Voltage Sags: Statistical Evaluation of Monitoring Results based on Predicted Stochastic Simulation

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Abstract— This paper presents a methodology specially developed for the estimation of voltage sag characteristics such as magnitude and frequency. The aim of this methodology is to evaluate sags monitoring results based on a stochastic assessment of long-term voltage sag indices. The measured sag indices are evaluated by means of two statistic tools, namely the confidence interval and analysis of variance based on hypothesis testing. A case study based on the evaluation of a six-month monitoring period shows the applicability of the proposed methodology.

***Index Terms*—Power quality, stochastic assessment, voltage sags, voltage dips.**

I. Introduction

VOLTAGE sags, similar to other power quality phenomena, should be treated as a compatibility problem between equipment and power supply. Information about equipment sensitivity can be obtained from manufacturers or via equipment tests. The performance of the supply system can be obtained either by monitoring or via stochastic prediction [1].

Monitoring programs can bring relevant results only if a long period of monitoring is performed. Unusual disturbances as voltage sags may demand around thirty years of measurement considering 90% of confidence level [2]. Thus, an acceptable alternative to avoid long monitoring periods is to use stochastic prediction tools. Another great advantage of stochastic prediction as compared to monitoring is that the required accuracy is obtained right away. Using stochastic prediction it is even possible to assess the power quality of a yet non-existing system [3].

In order to estimate voltage sag parameters and statistically evaluate monitoring results, a methodology has been developed and is presented in this work. First, according to the confidence interval bounds the validation of monitoring results is performed. Then, based on a hypothesis test, the same results are confirmed. Both steps are applied to a case study based on a Brazilian utility system to demonstrate the methodology functionality.

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II. Methodology Overview

The methodology proposed is based on a stochastic approach, which determines the random characteristics of the faults that generate sags. Therefore, the fault location, the fault type, and the fault impedance are stochastically estimated based on Monte Carlo simulation [4]. Some other variables, such as pre-fault voltage, automatic reclosers operation, and protective devices misoperation, will certainly be considered in a future approach.

A. Random Variables Analysis

The selection of the faulted line is based on the uniform probability distribution weighted by both the line length and the fault rate. So, the probability of a fault at line *j* is given by:

$$p(j) = \frac{\lambda_j \cdot \frac{l_j}{100}}{\sum \lambda_i \cdot \frac{l_i}{100}} \tag{1}$$

where λ_i and λ_j are the line fault rates, given in terms of number of faults per year and per a hundred kilometers; l_i and l_j are the line lengths, given in kilometers.

The fault position selection is usually performed in terms of uniform probability distribution, suggesting that each location has the same probability within a certain line. However, this methodology should consider some other distributions, e.g. exponential, gamma, beta, lognormal and weibull.

The fault type and the fault impedance are determined taking into account the respective probabilities of each line. In most cases, these probabilities are given by historical operation data. It is important to remark that in this methodology fault impedance is only considered for line-to-ground and double-line-to-ground faults.

After that procedure for specifying the conditions to randomly choose the variables values, all the necessary characteristics to calculate voltage sags are determined. Further, random numbers generation is performed to select the characteristics of each simulated fault. This process is repeated until the total expected number of faults is reached. This total number of faults is given by:

$$n_{faults} = \sum \lambda_i \cdot \frac{l_i}{100} \tag{2}$$

When more than one year of simulation is desired, this procedure has to be repeated until the number of years is reached. It is highly recommended to simulate a period of many years to avoid that the high randomness of this disturbance leads to inaccurate results.

B. Voltage Sags Calculation

The sag magnitude is calculated using the method of fault positions [5][6]. This method is based on the simulation of faults on a certain location k estimating the voltage sag magnitude at the busbar i. Then, the sag magnitude at busbar i due to a three-phase fault at busbar k is given by:

$$E_{i,k} = E_i^P - \frac{E_k^P}{Z_{kk} + Z_F} \cdot Z_{ik} \qquad (3)$$

where E_i^P is the pre-fault voltage at busbar i, E_k^P is the pre-fault voltage at busbar k, Z_{ik} is the transfer impedance between busbars i and k, Z_{kk} is the driving-point impedance for busbar k, and Z_F is the fault impedance.

Similar equations can be determined for the other types of faults.

Voltage sags frequency estimation, or how often they occur, is a simple task. It is only necessary to count all the events having the voltage sag magnitude under a specific desired limit. In case of simulating more than one year of the system behavior, the final expected sag frequency is the average between the annual sag frequencies.

C. Statistical Analysis

1) Percentile Method

The first step of the statistical procedure is the determination of the confidence interval for the simulation results. Among many existing methods to perform this task, the percentiles method has been chosen to determine the confidence interval bounds. The percentiles method has a great advantage: it can be used no matter what the data probability distribution is. Thus, given a significance level of α%, i.e. confidence level of (1-α)%, the confidence interval lower and upper bounds, respectively $P_{\alpha/2}$ and $P_{100-\alpha/2}$, are calculated. In this work, the adopted confidence level is 95%, i.e. α = 5%, and the confident interval bounds are $P_{2.5}$ and $P_{97.5}$. The confidence level of 95% is the most common level statistically adopted because of the balance between the accuracy (given by the confidence interval range) and the reliability (given by the confidence level).

Further, when the confidence interval bounds for the simulation results are calculated, it is possible to statistically evaluate voltage sags monitoring or even other simulated results simply verifying if the confidence interval contains those results. If any result is not included within the confidence interval it can be characterized as a very unlikely result. The unlikely results, also known as outliers, can usually be disregarded.

It is very important to remember, especially why due to the voltage sags inherent randomness, it is possible that a particular result from simulation cannot portray the expected average behavior of the system. This unlikely result would certainly spoil the results analysis. In order to avoid unlikely results to bring distortions, many years of simulation are required for the convergence of the average results. Since the required number of simulations is strongly dependent on the electrical network characteristic, it must be determined separately to each system.

2) Analysis of Variance - ANOVA

Another way to statistically evaluate the monitoring or new simulated results is the method of ANOVA – Analysis of Variance, based on some hypothesis tests. These tests allow an evaluation to distinguish between likely and unlikely sample results. The occurrence of most unlikely results can be explained by two ways: effectively an event with low probability has occurred or the assumptions taken at the beginning of the test are not true. Together with the evaluation previously mentioned, there are some other situations to apply this statistical concept. They are obtained by testing:

- If a monitoring result is statistically equivalent to an average result from simulation for an individual busbar;
- If different simulation sequences give the same average result for an individual busbar;
- If distinct monitoring results have the same average value for an individual busbar;
- Which busbar has the best result according either to simulation or monitoring results;
- Which busbar has the worst result according either to simulation or monitoring results.

Due to space limitations, only results for the first test will be presented in this paper.

Hypothesis tests include two hypotheses: the null hypothesis (denoted by H_0) and the alternative hypothesis (denoted by H_1). The former is the initial claim and is often specified using previous research or common knowledge. The latter is what is supposed to be true or desired to prove. The alternative hypothesis is sometimes called research hypothesis. The decision-making process for a hypothesis test can be based on the probability value (p-value) for the given test:

- If the p-value is less than or equal to the significance level α then the null hypothesis is rejected and a support for the alternative hypothesis is claimed.
- If the p-value is greater than α level, the test fails to reject the null hypothesis and cannot claim support for the alternative hypothesis.

The test intends to check the equality of mean values in order to prove that the simulation and the monitoring results are statistically equivalent. Therefore, the null hypothesis is $\mu_1 = \mu_2$ and the alternative hypothesis is $\mu_1 \neq \mu_2$. The methodology will be applied to a group of busbars, based on the individual analysis of each busbar performance. However, with small changes in the algorithm, the analysis can be performed in the whole group of busbars or in the entire network.

III. Case Study

In order to apply the methodology proposed a MatLab routine has been made. The routine performs the variables draws, runs the short-circuit calculation software, and reads its outcome. This implementation is the embryo of the future upgrades to be developed on the software described in [7].

The main characteristics of the system where the case study is carried out are: long and sub-compensated transmission lines at 230 and 138 kV; major loads are very far from the hydro generation stations; the generation is basically composed by hydro and gas-fired-thermal units. The system contains 95 transmission lines at 230 and 138 kV and 173 busbars at 230, 138, 34.5 and 13.8 kV. The simplified one-line diagram is shown in Fig. 1. The monitoring units P1 to P12 are also presented.

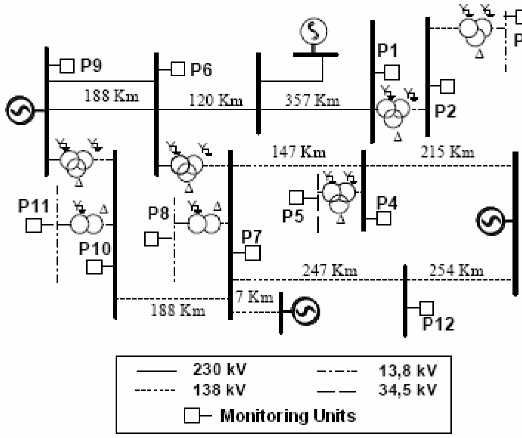

Fig. 1. Simplified one-line diagram of the analyzed network

The fault rates of the transmission lines classified into two voltage levels are presented in Table I. This table also presents the probability distribution among the four types of faults: line-to-ground (LG), double-line-to-ground (LLG), double-line (LL) and three-phase (3L).

TABLE I
TRANSMISSION LINES FAULT RATES

Voltage Level	Fault Rate (*)	LG	LLG	LL	3L
230 kV	1.5	80%	3%	7%	10%
138 kV	3.5	62%	14%	10%	14%

(*) number of faults / 6 months * 100 km

Since the aim of this case study is to evaluate sags monitoring results based on simulated stochastic prediction for a monitoring period six-month in length, the fault rates used in the simulation, presented in Table I, had to be adjusted to the same period.

For the stochastic assessment of voltage sags the fault impedance was considered only if the fault type is LG or LLG. The fault impedance distribution is presented in Table II.

During the stochastic assessment of voltage sags the following premises were taken into consideration:

- Phase-to-neutral voltages considered on simulations and measurements;
- Fixed pre-fault voltages equal to 1.0 p.u;
- Faults at busbars have been not simulated;
- The fault position follows a uniform distribution;
- The assessment is based on voltage sag magnitude and frequency.

TABLE II
FAULT IMPEDANCE DISTRIBUTION

Impedance (Ohms)	Probability
0	0.25
5	0.25
25	0.25
40	0.25

A. *Voltage Sag Monitoring*

Twelve busbars have been on purpose chosen as incident busbars at 230, 138, 34.5 and 13.8 kV geographically distributed in the system. According to the one-line diagram presented in Fig.1, the monitoring units have been installed at strategic positions aiming at covering some important network features: topology, load concentration, sensitive consumers, generation centers, large short-circuit level busbars, and transformers connections. As a result, the network behavior in terms of voltage sags is well portrayed by those twelve monitoring equipment.

It is important to remark that, as expected, the events recorded at the beginning of the monitoring period have been very concentrated between 0.90 and 0.85 p.u.. Those events do not qualitatively contribute to the results analysis, although highly overloads the communication system. Since the communication between the monitoring nodes and the data server has been done by a cellular telephone channel, the decision was to change the PQ-monitors trigger setting to 0.85 instead of 0.9 p.u.

B. *Statistical Analysis*

According to (2) 157 short-circuits per semester has been the number of faults for the network analysed. Thus, every simulation loop will consider 157 fault events.

Fig. 2 shows the voltage sag frequency evolution at P1 due to three independent simulation series out of 50 simulation loops. The results present a large variability for each simulation confirming the great voltage sags randomness. In spite of that, a good convergence can be gotten when focusing on average evolution as shown in Fig. 3.

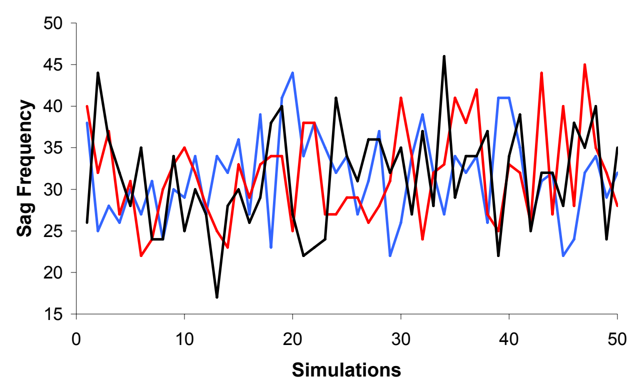

Fig. 2. Voltage sags frequency at P1 obtained from three independent series of simulations.

From Fig. 3 it is easy to observe that each simulated sequence has a distinct behavior at the beginning of the simulation. However, it is attenuated by the averaging process as the simulation loop runs. The expected situation is that any new sequence will give a final result very close to these three sequences at the 50th simulation. The other eleven analyzed busbars presented a similar behavior.

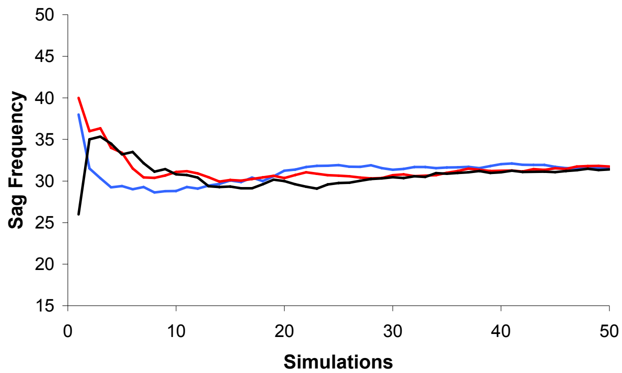

Fig. 3. Voltage sags average frequency at P1 obtained from three independent series of simulations.

Fig. 4 presents the frequency distribution for the voltage sags magnitudes considering the same three sequences of 50 simulation loops. According to previous comments, there is a very large concentration of events with magnitude above 0.80 p.u.

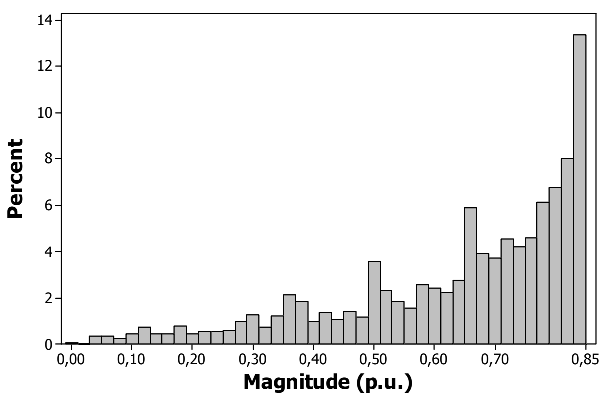

Fig. 4. Voltage sags magnitudes frequency distribution at P1 considering the three independent simulations results.

The statistical results of the sag frequency obtained by the stochastic assessment for the twelve analyzed busbars are presented in Table III. The statistical estimated values are: the average, the standard deviation, and the coefficient of variation. From inspection of Table III, it can be observed that P5 presents the best performance while busbar P3 experienced the largest number of sags. Further, P3 has the best coefficient of variation, indicating smaller dispersion than the other points, while P5 has the largest dispersion of the simulated results.

The 95 % confidence interval was calculated according to section II.C.1. Therefore, based on other four sequences out of 50 simulation loops, Fig. 5 through 7 show the sag frequency for each simulation and the confidence interval limits for the busbars P1, P2, and P12. In order to improve the quality of the confidence interval their limits have been calculated using the sag frequencies obtained during those four sequences of simulations.

TABLE III
SAG FREQUENCY STATISTICAL ANALYSIS

Location	Average	Standard Deviation	Coefficient of Variation (%)
P1	31.8	5.56	17.48
P2	35.6	5.10	14.35
P3	37.9	5.18	13.67
P4	35.9	5.06	14.08
P5	18.7	4.36	23.36
P6	19.2	4.33	22.60
P7	29.4	5.03	17.14
P8	28.4	4.48	15.82
P9	28.7	4.47	15.62
P10	35.3	5.25	14.88
P11	35.3	5.25	14.87
P12	35.7	5.31	14.90

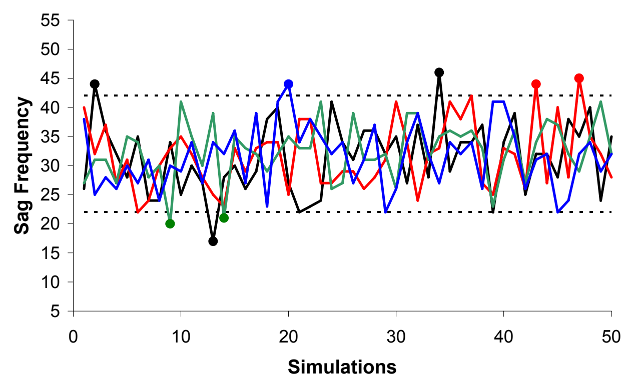

Fig. 5. 95% Confidence interval at P1 for the sag frequency obtained during the 4 sequences of simulations.

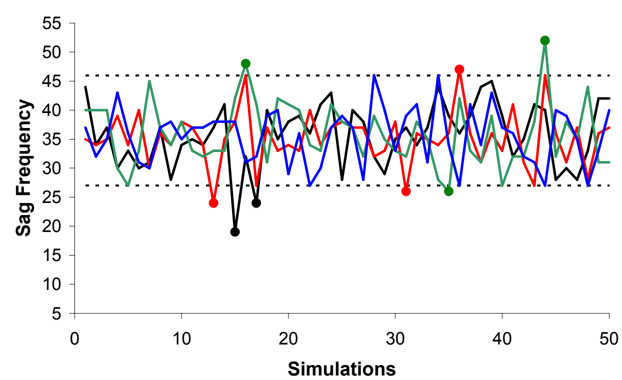

Fig. 6. 95% Confidence interval at P2 for the sag frequency obtained during the 4 sequences of simulations.

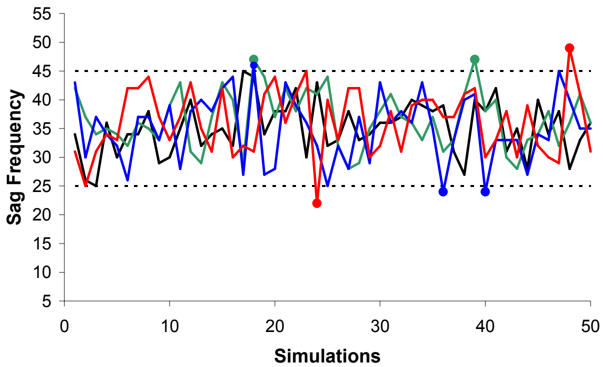

Fig. 7. 95% Confidence interval at P12 for the sag frequency obtained during the 4 sequences of simulations.

From these figures it is possible to observe once more the great randomness of voltage sags. Calculating a confidence interval it is possible to focus the analysis on those points that are not included in the confidence interval. According to what was previously discussed, those results have a low probability of occurrence.

C. Monitoring Results Statistical Validation

An important practical use of the confidence intervals discussed is the statistical evaluation of monitoring results. This is particularly true for those results obtained from very short monitoring periods. The main purpose of this evaluation is to establish how far the monitoring results are from the expected average behavior of the system determined by stochastic simulation. The goal is to quantify the probability of occurrence of the monitoring results.

In order to apply this procedure, it is firstly necessary to check whether the simulated system is correctly modeled and accurately portray the actual system behavior. The main features to be checked are: system topology, lines fault rates, fault positions distribution, fault types distribution, and generation dispatch. The closer that features are, the more accurate the results will be.

Table IV shows voltage sags frequency registered by each one of the twelve monitored points during six months. Furthermore, the last two columns present upper and lower bounds to 95% confidence interval calculated by stochastic simulation and graphically presented in Fig. 5 through 7.

TABLE IV
SAG FREQUENCY – MONITORING AND CONFIDENCE INTERVALS

Location	Monitoring	Confidence Interval	
		Lower	Upper
P1	26	22	42
P2	28	27	46
P3	39	29	49
P4	40	27	47
P5	46	11	28
P6	23	12	28
P7	17	21	40
P8	20	20	37
P9	31	20	38
P10	29	25	45
P11	25	25	45
P12	56	25	45

From this table it can be observed that sag measurements at the majority of the busbars are within the confidence intervals. However, the results at three of them failed to represent the long-term average values. This divergence is due to the combined effect of some factors, namely:

- If the premises taken into consideration during the stochastic simulation were not in accordance with the actual system situation, this initial divergence will certainly lead to some errors that will affect all the results. These premises include pre-fault voltages, distribution of fault positions along the lines, system topology and its modeling, occurrence of faults at different locations as busbars and medium voltage transmission lines;
- Secondly, the inherent random characteristic of the voltage sags can lead to unlikely results from the simulation and even the monitoring process;
- The short period of measurement can conduct to specific results different from the long-term average values
- Finally, during the monitoring period, it has been observed that some equipment experienced many types of troubles and as a consequence they might be out-of-service for some periods. Consequently, it is likely that some events which occurred during these periods were not registered.

The applicability of such a methodology can also be confirmed by the p-value method. The ANOVA was performed according to the following hypotheses: null hypothesis is $\mu_{simulation} = \mu_{monitoring}$ and the alternative one is $\mu_{simulation} \neq \mu_{monitoring}$. Table V shows the results for each of the 12 points monitored considering a confidence level of 95%. It can be concluded that, except for the points P5, P7 and P12, the simulation and monitoring results are statistically equivalent.

TABLE V
P-VALUE FOR THE 12 MONITORED BUSBARS

P1	**P2**	**P3**	**P4**	**P5**	**P6**
0.300	0.140	0.836	0.423	0	0.378
P7	**P8**	**P9**	**P10**	**P11**	**P12**
0.015	0.064	0.604	0.233	0.051	0

Further, since P8 and P11 values are near the significance level of 0.05, it can be noticed that those points had been almost rejected. The best p-value is obtained at P3, with 0.836, attesting a great adherence between monitoring and simulation results for that busbar. All those p-values can be taken as the occurrence probability of the monitoring results.

Analogous analysis can be conducted in voltage sags magnitudes. Table VI presents the average sag magnitudes per monitored point and the respective 95% confidence interval bounds calculated by the stochastic simulation.

TABLE VI
SAG MAGNITUDE– MONITORING AND CONFIDENCE INTERVALS

	Monitoring	Confidence Interval	
		Lower	**Upper**
P1	0.727	0.145	0.847
P2	0.716	0.203	0.846
P3	0.730	0.283	0.848
P4	0.724	0.326	0.846
P5	0.700	0.113	0.847
P6	0.684	0.270	0.847
P7	0.697	0.292	0.847
P8	0.720	0.145	0.844
P9	0.750	0.104	0.844
P10	0.768	0.151	0.840
P11	0.730	0.125	0.840
P12	0.680	0.107	0.840

From this table, it is observed that the measured sag magnitudes at all analysed busbars are within the 95% confidence interval. Thus, it can be concluded that the measured magnitude are statistically validated too. Due to space limitations, ANOVA tests for magnitude results are not discussed in this paper.

IV. CONCLUSIONS

This paper has presented a methodology which incorporates effective techniques for voltage sags strategic studies. This methodology allows the evaluation of voltage sag monitored results, based on the statistical analysis of two sag characteristics, namely magnitude and frequency.

It is also to be reminded that any distribution mode rather than the uniform distribution used in this article can be employed for the fault positions distribution used in the stochastic assessment of voltage sags.

In order to accurately compare monitoring and stochastic simulation results it is crucial to check the correspondence between the actual and the simulated system features for each situation, e.g. system topology, lines fault rates, fault positions distribution, fault types distribution, and generation dispatch

A great contribution of this methodology is the evaluation of monitoring results, considering the high randomness of the voltage sags and the short-term monitoring periods. Moreover, through the stochastic simulation it is possible to quantify the monitoring results probability of occurrence.

The case-study presented demonstrates how to statistically evaluate monitoring results in terms of two methods: confidence interval and p-value.

Future developments include the application of this methodology to electric systems with distinct characteristics from the one assessed here and the use of resampling techniques such as bootstrap and jackknife. Also, with small changes in the algorithm, this methodology proposed can be applied to evaluate economically feasible alternatives for mitigating voltage sags impact to sensitive loads and to quantify the cost and financial losses due to voltage sags.

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VI. BIOGRAPHIES

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