Power Quality in Modern Electric Distribution Systems Assessment using Probabilistic Approach

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Abstract—**This paper deals with the problem of assessing the impact of Distributed Generation on the existing electrical distribution systems from the reliability point of view. A main point in the reliability analysis performed in this work is the probabilistic characterization of the random variables involved in the reliability calculations, as time to failure, duration of service restoration and reclosure time. The reliability assessment has then been performed both for traditional distribution systems and for distribution systems containing distributed generation, by means of different types of analysis**

Keywords- electric distribution system, power quality, probabilities

I. INTRODUCTION

The necessity of reducing the high pollution produced by classical generation systems, the raising level of technological solutions available and, especially, an explicit trend – in several countries – towards strong incentives for using renewable sources are among the main reasons explaining the success of the so-called distributed or dispersed generation [1, 2, 3].

Retail sale of electric energy involves the delivery of power in ready-to-use form to the end users. Whether marketed by a local utility, load aggregator, or direct power retailer, this electric power must flow through a power delivery system on its way from power production to customer. This delivery system consist of thousands of transmission and distribution lines, substations, transformers and other equipment scattered over a wide geographical area and interconnected so that all function in concert to deliver power as needed to the utility's customers.

The term *power quality* represents a number of heterogeneous topics and phenomena, ranging from the continuity of supply to disturbances and waveforms, up to the management of economical aspects concerning commercial quality. The increasingly higher pressure from the customer side to improve the quality levels has pushed several countries towards the adoption of a dedicated regulation for the various aspects of the electricity services.

II. RELIABILITY ISSUES

The current trend in the reliability area is towards the introduction of reliability indices into risk management calculation programs able to assist the operators in undertaking decisions concerning system planning and operation. In the context of competitive electricity markets, the economic aspects include a well-designed risk management system, able to take into account both the supplier and the customer side [4]. Since the activity of both suppliers and customers is profit-oriented, it is important for the provider to include the uncertainty related to the customer choices into the risk management analysis tools. A crucial aspect is the trade-off between the need for reducing costs and the maintenance of a satisfactory level of reliability. Most of the techniques currently used for reliability analysis assume constant failure rate for the system components. This assumption strictly (and mathematically) corresponds to consider all the system components operating in their best life conditions, that is, in the lower (and constant) part of the well-known "bath-tube" curve representing the time evolution of the failure rate.

However, several measures aimed at reducing the operation costs, such as reduction of the maintenance cadence or postponement of the component substitution, may cause an increase of the age of the components and, in particular, an increase of their failure rate. Hence, the system reliability gets worse and may exceed the performance limits imposed by the regulation. The actual risk is the reliability worsening due to the intention of saving money in the short-term. Once started, in the long-term this worsening process could be very difficult to recover, since it would require huge investments. A careful investment scheduling is then essential in order to keep the system operation at acceptable levels.

On the technical point of view, handling non-constant failure rates is a key requirement for the reliability analysis tools that are included into risk analysis or risk assessment programs. In the same way, the reliability tools should use the full probability density functions (PDFs) instead of limiting the analysis to the expected values and standard deviations.

In fact, reliability is associated with rare events, whose probability distributions may significantly differ from the Normal ones. Combining the random variables involved in the reliability analysis in the presence of generic probability distributions is a difficult task, that can be handled by using different techniques. A typical technique uses the Monte Carlo simulation for computing the PDFs.

This technique is numerically intensive and cannot give unique results. Another analytical approach is aimed at computing the moments of the random variables of interest (the reliability indices), associating a posteriori these moments to well-known PDFs by means of an approximated evaluation of the values of the moments. An approximation of the PDFs by using the Weibull distribution is shown in [5]. The new promising technique illustrated in [6] computes numerically the PDFs by using a characteristic functions-based approach, providing a fast and complete evaluation of the PDF of the reliability indices.

One of the most challenging aspects of distribution reliability is the estimation of the costs associated to the interruptions [7,8]. When an interruption occurs, it is impossible to exactly establish the amount of load that would have been served during the period of interruption. Typically the amount of load is considered to be equal to the conventional load of each customer served by the portion of system affected by the interruption. A more refined possibility could be using the load profiles representing the time behavior of the customer consumption. However, these load profiles typically represent classes of customers and as such are not easy to be used or accepted for the assessment of the customers' interrupted load. While computing the interruption costs, usually constant interruption cost rates are assumed. We underline that current analysis is performed for the case in which duration of the interruption is equal with customer service restoration duration. This is due to the fact that in many cases, duration of the service restoration is bigger than duration of service interruption and therefore penalties calculation based upon interruption duration may lead to much too optimistic results (for example, a 2 minute interruption may lead to hour-long power restoration process).

Studies are in progress to identify non-constant cost rates. In [9] it has been shown that using constant interruption cost rates can significantly underestimate the annual interruption cost with respect to keeping the average cost variation into account. Finding a more accurate way to compute the interruption costs is a key challenge for the research in the reliability field.

A crucial aspect for distribution system reliability is the service restoration process after a fault. In this process, the number of customers affected by an interruption is progressively reduced by performing a set of switching and sectionalising actions aimed at locating the fault, isolating the faulted section and progressively restoring the service to all the customers involved in the interruption. For example, Fig. 1 shows for a real distribution system, the evolution in time of the number of customers that experience supply interruption during the execution of manual restoration operations after a fault.

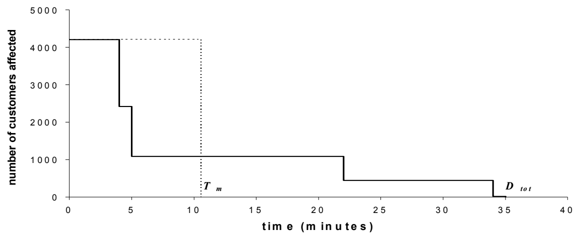

Figure 1. Evolution of the number of customers interrupted during the service restoration process.

The resulting curve, describing the ongoing process of service restoration, has a multi-step profile. The process of service restoration finishes when the last customer (or group of customers) is energised. The time instant at which all customers are supplied is used to compute the total duration D_{tot} of service restoration. Furthermore, an equivalent weighted restoration time T_m can be evaluated, corresponding to the weighted average of the duration of supply interruption during the restoration phases, assuming as weights the numbers of interrupted customers at each phase. The pair (D_{tot}, T_m) provides indicative information on the evolution of the restoration process.

III. Reliability Models of Distribution Systems

The framework for addressing continuity of supply is given by reliability analysis. Reliability indices are used by the utilities as performance limits, and the values of the indices are updated with time in order to force the distribution companies to reach a better performance level.

Distribution systems reliability is one of the most important topics for the electric power industry, due to its high impact on the cost of electricity and its high correlation with customer satisfaction. Reliability assessment of distribution systems is performed in order to evaluate the effectiveness of continuity of supply, resulting in the computation of reliability indices, which use is essential for setting up performance standards for the continuity of supply regulation. A typical distinction for reliability indices is made between local indices, referred to a single load point (e.g., frequency and duration of the interruptions, power and energy not supplied), and global indices, representing the overall reliability of the system [10, 11, 12].

The first step for applying probabilistic reliability analysis is to define the random variables (RVs) involved in the study. However, some indices are defined under the assumption of exponential distribution of the time to failure with constant failure rate $\boldsymbol{\lambda}$, so that the corresponding indices can be computed by using only the mean values of the RVs. A more complete view is to consider a set of random variables (e.g., restoration time $\boldsymbol{\tau}$, number of faults occurred in a specified time period $\boldsymbol{n}$) represented by their PDFs, thus computing the reliability indices by means of analytical or Monte Carlo simulations [13, 14, 15].

The reliability analysis is performed by considering number of occurrences of the faults and restoration times to be RVs subject to the randomness of the faults $f \in \Theta$ during the time interval $[0,T]$.

A key point in the reliability analysis performed in this work is the probabilistic characterization of the restoration times. Generally speaking, there is a multitude of distribution functions which can be used in calculation of $\boldsymbol{\tau}$.

A very important issue for distribution systems reliability is represented by the service restoration process after a fault occurrence. The number of customers affected by a fault and therefore subject to service restoration process, has a decreasing multi-step profile (Figure 1). The evolution of the number of customers interrupted during the service restoration process is characterized by two indices (D_{tot}, T_m) which can provide valuable information about the evolution of the ongoing process of service restoration.

If a set of data concerning the occurrence and evolution of faults in a real system is available, an effective assessment of the probability distributions for the fault-related quantities is possible by using suitable *goodness-of-fit* statistical tests [16].

The Normal, ***chi-square*** and ***Kolmogorov-Smirnov*** statistics are *continuous* distributions (in contrast to the Binomial and Poisson *discrete* distributions). Because continuous statistics are not limited to discrete values, there is almost no probability that a particular precise value will occur. We ask, therefore, about the probability of getting a particular value *or less,* or the value *or more.*

The probability distributions [17] tested in function of the time *t* include the (one-parameter) *Exponential* and *Rayleigh* distribution, the two-parameter *Normal*, *Weibull*, *Gamma*, *Lognormal* distributions and the three-parameter *Beta* distribution.

IV. Analytical Simulation Adopting the Characteristic Functions

Let *z* be a stochastic variable and *p*(*z*) be the probability density function for *z*; i.e., the probability of obtaining a value of *z* between *a* and *b* is:

$$\int_{a}^{b} p(z)dz \tag{1}$$

The expected value of any function of *z*, for example g(*z*), is defined as:

$$E\{g\} = \int_{-\infty}^{\infty} g(z)\cdot p(z)dz \tag{2}$$

.

The expected value of the function $e^{j\omega\cdot z}$ is called the characteristic function for the probability distribution *p*(*z*), where ω is the parameter that can have any real value and j is the square root of (-1). That is to say, the characteristic function of *p*(*z*) is:

$$\Phi(\omega) = E\{e^{j\omega\cdot z}\} = \int_{-\infty}^{\infty} e^{j\omega\cdot z}\cdot p(z)dz \tag{3}$$

.

The characteristic function will generally be a complex function, i.e.,

$$\Phi(\omega) = X(\omega) + jY(\omega) \tag{4}$$

.

Since

$$e^{j\omega\cdot z} = cos(\omega\cdot z) + j\,sin(\omega\cdot z) \tag{5}$$

,

the components of the characteristic function are given by:

$$X(\omega) = E\{cos(\omega\cdot z)\} = \int_{-\infty}^{\infty} cos(\omega\cdot z)\cdot p(z)dz \tag{6}$$

,

and

$$Y(\omega) = E\{sin(\omega\cdot z)\} = \int_{-\infty}^{\infty} sin(\omega\cdot z)\cdot p(z)dz \tag{7}$$

.

Thus, given a probability distribution *p*(*z*) it is a straightforward computation to calculate the real and imaginary components of its characteristic function.

The crucial property of characteristic functions is that the characteristic function of the sum of two independent random variables is the product of the characteristic functions of those variables.

It is usually more convenient to work with the logarithm of the characteristic function, also called *second characteristic function*:

$$\Psi_{\mathbf{z}}(\omega) = ln(\Phi_{\mathbf{z}}(\omega)). \tag{8}$$

The logarithm of the characteristic function will also be a complex function with real and imaginary components. In this case, the products of characteristic functions become sums of second characteristic functions. This property of characteristic functions can be represented as follows. If $\Phi_x(\omega)$ and $\Phi_y(\omega)$ are the characteristic functions of the independent RVs $\boldsymbol{x}$ and $\boldsymbol{y}$, respectively, then the characteristic function of a variable that involves taking an observation of $\boldsymbol{x}$ and an observation of $\boldsymbol{y}$ and adding them together to obtain $\boldsymbol{z} = \boldsymbol{x} + \boldsymbol{y}$ is given by:

$$\Phi_{\mathbf{z}}(\omega) = \Phi_x(\omega)\cdot\Phi_y(\omega) \tag{9}$$

,

and hence:

$$\Psi_z(\omega) = \Psi_x(\omega) + \Psi_y(\omega) \tag{10}$$

.

If two variables are not independent, the proposition concerning the characteristic function involves the characteristic function of the conditional probability distribution.

The process of aggregating data, such as combining monthly data to obtain quarterly or annual data, is easily presented in terms of characteristic functions. If the smaller unit data are statistically independent, then the proposition concerning the characteristic function of the sum of random variables applies.

There is another operation that is often involved with combining random variables. Suppose ***x*** and ***y*** have different probability distributions, but they are treated as coming from the same population. In effect the probability distribution of the combination involves the probabilities that an observation came from the ***x*** population or the ***y*** population. Let these probabilities be presented as p_x and p_y and their probability densities be denoted as $f(\boldsymbol{x})$ and $f(\boldsymbol{y})$, respectively. The probability density that an observation from the combined population has a value z is

$$f_{\mathbf{z}}(\mathbf{z}) = p_x \cdot f_x(z) + p_y \cdot f_y(z \quad (11)$$

.

If the characteristic functions for $f(\boldsymbol{x})$ and $f(\boldsymbol{y})$ are Φ_x and Φ_y then the characteristic function for the combined population is given by:

$$\Phi_z(\omega) = p_x \cdot \Phi_x(\omega) + p_y \cdot \Phi_y(\omega \quad (12)$$

.

In general, the characteristic function is not defined for any probability distribution. However, if it is not possible to define the characteristic function analytically, it is possible to provide a numerical evaluation of the characteristic function by sampling the PDF of the RV in the time domain and successively applying the Discrete Fourier Transform (DFT), as shown in [6].

V. Numerical Results

Two large real urban distribution systems fed at 6,3 kV and 22 kV have been considered. These system contain many underground cables, some of which with a very long operational life (up to 50 years or more). For characterizing the random variables involved in the restoration process, the 6,3 kV system has been used, with failure data related to three years of operation. Only manual operations are considered in the analysis of the restoration process, since no remote control was in place in the system during the time interval of the analysis. The evaluations are carried out through various *goodness of fit* statistical tests, using real data representing the faults occurred in a specific time period of observation on a 6,3 kV urban distribution system.

The distributions tested are Gamma, Exponential, Normal (Gauss), Log-normal, Inverse-normal, Beta (max), Weibull and Rayleigh. For all these distributions, an initial table is presented, containing the ***K-S test*** error calculated for each type of distribution, thus improving the overall analysis by displaying the most useful distributions, that is the ones with relatively low errors. The sample set contains 163 data, with sample mean of 149,3 hours and sample standard deviation of 208,6 hours (139%). The data sample contains also three faults involving pairs of cables fed by the same busbars in which, after the occurrence of a first fault, another fault could have been caused by transient phenomena during restoration and is characterised by almost null time to failure.

The ***goodness-of-fit test*** of different probability distributions has been carried out by first performing the ***K-S test***. The four distributions with lower error, i.e. Weibull, Inverse-Normal, Exponential and Gamma have been studied in more detail by performing the ***chi-square test***, by using classes with uniform width.

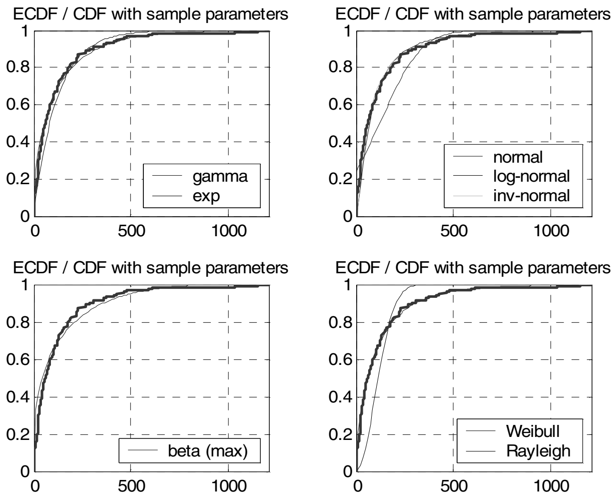

Figure 2. ECDF / CDF comparison for different distributions for *time to failure* assessment.

Weibull distribution: the calculated shape and scale parameters are α = 0,719 and β = 96,31. The ***K-S test***, performed with the level of significance of 5% showed that the hypothesis is impossible to be verified, due to the observed error (0,0829), which lies in the region between the minimum error for rejection (0,1131) and the maximum value for acceptance (0,0698).

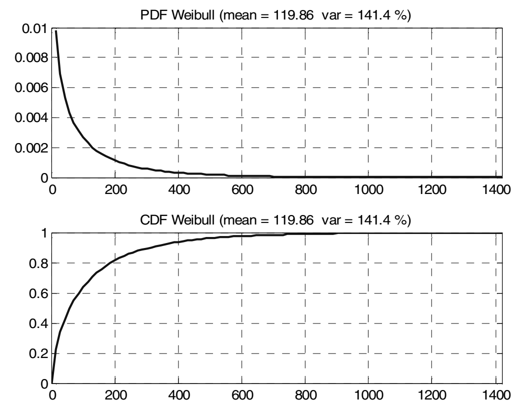

Figure 3. Weibull PDF and CDF with sample parameters.

A ***chi-square test*** has been performed with 14 uniform classes (see Fig. 4). The test refers to 11 degrees of freedom (with mean value and variance corresponding to the sample mean and the sample variance, respectively) and results in a maximum error for acceptance of 18,75%. The observed error was 15,62. The hypothesis was accepted with Λ=5% and the maximum level of significance for the acceptance is 13,98%.

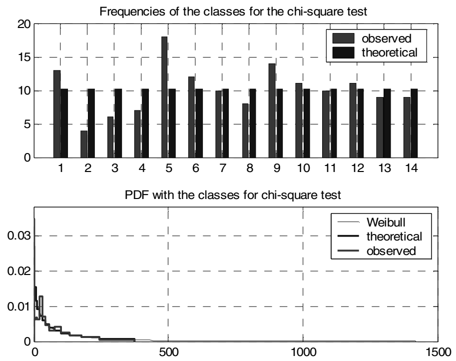

Figure 6. Inverse-Normal PDF and CDF with sample parameters

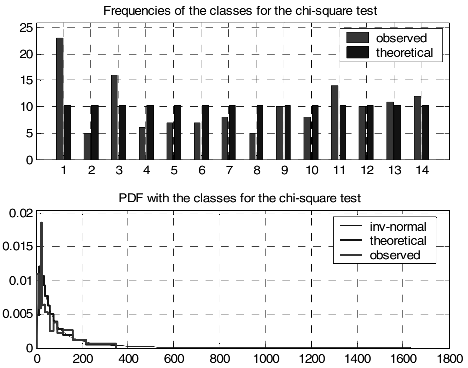

Figure 7. Results of the ***chi-square test*** for the time to failure with Inverse-Normal distribution and comparison between the ECDF and the Inverse-Normal CDF

The ***chi-square test*** performed showed that the hypothesis was rejected with Λ%=5%, the observed error (31,32) being bigger than the minimum error for acceptance (22,36), while the maximum error for the acceptance was 19,68 (see details in Fig: **7**). The maximum significance level for acceptance was Λ_{max}%=0,1%.

VI. CONCLUSIONS

This paper addressed the power quality aspects as continuity of supply for modern electrical distribution systems (intelligent, or containing distributed generation), investigating the corresponding reliability issues in a probabilistic way. The research efforts went mainly into the direction of evaluating the influence that power quality has on the electrical distribution systems. The first step for achieving this goal was the probabilistic characterization of the random variables involved in reliability assessment as inputs (number of the interruptions, time to failure, duration of service restoration and reclosure time). In order to perform a proper estimation of upper mentioned random variables, various goodness-of-fit tests (Chi-square, Kolmogorov-Smirnov and Geometrical adaptation) were used, performed on the data gathered from a large real electrical distribution system. This part of the analysis proved to be a particularly useful mean of evaluation of the most suitable probability distributions. The PDFs of the restoration times allowed for computing the probability distributions of the duration-dependent reliability indices by using different methods (e.g., analytical or Monte Carlo). In particular, the representation of the restoration time by using the Gamma PDFs presented the key advantage of simplifying the numerical treatment of the probability distributions, by enabling the use of analytical expression of the characteristic functions of the PDFs, thus offering the possibility to the distribution system operators to analytically evaluate the PDFs of local and global reliability indices in a fast and general way, even in the case of PDFs with multi-modal shape. Future developments include linking the results of the analysis performed in this paper to probabilistic evaluations of the economic indicators associated to the interruptions, in order to build a comprehensive probabilistic risk assessment framework for the continuity of supply of electricity distribution systems.

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