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Evaluation of Harmonic Variability in Electrical Power Systems through Statistical Control of Quality and Functional Data Analysis

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Abstract

The presence of harmonics in power systems and their problems and impact on quality of electricity supply is increasing due to the increase in society's use of the nonlinear loads that generate them, especially the electronic kind. Classic techniques such as Statistical Process Control (SPC) and Process Capability Analysis (PCA) that form the Statistical Quality Control, can be used to identify outliers or special causes of variability, and proceed with the implementation of actions allowing corrective disposal, provided that the harmonics are normally distributed. In the event that the distribution is unknown novel tools such as Functional Data Analysis (FDA), have been used successfully in this communication to study these phenomena in situations where the classic quality control cannot.

*Keywords:*harmonics; variability; outlier; statistical process control; functional data analysis

1. Introduction

In recent decades there has been a considerable increase in the use of equipment, both domestic and industrial, that includes electronic power converters, Balcells (2003). The functioning principle of these pieces of equipment consists of “cutting up” the sinusoidal waveform in order to control the power flow that they consume, or in rectifying, through the use of semiconductors, this sinusoidal wave to turn it into direct voltage. The commutation or rectification processes mean that the waveform of the intensity that these pieces of equipment consume is no longer sinusoidal, that is, they are non-linear loads. The circulation of these currents distorted by the impedances of the distribution system mean that, in turn, the voltage of the supply power grid also ceases to be purely sinusoidal,

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causing major negative consequences in industrial processes, Wargner (1993). That is why there is a need to study it, despite its difficulty.

However, the collection of data from electrical power systems is often voluminous and, in most cases, data are stored in large databases without them being studied, either due to the time required for the analysis or because the right tools are not available. This work successfully presents traditional and new tools to solve these contingencies, and thereby improves on some works carried out to date, Santoso et al. (2012).

2. Description and methodology of the case study

For the study carried out in this work, we used two samples relating to the measurements made in the 400V three-phase low-voltage output of the transformer substations for the two buildings of the Centro Universitario de la Defensa, between 04/11/2012 and 13/12/2012. The electrical measurements, whose characteristics appear in Table 1, were made by using the Circutor QNA-PV power quality analyzer and were recorded on the indicated dates at intervals of 10 minutes.

Table 1. Characteristics of the study samples.

	Name	Days	Data/day	n
Félix de Azara Building	Sample A	39	144	5616
Conde de Aranda Building	Sample B	39	144	5616

3. Analysis of variability and outliers in electrical power systems

In classic statistical terminology, an outlier is defined as an observation that by being atypical or erroneous has a very different behaviour compared to the other distribution data of which it is part, giving an approximate idea of the variability of the distribution. In the analysis of harmonics, when the variability and its causes are being analysed, the charts offered by the software of the majority of measuring equipment, as shown in Figure 1 for example, are not the most appropriate ones. Different techniques are proposed for the above purpose in the following sections.

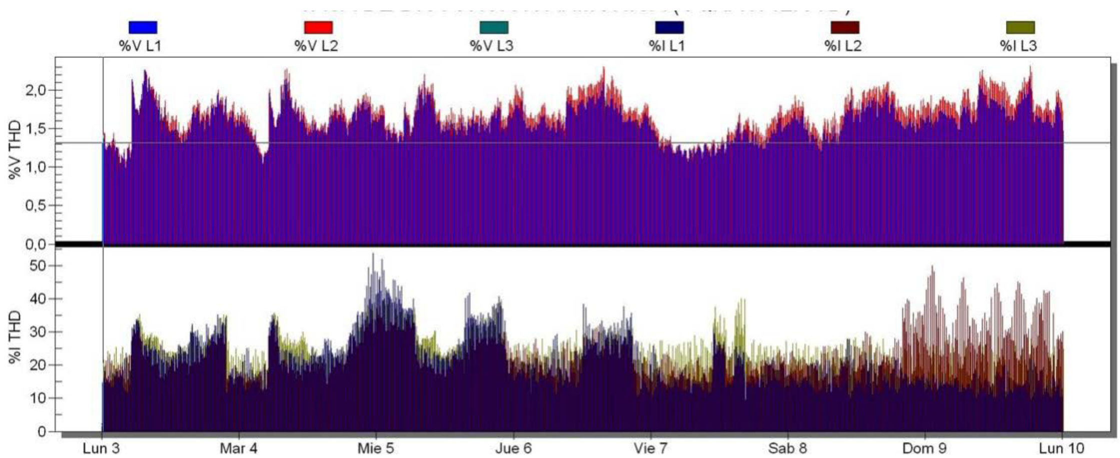

Fig. 1. Typical Chart for the Harmonic Distortion Rate.

3.1. Global Outliers. Analysis of Box Plots

Box plots are charts that simultaneously describe how all of the data being analysed are distributed. They make it possible to globally detect “abnormal” observations or outliers. Specifically, a box plot shows the three Q1, Q2, and Q3 quartiles (first, second or median, and third), the minimum and the maximum of the data in a rectangular box. To determine the presence of outliers it is necessary to determine the interquartile range (IQR), which is calculated as the difference between the upper quartile and the lower quartile of the distribution. In this context, an outlier is defined as any observation that is outside of the interval defined by the upper control limit (UCL) and lower control limit (LCL).

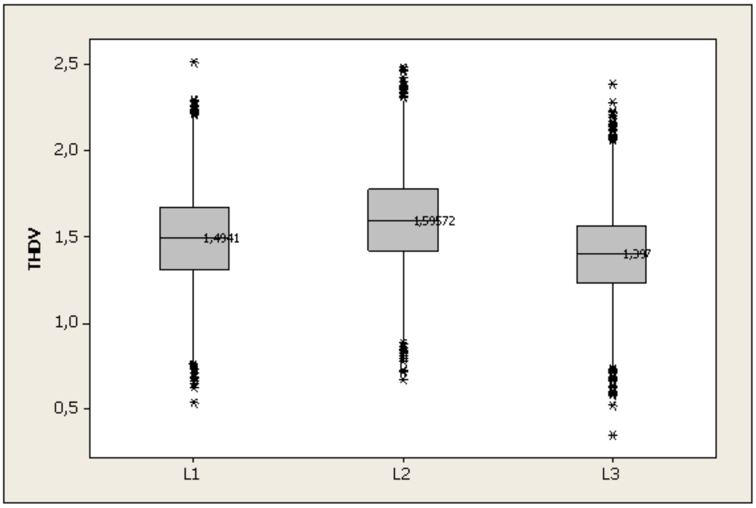

Fig. 2. Global Outliers for the THDV in Sample B.

Figure 2 shows the box plots for the Total Harmonic Distortion of Voltage (THDV), UNE-EN 61000-2-2 (2003), in the three phases of Sample B, where the data outside of the LCLs and UCLs appear as outliers. These types of charts offer information about the number of outliers, according to the aforementioned criteria, but do not give any information about their causes. Control charts and the concept of rational subgroups make it possible to analyse these causes.

3.2. Point Outliers. Statistical Process Control

The variability of a property is nothing more than the deviation of its value compared to the defined objectives. However controlled a process is, variability will always be present. The causes of variability can be divided into two categories: common causes and special causes. Common causes, also known as natural causes, are inherent to the process, while special causes, also known as assignable causes, are those due to causes outside of the process. Due to the fact that the latter do not form part of the process, they can be eliminated easily if they are identified correctly. A process in which there is only natural variability is said to be under statistical control.

Statistical Process Control (SPC) is a technique that makes it possible to monitor, analyse, predict, control and improve the variability of a determined quality characteristic through the use of control charts. Control charts were developed by W. Shewhart, Shewhart (1931), and nowadays are the most important tools in the analysis of the variability of processes in industrial environments. A typical control chart can be seen in Figure 3. The upper and lower lines represent the Upper Control Limit (UCL) and the Lower Control Limit (LCL) respectively. The central line (CL) relates to the mean of the value of the property studied. If all the points shown are between the UCL and the LCL, it is considered that the process is under statistical control, that is, there is an absence of outliers and of assignable causes of variability.

A key idea in the use of control charts is that of data collection in accordance with what Shewhart defined as the concept of a rational subgroup. According to this concept, the sample (the rational subgroup) must be taken in such a way that if the assignable cause is present, the probability of the appearance of significant differences within the subgroups is minimised. This means that samples or subgroups must be grouped together by following a criterion related to the cause of the special variation to be detected. Therefore, if it is suspected that the cause of variation is daily, weekly, monthly, seasonal or annual, then the data must be grouped together into rational subgroups in the same way. As an example, in the case proposed to be studied in this work, there is a dual channel to detect special causes of variation in the harmonics patterns: daily causes and weekly causes. The grouping into rational subgroups is as follows: daily subgroups (39 days) and weekly subgroups (8 weeks).

There are many kinds of control charts, Montgomery and Runger (2010), and rules to interpret them, Champ and Woodall (1987), in order to analyse the variability of processes, whether large or small. However, if it is considered that the studied quality characteristic follows a normal distribution $N(\mu_y, \sigma_y)$, then the control limits are given, generally, as:

$$UCL = \mu_y + k\cdot\sigma_y \qquad CL = \mu_y \qquad LCL = \mu_y - k\cdot\sigma_y$$

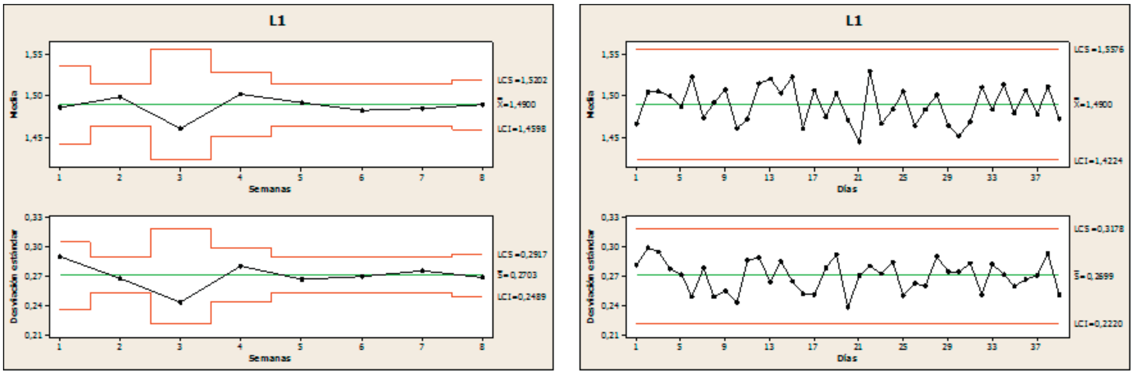

Fig. 3. Xbar-S Charts for the THDV of the L1 Phase of Sample B (Subgroups by Weeks and Days).

Figure 3 shows the Xbar-S control chart for the THDV of the L1 phase of Sample B, with rational subgroups grouped together by days and by weeks. In the figure it can be seen that in both cases the process is stable and is under statistical control, since there are no outliers, or any violations of additional rules for the detection of small standard deviation variations, or unusual patterns (in the weekly control chart the control limits are variables because the sizes of the sample are different). In this situation it can be concluded that the analysed process is solely subject to natural variability and is therefore under statistical control. Consequently, it can be stated that in phase L1 of Sample B the harmonics have a normal pattern with a variability that is solely due to natural causes.

The same cannot be deduced from the control charts related to the THDV of phases L2 and L3 of Sample B shown in Figure 4. In phase L2, in the daily control chart we can see a pattern relating to the violation of a rule that detects small standard deviation variations, at points 25, 26, 27, 28. Also, in phase L3 points 11 and 31 are outside of the UCL and LCL respectively, showing that the process suffers from large standard deviation variations. In both cases the THDv falls outside statistical control, with daily assignable causes of variability on days 25, 26, 27 and 28 in phase L2 and on days 11 and 31 in phase L3, which must be identified and, through the implementation of corrective actions, eliminated so that the process can come under statistical control again. However, the weekly control chart shows that the process is under statistical control and that there are no special weekly causes of variation, hence the importance of the selection criteria for rational subgroups.

As has been shown, SPC is a useful tool for the detection of outliers and harmonics patterns in electrical networks. However, its use is dependent upon the data of the studied sample being distributed normally or known.

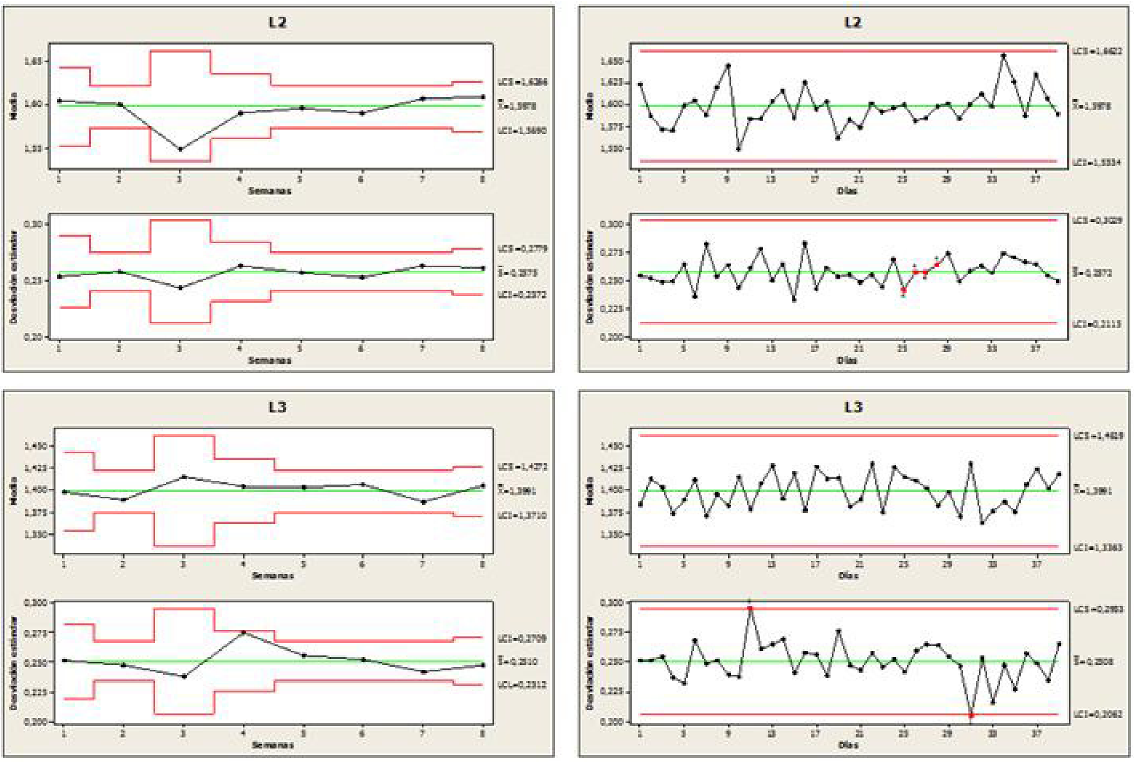

Fig. 4. Xbar-S Charts for the THDV of the L2 and L3 Phases of Sample B (Subgroups by Weeks and Days).

If a Kolmogorov-Smirnov normality test (K-S test), Canavos (1984), is done, with a significance level of $\alpha = 0.05$ on the data from Sample B, it shows that the analysed data follow a normal distribution, as the calculated p-value, equal to 0.15, is higher than the significance level α. The same results are obtained if a similar test is done for phases L2 and L3.

However, in the electrical power systems studied, harmonics are not normally distributed on most occasions. Table 2 shows the p-values obtained when running a K-S normality test on the data relating to the THDV and other harmonics from Sample A. All of these p-values are lower than the α significance and therefore it can be concluded that none of the data sets of the harmonics studied is normally distributed.

Table 2. Results of K-S Normality Test with $\alpha = 0.05$ for Phase L1 of Sample A.

	THD	3º	5º	7º	11º	13º
p-value	0.003	0.0021	0.0012	0.0157	0.00234	0.00125

When control charts are created for abnormal data distributions, as in the studied case, the results are as seen in Figure 5. In this figure, the control graph for the THDV of the L1 phase of Sample A shows a very high number of outliers, 37 out of a set of 39 elements, which is totally contrary to the definition of outlier in section 2 of this work. This behaviour persists even when submitting the data set to a Box-Cox transformation, Box and Cox (1964), in an attempt to correct the distribution bias, the differences of the variances on the time axis or the possible nonlinearity of the data.

Therefore, when a control chart is used to monitor a process including data that is not normally distributed, the traditional analyses for the detection of a specific variability are of no use and consequently any interpretations are incorrect.

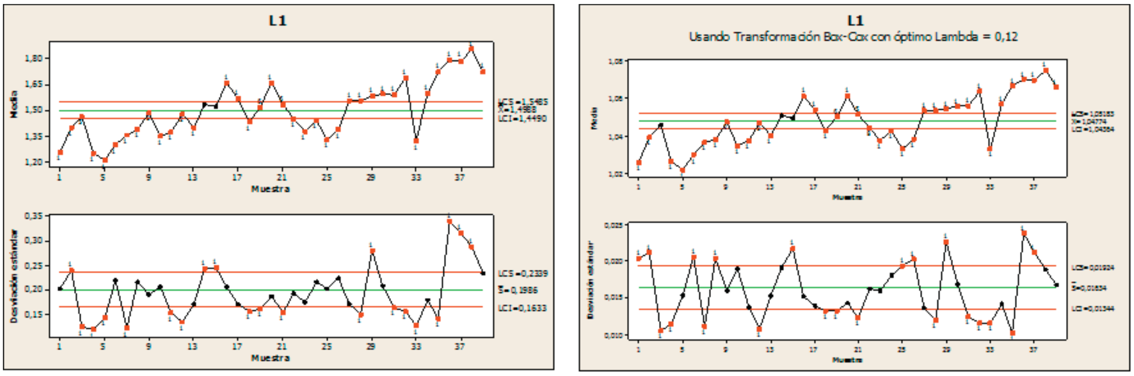

Fig. 5.Control Graphs for the THDv of Phase L1 of Sample A (Daily Subgroups).

To resolve the impossibility of analysis in non-normality cases in the distribution of data, which are typical in certain chemical and electrical processes for example, several authors, Erto and Pallota (2007) and Chen (2004), have proposed the design of different control graphs based on different distributions to help overcome these difficulties, provided that the studied distributions are identified (Weibull, Burr XII, Extreme Value etc.). However, there is a tool that permits the treatment of outliers, regardless of the type of distribution being studied.

3.3. Functional outliers. Functional data analysis

The use of Functional Data Analysis (FDA), Ramsay and Silverman (2010), González-Manteiga and Philippe Vieu (2007), comes from the need to analyse time data, and therefore data that can be seen from the viewpoint of functions. This working methodology has therefore also been applied in the detection of outliers, being used successfully in previous works, Febrero et al. (2008), Ordóñez et al. (2011), Díaz-Muñiz et al. (2012), Ramsay and Silverman (1997).

The study of the outliers of a sample from a functional perspective has the following advantages:

- No need for normality in data. Unlike the classical techniques based on SCP for the detection of outliers, normality is not necessary in the data set, nor is it necessary to make any transformation as the analysis is not carried out on the original point values.
- The analysis of time sets as a unit. The sample is analysed by considering complete time units, that is, not point values recorded at specific times.
- Trend analysis. This technique not only makes it possible to determine outlier values, it also makes it possible to analyse the fact that, although a set of values may not become outliers, they do show small deviations compared to the normality of the data.
- Homogeneity analysis. Outliers are not simply determined as those observations that exceed a certain cut-off limit without being able to conclude if this is a one-off or regular event. In other words, it is possible that various points will exceed the cut-off but will however show small deviations on a constant basis.

It is necessary to follow the methodology below for the determination of functional outliers:

- Create the functional sample. The curves are created based on discrete data, recording each function based on an expansion of basic functions, Ramsay and Silverman (1997). In this way there is a functional sample, where each function represents the measurement already within a complete time unit.
- Determine the functional depth. Depth is a standard concept in statistics and measures the deviation of one element compared to the sample mean. Therefore, this concept can be extended to a functional sample, Fraiman and Muniz (2001), Cuevas et al. (2006), so that the depth of a function will give an idea of the shown deviation compared to the mean in absolute terms.

- Determine functional outliers. According to the concept of depth, functional outliers are elements that show a lower depth value, in other words, that are farther away from the mean of the functional sample.

This means that a cut-off limit must be established for functional depths, so that the observations incorrectly classified as outliers do not exceed 1%, Febrero et al. (2008). A bootstrap process, Peng and Qi (2008), is carried out to determine the cut-off limit, which calculates this cut-off parameter by determining functions with depths below the calculated value as functional outliers. This is proposed below for the first time as a valid tool for the analysis of quality characteristics of electrical power systems and particularly for the analysis of harmonics.

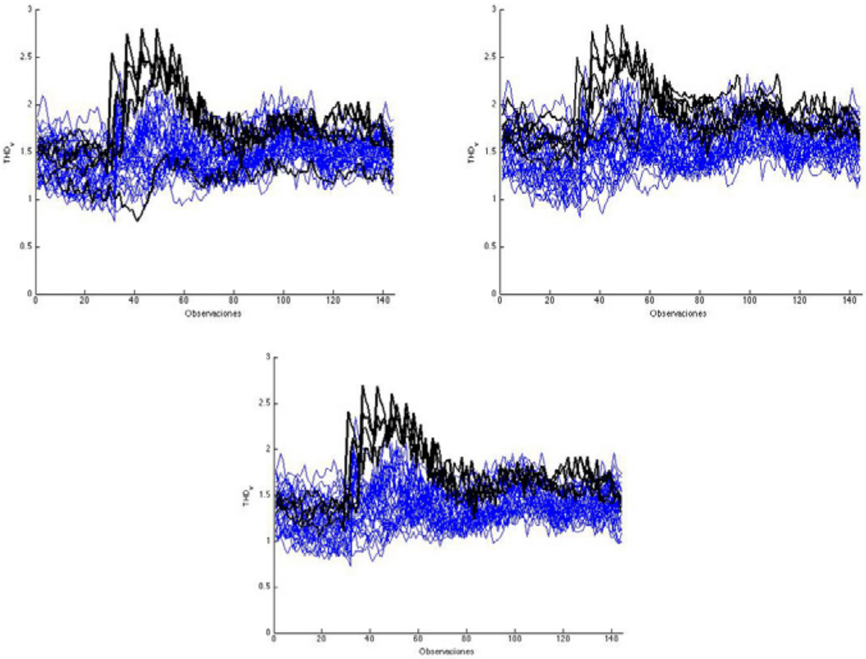

Fig. 6. Functional Outliers for the THDv of Phases L1, L2 and L3 of Sample A.

Figure 6 contains a graph that shows the results of the functional outliers obtained for the THDv of Sample A, which could not be analysed using traditional SCP control graphs as it contained an abnormal data distribution. The 39 functions recorded based on the 144 data/day appear in each of the graphs. The black curves relate to the functional outliers determined by considering the lowest depths. The results are summarised in Table 3.

Table 3. Functional Outlier Results of the THD_V of Sample A.

	Outliers	Day
L1	5	5, 36, 37, 38, 39
L2	6	32, 35, 36, 37, 38, 39
L3	4	36, 37, 38, 39

When identifying the outliers with specific causes of variability in harmonics it has been confirmed that between days 36 and 39 a cold front caused an increase in the use of the equipment allocated to heating the building studied in this sample

4. Conclusions

Control charts and the concept of rational subgroups can be used successfully in the search and elimination of outliers in harmonics present in electrical systems, provided that the data set follows a normal distribution. When data do not follow a normal distribution, Functional Data Analysis can be used effectively in the detection of outliers, also contributing major advantages in the detection of specific variability compared to traditional techniques such as Statistical Control Process.

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