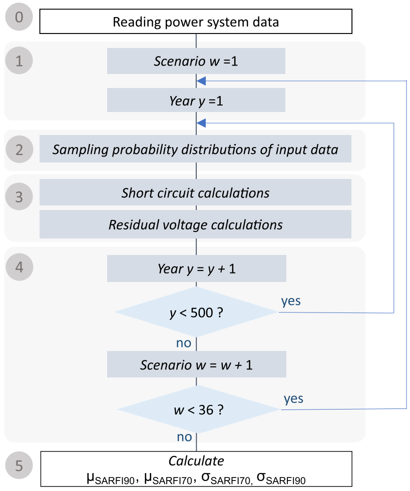

FIGURE 9. Algorithm for the sensitivity analysis flowchart.

the analyzed response variable. The alternative hypothesis indicates that the considered factor makes a significant influence over the output variable [38].

C. ALGORITHM FOR THE SENSITIVITY ANALYSIS

The algorithm proposed for the sensitivity analysis is based in the following steps, summarized in Fig. 9:

Step 0) Reading the data for the selected power system.

Step 1) Initialization of year counter ($y = 1$) and scenario counter ($\omega = 1$). Random seed initialization.

Step 2) According to the values for the ω-th scenario in Table 3, random values are generated for input variables.

Step 3) Calculation of short-circuit currents. Voltage residuals are computed for each bus of the system.

Step 4) Update year counter: $y = y + 1$. If counter $y \leq 500$ go to Step 2). Otherwise, update scenario counter: $\omega = \omega + 1$. If counter $\omega \leq 36$, go to Step 3); otherwise, continue.

Step 5) Indices SARFI90 and SARFI70 are computed for each bus. Mean and standard deviation ($\mu_{SARFI90}$, $\mu_{SARFI70}$, $\sigma_{SARFI70}$ and $\sigma_{SARFI90}$) are estimated.

Finally, an ANOVA analysis is performed using the values obtained from Step 5) above and the input values from Table 3.

VI. SENSITIVITY ANALYSIS: RESULTS

The ANOVA technique detailed in section V-B has been applied to all the buses of the three networks described in section IV with 95% confidence. That is, when the p-value is greater than 0.05, it is considered that the levels of the factor studied do not significantly affect the output variable evaluated at this bus. If the p-value is less than 0.05, it is established that the levels of the factor studied do significantly affect the response of the model.

A. CASE A: EFFECT OF THE UNCERTAINTY IN THE FAULT RATE COEFFICIENT C_f

In order to introduce the statistical technique in a simple case and to become familiar with the detailed results, the sensitivity analysis has been developed through two approaches:

- Graphically, observing in detail an illustrative sample of four buses of the IEEE 24-buses network:
  - bus 2, generator bus in the in the 138 kV level
  - bus 8, load bus in the 138 kV level
  - bus 18, generator bus in the in the 230 kV level
  - bus 19, load bus in the in the 230 kV level.
- Through a generalized study of sensitivity results at all nodes in the three analyzed networks: IEEE 24-buses network, IEEE 118-buses network, and Ecuadorian network with 357 buses.

Figs. 10 and 11 show the effect of the uncertainty in fault rate C_f on the average and on the deviation of voltage sags indices in the 4 representative buses above mentioned. In the figures, the values of the output parameters analyzed ($\mu_{SARFI90}$, $\mu_{SARFI70}$, $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$) is observed together with their confidence interval (for 95% confidence level). Very little variation in the output values is observed in the output parameters at these buses. These results have be analyzed in a systematic way by means of DoE and ANOVA for all the buses of the three analyzed networks. The results obtained are summarized in Table 4. The following conclusions can be drawn:

- Uncertainty in the number of faults per year does not significantly influence the average SARFI90 or SARFI70 in any of the networks. Just in 4.2% and 5.9% of the buses of the IEEE 118 buses network the average SARFI90 or SARFI70 was affected, respectively.
- Uncertainty in the fault rate does not have a generalized affect in the variability of SARFI90 or SARFI70. In the IEEE 118 buses network there are 65.3% and 29.7% of influenced buses in the outputs $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$. The variability of SARFI70 is affected in a very reduced number of buses by the variability of the fault rate in the three networks.

As a result of this case study, it can be concluded that the uncertainty in the variation of the yearly fault rate is not a very significant variable in the analysis of voltage sags indices.

B. CASE B: EFFECT OF THE AVERAGE FAULT IMPEDANCE Z_f

Figs. 12 and 13 show the effect of the selected average fault impedance value in the output of voltage sags indices at the 4 selected representative buses in the IEEE 24 buses network. In this case, a great variation in the voltage sag indices values can be observed depending on the average impedance value considered. This strong influence is observed in $\mu_{SARFI90}$ and $\mu_{SARFI70}$, as well as in the deviation parameters $\sigma_{SARFI90}$ and

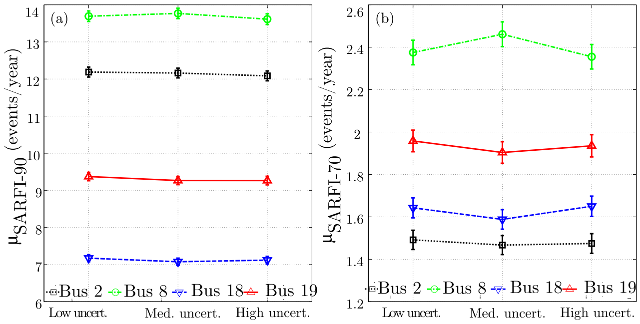

FIGURE 10. Effect of C_f in $\mu_{SARFI90}$ and $\mu_{SARFI70}$ for different representative buses of IEEE 24-buses network.

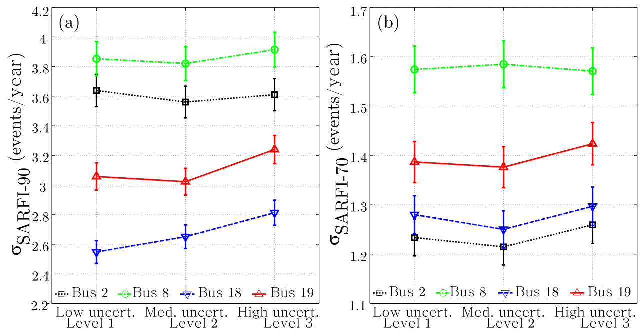

FIGURE 11. Effect of C_f in $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$ for different representative buses of IEEE-24 buses network.

TABLE 4. Percentage of system buses that are significantly influenced ($p < 0.05$) by the uncertainty in C_f (fault rate).

Factor	Output variable	Network		
		IEEE-24	IEEE-118	EC-357
σ_{C_f}	μ_{SARFI90}	0%	4.2%	0.3%
	μ_{SARFI70}	0%	5.9%	4.5%
	σ_{SARFI90}	83.3%	65.3%	76.2%
	σ_{SARFI70}	16.7%	29.7%	17.4%

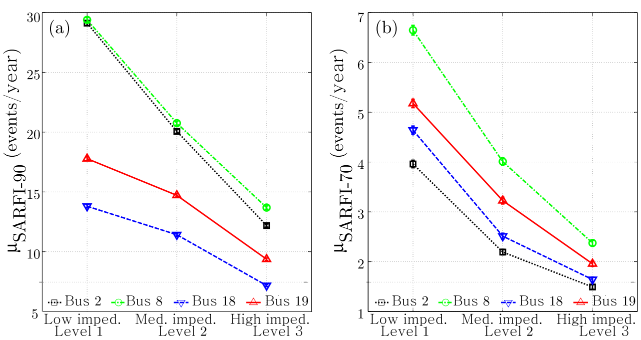

FIGURE 12. Effect of average Z_f in $\mu_{SARFI90}$ and $\mu_{SARFI70}$ for different representative buses of IEEE-24 buses network.

$\sigma_{SARFI70}$. Fig. 12 and Fig. 13 show that both the average and the deviation in SARFI values decrease when the average fault impedance increases.

Table 5 shows the systematized results applied by means of the sensitivity analysis applied to all the buses of the three

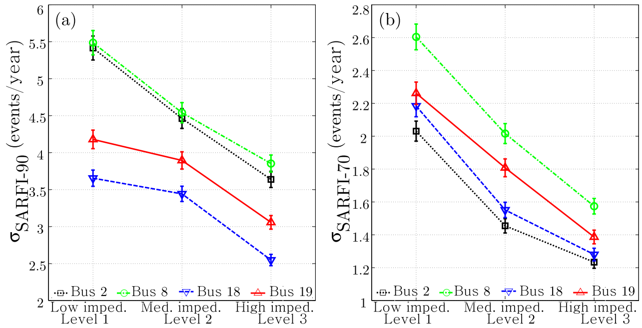

FIGURE 13. Effect of average Z_f in $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$ for representative buses of IEEE 24-buses network.

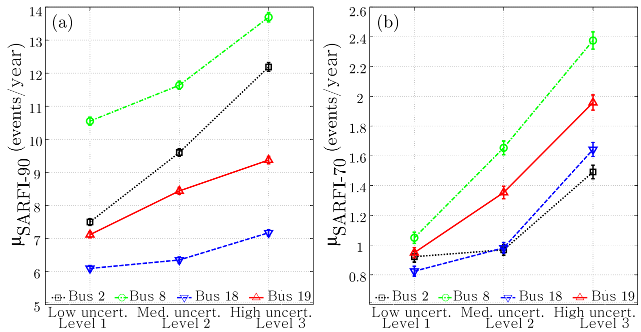

FIGURE 14. Effect of Z_f uncertainty in $\mu_{SARFI90}$ and $\mu_{SARFI70}$ for representative buses of IEEE 24-buses network.

systems under study. In this case, the average fault impedance value has a clear effect in the average SARFI90 or SARFI70 of all the buses and all the networks tested. The average value of the fault impedance considered also affects the uncertainty in the SARFI90 or SARFI70 represented by $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$.

TABLE 5. Percentage of system buses that are significantly influenced ($p < 0.05$) by the uncertainty in the average μ_{Z_f} (fault impedance).

Factor	Output variable	Network		
		IEEE-24	IEEE-118	EC-357
μ_{Z_f}	μ_{SARFI90}	100%	100%	100%
	μ_{SARFI70}	100%	100%	100%
	σ_{SARFI90}	100%	100%	100%
	σ_{SARFI70}	100%	100%	100%

C. CASE C: EFFECT OF THE UNCERTAINTY IN FAULT IMPEDANCE Z_f

The effect of the level of uncertainty (or variability range) in the fault impedance Z_f values is analyzed in Figs. 14 and 15. In the four analyzed buses it can be observed that the higher the fault impedance uncertainty, the higher the average and the deviation of SARFI indices.

Previous results are generalized for all the system buses at all the three networks under study in Table 6. From the analysis of these results, it can be observed that:

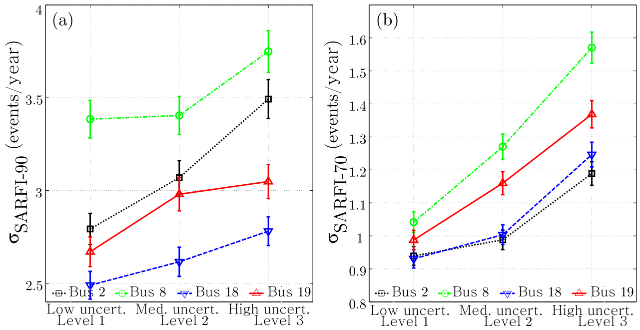

FIGURE 15. Effect of Z_f uncertainty in $\sigma_{SARFI90}$ and $\sigma_{SARFI70}$ for representative buses of IEEE 24-buses network.

- The deviation in the fault impedance value has a clear effect in the average SARFI90 or SARFI70 of all the buses and all the networks tested (at least 99.2% buses are affected by this variation). This result shows that, not only influences the average fault impedance the estimated number of sags, but also the deviation of Z_f has an effect.
- In addition, the deviation of the fault impedance considered also affects the uncertainty in the SARFI90 and SARFI70 ($\sigma_{SARFI90}$ and $\sigma_{SARFI70}$) in, at least 87.4% of the buses affected.

TABLE 6. Percentage of system buses that are significantly influenced ($p < 0.05$) by the uncertainty in σ_{Z_f} (fault impedance).

Factor	Output variable	Network		
		IEEE-24	IEEE-118	EC-357
σ_{Z_f}	$\mu_{SARFI90}$	100%	100%	93.3%
	$\mu_{SARFI70}$	100%	99.2%	93.3%
	$\sigma_{SARFI90}$	100%	95.8%	87.4%
	$\sigma_{SARFI70}$	100%	99.2%	91.6%

D. CASE D: EFFECT OF THE FAULT IMPEDANCE Z_f PROBABILITY DISTRIBUTION MODEL

The effect of selecting a uniformly-distributed or a normal-distributed fault impedance model has been analyzed under the conditions explained in section III-E. These results are shown in Table 7.

According to these results different effects can be observed. In general, the type of probability distribution used to model fault impedance significantly affects voltage sag indices for the majority of buses. For instance, the average values of SARFI indices are influenced by the type of probability distribution used to model fault impedance in between around 50% and 69% of the buses of the three considered networks. A similar effect is observed in the deviation value of SARFI indices with a slightly higher sensitivity to probability distribution employed in networks with higher number of buses. For instance, $\sigma_{SARFI90}$ which represents the inter-annual variability in the SARFI90 index, is affected by the fault impedance probability distribution in

TABLE 7. Percentage of system buses that are significantly influenced ($p < 0.05$) by the selection of the distribution model for Z_f.

Factor	Output variable	Network		
		IEEE-24	IEEE-118	EC-357
$\mathcal{P}(Z_f)$	$\mu_{SARFI90}$	58.4	62.7	50.4
	$\mu_{SARFI70}$	68.8	61.9	59.3
	$\sigma_{SARFI90}$	50.1	24.2	15.2
	$\sigma_{SARFI70}$	56.3	36.9	30.4

50.1% of the buses in the IEEE 24-buses network and only in 15.2% of the buses in the Ecuadorian system.

It follows from these results that a better understanding of the actual probability distribution of the fault impedance would be necessary as the different models applied in the literature lead to statistically different results for a considerable number of buses.

VII. CONCLUSION

The analysis of voltage sags is typically approached by means of probabilistic studies where the stochastic values associated to fault characteristics (fault rate, fault impedance, etc.) are modeled throughout different probability distributions. The difficulties in the selection and parametrization of these probability distributions make that very inconsistent approaches can be found in the literature. In this paper, the sensitivity of voltage sags severity to the uncertain faults parameters is systematically analyzed by means of DoE and ANOVA techniques in order to obtain with statistical rigor whether the analyzed parameters affect voltage sags indices SARFI90 and SARFI70 or not, using a significance level of 5%. Sensitivity studies have been performed at three different size test networks (IEEE 24-buses test reliability system and IEEE 118-buses network) and to the real Ecuadorian transmission network with 357 buses. These results have shown that the uncertainty in the yearly variation of fault rates has a reduced effect on the average and standard deviation of voltage sags severity indices. Therefore, its effect can be neglected in voltage sag studies. On the contrary, the results in the three analyzed networks show that average fault impedance as well as the fault impedance variability (or uncertainty) are critical values for both, average and standard deviation in voltage sags indices. Also, the probability distribution used to model fault impedance has a significant impact on voltage sags levels. The diversity in fault impedance models encountered in literature can therefore impact on the obtained voltage sags results and careful attention must be paid to model realistically this variable.

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