Part I

GENERAL CONCEPTS AND DEFINITIONS

This part covers general and introductory concepts. Chapter 1 presents an overview of probabilistic aspects of harmonics where initial models were restricted to the analysis of instantaneous values of voltages and currents. Direct analytical methods were originally applied with many simplifications. Attempts to use phasor representation of current also used direct mathematical analysis and simple distributions of amplitude and phase angle. Direct simulation was applied to test the assumptions used. When power systems measurement became more powerful the real distributions were measured for some loads and this enabled a significant increase in the accuracy of observations. The limitations to the application of harmonic analysis in general, and the issues that determine whether full spectral analysis should be used, are discussed. The chapter also reviews existing methods associated with harmonic measurement of nonstationary voltages and currents waveform, characterization of recorded data, harmonic summation and cancelation in systems with multiple nonlinear loads and probabilistic harmonic power flow.

Chapter 2 attempts to integrate spectral analysis and probability distribution concepts, for a better understanding of the nature of time-varying harmonics and possibly as a more precise way to treat time-varying harmonics and validate harmonic summation studies. Similarities between spectral analysis and probability distribution functions are considered and discussed.

Chapter 3 explores the basic definitions of harmonics (Fourier/spectral analysis) of periodic and nonperiodic functions, that is, discrete and continuous range of frequencies. Definitions of typical harmonics and transients phenomena are proposed.

Chapter 4 deals with the correct definitions that characterize the flow of electric power/energy under probabilistic conditions.

Finally, Chapter 5 presents Joseph Fourier’s heat transfer experiment through the use of finite element analysis. An iron ring is modeled and transient thermal analysis is performed to reproduce the data Fourier obtained experimentally. Simulated data give a clear view of how Fourier first thought of representing temperature distribution in a ring as a combination of sinusoidal functions and how this experiment gave information about how harmonics content is modified in time. The use of new signal processing methods, based on time–frequency decomposition, further illustrates Joseph Fourier’s physical intuition to visualize the time varying components long before the mathematical foundation was developed.
1

Probabilistic aspects of time-varying harmonics

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1.1 Introduction

This chapter presents an overview of the motivation, importance and previous development of the text. This chapter considers the early development of probabilistic methods to model power system harmonic distortion. Initial models were restricted to the analysis of instantaneous values of current. Direct analytical methods were originally applied with many simplifications. Initial attempts to use phasor representation of current also used direct mathematical analysis and simple distributions of amplitude and phase angle. Direct simulation was applied to test assumptions used. When power systems measurement systems became sufficiently powerful the real distributions were measured for some loads and this enabled a significant increase of accuracy. However, there is still a lack of knowledge of the distributions that might be used to model converter harmonic currents. The chapter concludes by considering the limitations to the application of harmonic analysis.

The application of probabilistic methods for analyzing power system harmonic distortion commenced in the late 1960s. Initially, direct mathematical analysis was applied based on instantaneous values of current from individual harmonic components [1]. Methods were devised to calculate the probability density function (pdf) of one total harmonic current generated by a number of loads, given the pdfs for the individual load currents. One of the first attempts to use phasor notation was applied by Rowe [2] in 1974. He considered the addition
of a series of currents modeled as phasors with random amplitude and random phase angle. Further, the assumption was made that the amplitude of each harmonic current was variable with uniform probability density from zero to a peak value and the phase angle of each current was variable from 0 to $2\pi$. Rowe’s analysis was limited to the derivation of the properties of the summation current from a group of distorted loads connected at one node. Properties of the summation current were obtained by simplifying the analysis by means of the Rayleigh distribution. Unfortunately once such simplifications are applied, flexibility on modeling is not retained and the ability to model a bus bar containing a small number of loads is lost. However, Rowe was able to show that the highest expected value of current due to a group of loads could be predicted from the Equation (1.1):

$$I_s = K(1^2 + I_2^2 + I_3^2 + \cdots)^{1/2}$$

where $I_s$ is the summation current from individual load currents ($I_1, I_2, I_3$, etc.) and $K$ is close to 1.5.

Equation (1.1) indicates that the highest expected value of summation current was not related to the arithmetic sum of all the individual harmonic current amplitudes. This factor was a major step forward. Also, by introducing the concept of the highest expected current it was noted that this would be less than the highest possible value of current, namely, the arithmetic sum. It was necessary to define the highest expected current as the lowest value which would be exceeded for a negligible part of the time. Negligible was taken to be 1%. To calculate this value, the 99th percentile was frequently referred to.

The early analysis depended on assumed probability distributions as well as variable ranges. Subsequently, some of the actual probability density functions were measured [3] and found to differ from the assumed pdfs stated above. Simulations were arranged to derive the cumulative distribution function (cdf) of the summation current for low-order harmonic current components. The estimated cdfs were then compared with the measured cdfs with reasonable agreement as shown in Figure 1.1.

![Figure 1.1 Measured (lower curve) and simulated (upper curve) cdf of fifth harmonic current at a 25kV AC traction substation](image)
However, some shortcomings were noted in relation to the early methods of analysis:

- There was a lack of knowledge concerning the actual distributions for all but a limited number of loads.
- The interrelationship between the different harmonic currents for a single load was recognized as complex. However, there remained a lack of knowledge of the degree of independence between the different harmonic currents.

These problems remain and may be solved only following an extensive testing program. For a period of time, there was little activity in the probabilistic modeling of harmonic currents since the interpretation of statistical parameters was difficult without extensive measurements. However, it was recognized by the engineers who were involved in the development of harmonic standards that some concepts from probability theory would have to be applied [5]. The concept of a compatibility level was introduced which corresponds to the 95th percentile of a parameter. To apply the standards, it was necessary to measure the 95th percentile of particular harmonic voltages to determine whether a location in a power system contained excessive distortion. Once this concept was introduced from a measurement point of view, it was important to be able to calculate the 95th percentile in order to effect the comparison between the calculated values and the maximum acceptable levels to determine whether a load would be acceptable at the planning stage of a project. This concept required knowledge of the true variation of the harmonic distortion, random or otherwise.

It was noted that the actual variation of power system distortion may not be totally random; that is, there is likely to be a degree of deterministic behavior [6]. Measurements made over 24 hours [4] clearly show that a good deal of variation is due to the normal daily load fluctuation. This factor complicates the analysis since it provokes a degree of deterministic behavior resulting in a nonstationary process. When considering a nonstationary process, it is known that the measured statistics are influenced by the starting time and the time window considered in the measurement. National power quality standards normally cover tests made over 24 hours, thus spanning a period within which it is not possible to assume that the variation of harmonic distortion is stationary. The so-called compatibility level is a 95th percentile which is intended to apply to the complete 24 hour period. Therefore, the methods used to evaluate harmonic levels at the planning stage must account for the nonstationary nature. To model the nonstationary effects, the variation of the mean harmonic current with time must be taken into account.

In order to model the complete nonstationary nature of power system distortion, it is necessary to gain additional knowledge from realistic systems. Measurements are needed to determine 24 hour trend values to enable suitable models to be found. The present harmonic audits may reveal such information [7].

1.2 Spectral analysis or harmonic analysis

Strictly speaking, harmonic analysis may be applied only when currents and voltages are perfectly steady. This is because the Fourier transform of a perfectly steady distorted waveform is a series of impulses suggesting that the signal energy is concentrated at a set of discrete frequencies. Thus, the transfer relationship between current and voltage
(impedance) is a single value at each component of frequency (harmonic), although different impedances at different frequencies have different values.

When there is variation of the distorted waveform, the Fourier transform of the waveform is no longer concentrated at discrete frequencies and the energy associated with each harmonic component occupies a particular region within the frequency band. This is illustrated in Figure 1.2 which shows the spectrum of an actual time-varying current waveform.

If the waveform variation is slow, the frequency range containing 80% of the energy associated with the signal variation may be restricted. Figure 1.3 shows a typical fifth harmonic voltage variation on a high voltage (230 kV) transmission bus during a world cup soccer event in Brazil [23].

Tests have also been carried out to determine the ‘spread’ of energy in the frequency domain for a limited set of loads in the past. An analysis carried out for an AC traction system demonstrated that the 80% energy bandwidth was less than 0.6 Hz for components up to the 19th harmonic [4].

For harmonic analysis to apply, there must be negligible variation of the system impedance within the frequency range covered by the 80% energy bandwidth. It was demonstrated [4] that

![Figure 1.2 Spectrum of a time-varying current waveform](image1)

![Figure 1.3 Fourier transform derived from fifth harmonic voltage variation](image2)
variation of system impedance over a range of 0.6 Hz is less than 2% even in unfavorable system circumstances. Thus, harmonic analysis is justified for applications using some types of locomotive load.

Clearly, further measurement should be carried out to demonstrate that harmonic analysis is also applicable to other types of loads when changes in current waveform properties may be more rapid than found in locomotive loads.

1.3 Observations

Probabilistic techniques may be applied to the analysis of harmonic currents from several sources. However, to generalize the analysis, there is a need to measure the pdfs describing harmonic current variation for a variety of loads. There is also a need to understand the nonstationary nature of the current variation in order to predict the compatibility levels. It is probable that the harmonic audits (currently in progress) could yield the appropriate information. To determine the compatibility level by calculation, it will be necessary to determine the nonstationary trends within the natural variation of power system harmonic distortion.

There are circumstances where harmonic analysis does not apply because the rate of change of current variation is too fast. It is possible to determine the limit to which harmonic distortion should be applied by considering information transferred into the frequency domain. A formal approach to understanding this problem might present new insight into the limit to which harmonic analysis is appropriate.

1.4 Typical harmonic variation signals

To show typical variation of harmonic signals, recorded data at two different industrial sites, denoted by Sites A and B, are presented. Site A represents a customer’s 13.8 kV bus having a rolling mill that is equipped with solid-state 12-pulse DC drives and tuned harmonic filters. Figure 1.4 shows the variation of the current and voltage total harmonic distortion (THD) of one phase over a 6 hour period. The time interval between readings is 1 min, and each data point represents the average FFT for a window size of 16 cycles. It is known that the rolling mill was in operation only during the first 2.5 hours of the total recording time interval.

Note the reduction in current and voltage harmonic levels at Site A after 2.5 hours of recording. After this time, the rolling mill was shut down for maintenance and only secondary loads are left operating. The resulting low distortion in current and voltage are caused by background harmonics.

Site B is another customer’s bus loaded with a 66 MW DC arc furnace that is also equipped with passive harmonic filters. Figure 1.5 shows the changes in current and voltage THDs during a period of 1 hour, but with a time interval of 1 s between readings and a window size of 60 cycles. The sampling rate of the voltage and current signals is 128 times per cycle at both sites. Finally, Figure 1.6 shows a polar plot of the current variation for a typical six-pulse converter with a firing angle variation.

While previous examples show long-term harmonic variation some kinds of load and equipment present a short-term harmonic variation. The illustrative case portrayed in Figure 1.7 is the well-known inrush current during transformer energization. The voltage and current variation presents a short-term nonstationary behavior and special digital signal processing tools should be used to analyze the frequency behavior. The waveforms
of the odd harmonic components are shown in Figure 1.8. These waveforms were obtained using the digital signal tools described in Chapter 22.

Figure 1.5 indicates that the voltage THD is quite low although it is known that the arc furnace load was operating during the 1 hour time span. This is due to the fact that the system supplying such a load is quite stiff. Note that the voltage and current THD drop simultaneously during two periods (4–10 min and 27–30 min) when the furnace was being charged. The two bursts of current THD occurring at 10 min and 30 min represent furnace transformer energization after charging.

It is of interest to analyze the effect of current distortion produced by a large nonlinear load on the distortion of the voltage supplying this load. One graphical way to check for correlation between these two variables is to plot one as a function of the other, or to display a scatter plot.

Figure 1.9 shows such a plot for Site B. In this particular case, it is clear that there is no simple relationship between the two THDs. In fact, the correlation coefficient which measures the strength of a linear relationship is found to be only 0.32.

Figure 1.4  Variation of (a) current and (b) voltage THD at Site A
1.5 Harmonic measurement of time-varying signals

Harmonics are a steady-state concept where the waveform to be analyzed is assumed to repeat itself forever. The most common techniques used in harmonic calculations are based on the fast Fourier transform (FFT) – a computationally efficient implementation of the discrete Fourier transform (DFT). This algorithm gives accurate results under the following conditions: (i) the signal is stationary, (ii) the sampling frequency is greater than two times the highest frequency within the signal, (iii) the number of periods sampled is an integer and (iv) the waveform does not contain frequencies that are noninteger multiples (i.e. interharmonics) of the fundamental frequency.

If the above conditions are satisfied, the FFT algorithm provides accurate results. In such a case, only a single measurement or ‘snapshot’ is needed. On the other hand, if interharmonics are present in the signal, multiple periods need to be sampled in order to obtain accurate harmonic magnitudes.
In practical situations, however, the voltage and current distortion levels as well as their fundamental components are continually changing in time. Time-variation of each individual current and voltage harmonic is analyzed by a windowed Fourier transformation (short-time Fourier transform) and each harmonic spectrum corresponds to each window section of the continuous signal. However, because deviations exist within the smallest selected window

![Figure 1.6 Polar plot of harmonic currents of six-pulse converter with varying load (firing angle variation)](image)

**Figure 1.6** Polar plot of harmonic currents of six-pulse converter with varying load (firing angle variation)

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![Figure 1.7 Inrush current during transformer energization, a typical short-term time-varying harmonic](image)

**Figure 1.7** Inrush current during transformer energization, a typical short-term time-varying harmonic
length, different sized windows (i.e. the number of fundamental cycles included in the FFT) give different harmonic spectra. Furthermore, adequate window function length is a complex issue that is still being debated [13]. Besides hardware-induced errors, for example analog-to-digital converters and nonlinearity of potential and current transformers [14], several

![Harmonic decomposition for the inrush current during transformer energization, a typical short-term time-varying harmonic](image)

*Figure 1.8* Harmonic decomposition for the inrush current during transformer energization, a typical short-term time-varying harmonic

![Scatter plot of voltage THD as a function of current THD at Site B](image)

*Figure 1.9* Scatter plot of voltage THD as a function of current THD at Site B
software-induced errors also occur when calculating harmonic levels by direct application of windowed FFTs. These include aliasing, leakage and the picket-fence effect [15].

Aliasing is a consequence of under-sampling, and the problem can be alleviated by use of anti-aliasing filters or by increasing the sampling frequency to a value greater than twice the highest frequency of components in the signal of interest. However, most modern measurements are relatively fast and a fourfold increase of frequency is considered more appropriate. Leakage refers to apparent spreading of energy from one frequency into adjacent ones if the number of periods sampled is not an integer multiple of the signals of interest. The picket-fence effect occurs if the analyzed waveform includes a frequency which is not an integer multiple of the fundamental frequency (reciprocal of the window length). Both leakage and picket-fence effects can be mitigated by spectral windows.

Several approaches have been proposed in recent years to improve the accuracy of harmonic magnitudes in time-varying conditions. These include the Kalman filter based analyzer [15, 18], the self-synchronizing Kalman filter approach [17], a scheme based on Parseval’s relation and energy concept [11] and a Fourier linear combiner using adaptive neural networks [19]. Each one of these methods has advantages and disadvantages, and the search for better methods continues to be an active research area in signal processing.

1.6 Characterization of measured data

When considering charts of harmonic component variations with time, one often finds that the variables contain a large number of irregularities which fail to conform to coherent patterns. The physical processes which produce these irregularities involve a large number of factors whose individual effects on harmonic levels cannot be predicted. Due to these elements of uncertainty, the variations generally have a random character and the only way one can describe the behavior of such characteristics is in statistical terms which transform large volumes of data into compressed and interpretable forms [20].

At times, however, some general patterns can be noticed when examining some of the charts, thus indicating if a deterministic component exists in the recorded signal. In such cases, a more accurate description is to express the signal as the sum of a deterministic component and a random component. These descriptions are addressed below with illustrations using the recorded data (THD) shown in the previous section. These techniques can also be applied to individual harmonics, but such data were not recorded at the sites.

1.6.1 Statistical measures

Numerical descriptive measures are the simplest forms of representing a set of measurements. These measures include minimum value, maximum value, average or mean value and standard deviation which measures the spread and enables one to construct an approximate image of the relative distribution of the data set.

Mathematically, consider a set of \( n \) measurements \( X_i, i = 1, \ldots, n \), with minimum value \( X_{\text{min}} \) and maximum value \( X_{\text{max}} \). The average value \( X_{\text{avg}} \) and standard deviation \( \sigma_x \) are calculated by

\[
X_{\text{avg}} = \frac{\sum_{i=1}^{n} X_i}{n},
\]

(1.2)
The statistical measures for the recorded data at Sites A and B are listed in Table 1.1 below. Given \( X_{\text{avg}} \) and \( s x \), one might think that the data is spread according to the Gaussian distribution,

\[
p(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x - X_{\text{avg}})^2}{2\sigma^2}\right).
\]  

The accuracy of this proposition depends on the level of randomness of the signal and whether it contains a deterministic component. If the signal is completely random, then the assumption of a Gaussian distribution is accurate. On the other hand, if the statistical measures are derived directly from a signal with a significant deterministic component such as Figure 1.5(a), then the actual probability distribution is expected to deviate significantly from a Gaussian distribution as will be seen in the next section. Furthermore, the time factor is completely lost with such statistical measures. For example, one cannot tell when the maximum distortion took place within the recording time interval an important element in trouble shooting.

### 1.6.2 Histograms or probability density functions

Because it is often difficult to determine a priori the best distribution to describe a set of measurements, a more accurate method is a graph that provides the relative frequency of occurrence. This type of graph, known as a histogram, shows the portions of the total set of measurements that fall in various intervals. When scaled such that the total area covered in each histogram is equal to one, the histogram becomes the density function (pdf) of the signal.

Figures 1.10 and 1.11 are the probability density functions corresponding to the recorded data in Figures 1.4 and 1.5, respectively. Note that pdfs of the current at Site A and voltage at Site B contain multiple peaks and cannot be described in terms of the common distribution functions. These irregularities are due to the presence of a deterministic component in both signals [21].

While histograms represent the measured data in a compressed form and provide more information than the statistical measures above, they hide some information, for example when an event takes place in time. Although they provide the total time duration during which

<table>
<thead>
<tr>
<th>Site</th>
<th>( X )</th>
<th>( X_{\text{min}} )</th>
<th>( X_{\text{max}} )</th>
<th>( X_{\text{avg}} )</th>
<th>( \sigma_{\text{min}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>VTHD (%)</td>
<td>0.70</td>
<td>5.01</td>
<td>1.23</td>
<td>0.78</td>
</tr>
<tr>
<td>B</td>
<td>VTHD (%)</td>
<td>0.70</td>
<td>1.36</td>
<td>1.09</td>
<td>0.13</td>
</tr>
<tr>
<td>A</td>
<td>ITHD (%)</td>
<td>1.70</td>
<td>9.20</td>
<td>3.69</td>
<td>1.53</td>
</tr>
<tr>
<td>B</td>
<td>ITHD (%)</td>
<td>2.15</td>
<td>19.95</td>
<td>7.37</td>
<td>1.20</td>
</tr>
</tbody>
</table>
a harmonic component or distortion level is exceeded, one cannot determine whether such a level occurred in a continuous or in a pulsed fashion. Such knowledge is crucial when studying the thermal effects of harmonics on equipment.

1.6.3 Probability distribution functions

A probability distribution function $P_X(x)$ represents the same information as a pdf, $p_x(x)$, in a different form: $P_X(x)$ gives the summation of all the time intervals in which the variable exceeds a certain level. Mathematically, a distribution function represents the integral of a density function. One can also use it to express the probability of the event that the observed variable $X$ is greater than a certain value $x$. Since this event is simply the complement of the event having probability $P_X(z)$, it follows that

$$Pr(X > x) = 1 - P_X(x) = 1 - \int_{-\infty}^{x} p_x(\tau)d\tau.$$  \hspace{1cm} (1.5)

Such probability curves are shown in Figure 1.12 for the recorded signals in Figures 1.4 and 1.5. The same advantages and disadvantages as previously mentioned for histograms apply to the statistical description of data by means of probability distribution functions.

1.6.4 Statistical description at sub-time intervals

One way to simplify complex probability density functions or histograms with multiple peaks and provide more accurate descriptive values, such as those in Figures 1.10(a) and 1.11(b), is to...
examine the recorded strip-charts and search for distinct variations at specific sub-intervals of recording time. Then, one can calculate the statistical variables for each of these intervals. To illustrate the point, it can be clearly seen that the variation in current THD at site A changes dramatically from one mode to another at $t = 2.5$ hours. Hence, two separate histograms should be derived: one for the time period between 0 and 2.5 hours and the other for the rest of the time, that is 2.5 to 6 hours.

One can visualize that this procedure decomposes the histogram in Figure 1.11(b) into two distinct ones, each having a single peak, thus making it easier to describe analytically. The same procedure can be applied to the voltage THD at Site B. Once again, two distinct modes are noticed: one corresponds to VTHD less than 0.9% (between 4–10 min and 27–30 min), and the other corresponds to a THD greater than 0.9% for the rest of the time. It should be clear that the two resulting histograms are equivalent to the two distinct ones shown in Figure 1.11(b). This method preserves the time factor to some extent while providing simple shapes of probability density functions, but an extra effort in examining the strip-charts is necessary.

1.6.5 Combined deterministic/statistical description

The recorded signals shown in Figures 1.4 and 1.5 are obviously nonstationary, their probability distribution functions change with the time, due to changes in load conditions (shutting down the rolling mill at Site A, and charging the arc furnace at Site B). Multiple peaks on histograms may also show signs of nonstationary signals, or the presence of a deterministic component within the signal. Theoretical analysis of nonstationary signals is complex, some
of which can be found in reference [22]. This section covers an alternative method to improve the accuracy of the above descriptions by treating the recorded signal as the sum of a deterministic component $X_D$ and a random component $X_R$. The values of $X_D$ can be extracted by fitting a polynomial function of a certain degree to the recorded measurements using the method of least squared error. $X_R$ is then defined as the difference between the actual signal and the deterministic component. It can be shown that the distribution of $X_R$ approaches a normal distribution as the degree of the polynomial function representing $X_D$ increases. In practice, however, it is desirable to work with the simplest model possible: either a linear or a quadratic function.

1.7 Conclusions

This chapter reviewed basic concepts associated with harmonic component variation and measurement of time-varying waveforms, and various ways of describing recorded data graphically and statistically. Statistical measures and histograms are the most commonly used methods. The shapes of probability densities are often found to have multiple peaks and cannot be represented by common probability functions. It is further known that these descriptions completely eliminate the time of occurrence of a certain event.
References


