Blind source separation methods applied to evaluate harmonic contribution

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Summary
One of the greatest challenges found in power quality has been, and still is, the establishing of a reliable noninvasive method for quantifying the harmonic contributions of an electric utility and a consumer at the point of common coupling (PCC). This difficulty arises from the fact that the harmonic distortions measured on the PCC are unidentifiable mixtures from both parties. Currently, some work has focused on exploring the use of blind source separation (BSS) techniques to promote the sharing of harmonic responsibilities in a noninvasive way. However, the usage of this methodology is very recent and still requires thorough evaluations, not only from the point of view of the BSS techniques available in the literature, but also from the perspective of the electrical power systems and the nature of their loads. Thus, seeking to contribute to the consolidation of the use of BSS techniques in the sharing of harmonic responsibilities, this work aimed to investigate the impact of the variation of harmonic current sources on the accuracy of BSS methods. In addition, three algorithms suitable for complex-valued signals were evaluated computationally and experimentally; the results obtained computationally were compared with the results of the method based on the covariance characteristic of the random vectors, and the experimental results was compared to that obtained through an invasive procedure.

KEYWORDS
blind source separation, harmonic contributions, independent component analysis, noninvasive method, power quality, sharing of harmonic responsibility

1 | INTRODUCTION

Among the different problems related to power quality in electric power systems (EPS), harmonic distortions stand out, since these are amply present on the electrical network. Currently, several standards seek to limit individual and total
harmonic distortion under certain limits in order to ensure the proper functioning of the system,
however, without directing any discussion related to pertinent questions of who essentially holds greater responsibility in terms of creating the observed distortion.

Accordingly, in light of the aforementioned, measured harmonic distortions are frequent subjects of discussion between the electric utility and consumer. Hence, the lack of agreement between the parties occurs as a result of the distortions measured at a given point of common coupling (PCC) being contemplated as harmonics produced by both, in an unidentified mixture. In this way, when corrective measures need to be taken, the task of quantifying the individual contributions is impractical, and consequently the financial investments that each party must make are unfeasible.

The installation of components, such as filters, reactors, among others, demonstrate good results when assigning responsibilities regarding the presence of harmonic distortions. Nonetheless, these invasive methods are expensive and difficult to implement, especially when dealing with high- and medium-voltage networks.

On the other hand, considering the current grid code requirements which govern harmonic measurement methods, several efforts have been made to allow the sharing of harmonic responsibilities in a noninvasive way, using only measurement data obtained from a power quality meter. Thus, different noninvasive methods have been proposed to estimate the harmonic equivalent impedance of the system, and consequently the harmonic contribution, for example, the method based on covariance characteristic of random vectors, the fluctuation method, the linear regression method, the method based on data selection, among others. However, these methods adopt simplifying assumptions, such as that the utility’s impedance is much larger than the consumer’s and are sensitive to background voltage harmonics and to the changes of frequency.

Given the above, the use of blind source separation (BSS) techniques to identify harmonic contributions at the PCC is a promising alternative, as it does not require the installation of any specific equipment and that does not require the impedance of the supplying system to be much higher than that of the consumer.

BSS is a classic problem in signal analysis, proposed at the end of the 1980s by Herault and Jutten, which aims at recovering the sources of signals from observed mixtures. The term “blind” implies that the sources are latent variables, meaning that these cannot be directly observed, and there is no a priori information concerning how the sources are mixed.

Due to its vast field of application, BSS has attracted the attention of many researchers from several areas. Consequently, different BSS techniques have been proposed and are well-established in academic fields, such as telecommunications, audio signal separation, feature extraction, biomedical signal processing, pattern recognition, and financial time series analysis. In EPS, more specifically in power quality issues, the BSS methods have been used for harmonic load identification, in the separation of harmonic components and to estimate the utility and consumer harmonic impedance at PCC.

Although a methodology for determining the harmonic contribution through the BSS method already exists in the literature, by using the ICA approach, the application of this technique is not consolidated yet due to the complexity characteristic of BSS methods and the absence of more comprehensive analyses considering the nature of the EPS. For example, several articles make computational evaluations using hypothetical current sources with the same mean and variance for both utility and the consumer. However, in practice, it is known that the harmonic emission of the consumer is more fluctuating than that of the utility one. What is more, other papers computationally evaluate cases where the utility source is k times larger than the consumer’s source by multiplying the utility’s current source by a scalar factor. Nonetheless, simply multiplying the utility signal by a scalar factor will not change the signal-to-noise ratio of the source signals, that is, the level of variation of the signal sources will remain proportional to their magnitude.

Furthermore, it is also possible to find in the literature published papers that contradict each other, because according to one work, the estimation errors increase when $|Zu| << |Zc|$, or when $|Zu| >> |Zc|$; while according to the other the estimation errors are lower when $|Zu| << |Zc|$. However, according to the studies performed during this research, none of these conclusions are supported by the ICA technique.

Thus, to contribute to the consolidation of the BSS techniques in the problem of sharing harmonic responsibilities, this paper investigates the impact of the harmonic current sources variances on the accuracy of the BSS methods since this is a relevant variable from the BSS point of view and somewhat neglected in the EPS analyses. For this purpose, first, the method to identify the harmonic contribution is computationally evaluated by three BSS algorithms suitable for complex-valued signals, using a hypothetical electrical system with source signals of different variances values. After that, a field test in an installation containing a combination of linear and nonlinear components fed by a pre-distorted
utility is performed. And the results obtained by the BSS methodology are compared with the invasive dominant impedance method (DIM) results.

## 2 | BLIND SOURCE SEPARATION

The rapid development of new technologies, associated with the low cost of processors, triggered the emergence of several techniques for signal processing, consequently increasing the number of algorithms proposed for BSS. Until the present moment, the vast majority of developed BSS methods are unsupervised learning methods based on a priori information concerning the latent variables or a theoretically constructed objective function. Therefore, it may be considered, in a simplified form, that BSS implies the exploration of prior information about the real nature and structure of the data through an appropriate optimization procedure.

Basically, BSS algorithms can be classified into three fundamental approaches: independent component analysis (ICA), non-negative matrix factorization (NMF), and sparse component analysis (SCA).

Currently, the most widespread and appropriate method to achieve the objectives proposed in this work, from all those available, is ICA. Based on higher-order statistical characteristics, ICA algorithms seek to find a linear representation of non-Gaussian data that are statistically independent, or as independent as possible. The ICA technique adopts the following assumptions:

1. The source signals are statistically independent with a zero mean.
2. The number of source signals $N$ should be less than or equal to the number of observed signals $M$ ($N \leq M$).
3. At most one of the source signals has Gaussian distribution.

Mathematically, using matrix notation, the ICA model for $M$ observed signals from $N$ independent sources can be expressed as follows:

$$X = As$$

where $X = (x_1(t_i), \cdots, x_M(t_i))$ is the vector of observed random variables, $s = (s_1(t_i), \cdots, s_N(t_i))$ is the vector of source signals, called independent components, $A$ is an unknown constant mixing matrix and $i = 1, 2, \cdots, T$ is the time index.

According to the central limit theorem, under certain conditions, the sum of independent random variables tends towards a Gaussian distribution. Thus, ICA techniques utilize a quantitative measure of non-Gaussianity to estimate a separation matrix ($W$) and then the independent components by:

$$\hat{S} = WX$$

where $\hat{S}$ is an estimated vector of source signals. However, since both the mixing matrix and the source signals are unknown, in the ICA model, there are two ambiguities related to the order and scale of the components recovered.

Noteworthy here is that there are several ways to measure non-Gaussianity, with different methods to maximize it. Therefore, several algorithms based on the ICA technique have already been proposed and are fully available.

Although previously published papers compare some of those different ICA algorithms, the results obtained differ according to the data analyzed and the criteria used in their evaluation. Consequently, no algorithm can be considered invariably the best for any particular application and, in some cases, can even lead to incorrect results. Following this reasoning, three algorithms, based on ICA techniques, and suitable for complex-valued signals, will be applied in this work. These algorithms are identified as FastICA, RobustICA, and JADE.

The FastICA algorithm adapted for complex operations was presented by Bingham and Hyvärinen, as a natural development of the algorithm for real signals. Basically, the proposal of the algorithm consists of maximizing the non-Gaussianity of the observed signals using approximations of negentropy, based on the maximum-entropy principle, through the application of the fixed-point iteration theory. However, this algorithm is complicated to some degree, since it is necessary to choose a contrast function for the estimator according to the data analyzed. Moreover, before applying the algorithm, the data must go through a preprocessing step of centering and whitening the observed variables, which reduces the complexity of the problem.
The RobustICA algorithm is based on the normalized kurtosis contrast function, optimized by an iterative technique to improve computational efficiency. This technique computes algebraically the step size, globally optimizing the contrast in the search direction at each iteration. Thus, any independent component with non-zero kurtosis can be extracted in this way. The main advantage of RobustICA is that both the real and complex signals are treated by the same algorithm, so the mixing matrix can be real or complex, regardless of source type. Furthermore, in this algorithm, prewhitening is not required.

Finally, to estimate the independent components, the JADE (Joint Approximate Diagonalization of Eigenmatrices) algorithm is based on joint diagonalization of 4th-order cumulant matrices. This algorithm has the great advantage of not demanding parameter adjustments, as well as it works with real and complex numbers. Nonetheless, the volume of calculations required by the cumulants of high orders limits the application of this algorithm to low dimension problems.

3 | HARMONIC CONTRIBUTIONS AND THE ICA MODEL

The superposition theorem applied to a Norton equivalent circuit is the most widely used technique in methods for the sharing of harmonic responsibility at the PCC. Generally, in this method, shown in Figure 1, each harmonic order is represented separately by a Norton equivalent circuit.

Thus, accordingly with Figure 1, the recorded harmonic voltage and current, at the PCC, can be expressed mathematically as follows:

\[
\begin{bmatrix}
U_h^PCC \\
I_h^PCC
\end{bmatrix} =
\begin{bmatrix}
Z_{c}^{h}Z_{u}^{h} & Z_{c}^{h}Z_{u}^{h} \\
\frac{Z_{c}^{h}Z_{u}^{h}}{Z_{c}^{h} + Z_{u}^{h}} & \frac{Z_{c}^{h}Z_{u}^{h}}{Z_{c}^{h} + Z_{u}^{h}}
\end{bmatrix}
\begin{bmatrix}
I_c^h \\
I_u^h
\end{bmatrix}
\]

Or, in a simplified way by:

\[
Y = ZI
\]

where \(Y\) is the recorded signals at the PCC, \(Z\) is the impedance matrix, and \(I\) represents the consumer and utility harmonic sources. Through a comparison of Equation (1) with Equation (4), one notes that these equations are quite similar, with \(Y\) being the vector of known measures, \(Z\) the mixing matrix, and \(I\) the independent sources.

However, before applying the ICA technique, it is necessary to check if the ICA assumptions are satisfied. In other words, if the number of observed signals is greater, or equal, to the number of source signals, and if the sources are statistically independent, with a non-Gaussian distribution.
In general, electrical loads are composed of a deterministic process, with a slow variation component, associated with factors such as time of day, day of the week, season, weather conditions, etc., and a stochastic process, with a fast-varying component, which represents those fluctuations that are difficult to predict. Fortunately, according to experimental results, the fast-varying components are statically independent and have a super-Gaussian distribution. Therefore, the ICA method can be applied to fast-varying components, obtained from the original signals by a moving average filter.

Moreover, it is clear that the number of observed signals ($U_{PCC}^h$ and $I_{PCC}^h$) is equal to the number of source signals ($I_c^h$ and $I_u^h$), in this approach. Consequently, all the assumptions imposed by the ICA method are satisfied.

Although the uncertainties imposed by the method at first glance seem to invalidate the use of the ICA method in the sharing of harmonic responsibilities, these can be solved using a correction factor and features of EPS. Mathematically, the latent harmonic sources can be estimated by:

$$\hat{I} = WY$$  \hspace{1cm} (5)

Then, the estimated sources can be related to the real sources, using complex correction factors ($k_1$ and $k_2$) as follows:

$$\hat{I} = \begin{bmatrix} k_1 I_c^h \\ k_2 I_u^h \end{bmatrix}$$  \hspace{1cm} (6)

Rewriting Equation (5), based on Equation (6), one has:

$$\hat{I} = \begin{bmatrix} w_{11} & w_{12} \\ k_1 & k_1 \\ w_{21} & w_{22} \\ k_2 & k_2 \end{bmatrix} \begin{bmatrix} U_{PCC}^h \\ I_{PCC}^h \end{bmatrix}$$  \hspace{1cm} (7)

The inverse matrix of Equation (3) is given by:

$$\begin{bmatrix} I_c^h \\ I_u^h \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ Z_c^h & 1 \\ Z_u^h & 1 \end{bmatrix} \begin{bmatrix} U_{PCC}^h \\ I_{PCC}^h \end{bmatrix}$$  \hspace{1cm} (8)

Through the comparison of the elements of the matrix in Equations (7) and (8), one has:

$$-Z_c^h = \frac{w_{12}}{w_{11}}$$  \hspace{1cm} (9)

$$Z_u^h = \frac{w_{22}}{w_{21}}$$  \hspace{1cm} (10)

With regard to the ordering indeterminacies, the resistive part of impedance in power networks is always positive. Consequently, to solve these indeterminacies, initially an arbitrary definition is made, where the sources are recovered in the order presented in Equation (3). If the real part of the utility impedance is positive, then the order chosen is correct. Otherwise, the order should be reversed.

Finally, once the impedances and the harmonic voltages of the utility and consumer are determined, the projection of the phasors is made to provide scalar harmonic contribution indices, as illustrated in Figure 2.
FIGURE 2  Decompose of harmonic voltage vector into two scalar components

FIGURE 3  One-line diagram of the test system

FIGURE 4  Samples of the harmonic current sources with different variances used in the simulation
In this section, the performance of the ICA methods in the assignment of harmonic responsibilities is computationally evaluated using the software Matlab/Simulink. The test system used was proposed by de Paula Silva and de Oliveira and is basically composed of a distorted source that feeds a consumer with linear and nonlinear loads, which are represented by a parallel association of a resistor, a capacitor, an inductor, and a current source, as shown in Figure 3.
Thus, based on the circuit model shown in Figure 3, 1000 samples of harmonic voltages and currents data at the PCC were generated according to Equation (3) using the harmonic current sources shown in Figure 4. These harmonic currents sources were created by adding zero-mean Laplace distributed random variables (fast-varying components) to hypothetical harmonic load profiles (slow-varying components).

To evaluate the impact of source variance on the BSS method, several simulations were performed considering fast-varying components with variance between 0.01 and 0.1. Furthermore, aiming to ensure the reliability of the results and validate the performance of the BSS algorithms, for each case analyzed, the harmonic contribution was evaluated

**Figure 6** MAPE of the ICA method in sharing responsibilities for 5th-order harmonic of case 01

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100 times and all obtained results were compared with those provided by the method based on the characteristic covariance of random vectors.

It should be highlighted that among the different noninvasive techniques available in the literature, in this work it was chosen to use the method based on the characteristic covariance of random vectors because the fundamental idea of the method, as in the BSS technique, is based on the statistical characteristic of independent random vectors.

As previously mentioned, in the ICA method, the mixing matrix is considered constant; however, in EPS, the harmonic impedances vary with the connected loads. Therefore, to perform a more reliable evaluation, two main cases were examined. In the first case, to create the voltage and current data at the PCC over the analyzed period, the mean

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**FIGURE 7** MAPE of the ICA method in sharing responsibilities for 7th-order harmonic of case 01
values for both impedances, the utility and consumer, were considered. Following this, in the second case, it is assumed that under a stable mode of operation, the utility impedance changes little, whereas the consumer impedance varies according to loads plugged. That is, in Case 01, harmonic impedances were kept constant, and in Case 02, normally distributed random variations were added only to the consumer harmonic impedance.

4.1 Case 01

In this first case analyzed, the ICA model was applied to the fast-varying components of voltage and current harmonics at the PCC, extracted from the simulated data by an 8-point moving average filter.

Figure 5 shows the mean absolute percentage error (MAPE) of the 3rd-order harmonic scalar contributions for the BSS algorithms and for the method based on covariance characteristic of random vectors. The MAPE was used here to measure the accuracy of the results estimated and can be defined as follows:

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{H_{\text{real}}^i - H_{\text{estimated}}^i}{H_{\text{real}}^i} \right| \cdot 100
\]

where \( n \) is the number of simulations performed for each source analyzed, in this case 100, and \( H_{\text{real}} \) and \( H_{\text{estimated}} \) are the real and the estimated harmonic contribution, respectively.

Through the analysis of Figure 5, one can see that although all BSS algorithms showed good results, in comparison with the other noninvasive technique evaluated in this work, the algorithm that presented the best performance was FastICA. It is also observed that, in this case, all the algorithms evaluated presented a better performance in assigning the supplier's responsibility, which may be associated with the higher amplitude of its harmonic source and will be better investigated in the next section.

Figures 6 and 7 show, respectively, the MAPE of the harmonic contribution achieved by the algorithms for the 5th and the 7th order.
The results for these orders in question reinforce the tendency of the methods to present minor errors for the harmonic current source of greater amplitude; that is, for the 5th and 7th harmonic order, the errors in estimating the consumer’s contribution are lower (see Figure 4).

Thus, through an analysis of the results obtained in this first case, in which no significant variations of harmonic impedances occur, it can be concluded that to sharing harmonic responsibilities, in a noninvasive way, the BSS method showed better results than the method based on covariance characteristic of random vectors.
4.1.1 | Analysis of the influence of source amplitudes on the BSS estimation of the harmonic contribution

In this section, a more detailed analysis is made to verify the tendency of the BSS algorithms to present lower errors in estimating the harmonic contribution of sources of larger amplitudes. For this, three cases will be analyzed, considering the 5th-order harmonics with fast-varying components with zero mean and variance of 0.1 for both current sources. In

![Graphs showing MAPE of the ICA method in sharing responsibilities for 5th-order harmonic of case 02](image)
the first case, the amplitude of both sources will be similar; in the second case, the amplitude of $I_{5th}$ will be much larger than that of the $I_{5th}$; and, finally, in the third case, the amplitude of $I_{5th}$ will be much larger than $I_{5th}$ as shown in Figure 8.

Table 1 presents the errors of the different BSS algorithms and the method based on the covariance of random vectors in the assignment of harmonic responsibilities between the utility and the consumer. As expected, all the evaluated methods presented lower errors in the estimation of the higher amplitude source.
4.2 Case 02

In this case, the impact caused by the presence of variations on the consumer harmonic impedance over the analyzed interval is evaluated. To do this, normally distributed random variations, with variance of 10% over the values shown in Figure 3, were added to the consumer’s impedance. The MAPE in the assignment of harmonic responsibilities for the 3rd, 5th, and 7th order, of the utility and consumer, are shown in Figures 9-11, respectively.

Thus, based on the results obtained in this second case, the conclusion is reached that the existence of some variations in the consumer impedance, that is, in the mixing matrix, does not negatively impact the performance of the BSS technique in the assignment of harmonic responsibility over observed distortion at PCC.

Furthermore, one notes that, among the evaluated ICA algorithms, the FastICA was the one that presented the lowest error and the best performance in both cases analyzed and in all harmonic orders assessed.

5 FIELD CASE

This section presents a practical validation of the BSS method in assigning harmonic responsibilities, using voltage and current data measured in the secondary of a power transformer that feeds a typical university load, located at Umuarama Campus of the Federal University of Uberlandia.

In order to obtain a comparison parameter for the results given by the BSS algorithms, the responsibility sharing was also evaluated by the noninvasive method based on the covariance characteristic of random vectors and by the invasive DIM. For this purpose, a harmonic filter tuned to the 5th order was installed in the internal busbar of this student sector, as shown in the simplified single line diagram of Figure 12, making the analyses performed restricted to this order of harmonics under test.

Before any results presentation, it is worth highlighting that, unfortunately, due to the emergency remote teaching conditions imposed by the coronavirus pandemic in Brazil, these experiments were conducted in a period with few consumer loads connected to the system. Consequently, it is already expected that the supplying system will be the one assigned as the main responsible for the harmonic distortions observed in the assessed methods.

The voltage and current signals, shown in Figure 13, were acquired with the power quality analyzer Fluke 435 - II. To evaluate the harmonic contribution by the BSS method before and after the filter connection, samples of voltage and current with 1s of aggregated measurements, of the observed signals were collected, according to the IEC 61000-4-7, for both the deactivated and activated filter, and then the fast and slow-varying components of the signals were separated by an 8-point moving average filter.

In Figure 14, the scalar contributions estimated by the ICA algorithms for the 5th harmonic order are compared with the results obtained by the others tested methods. It should be emphasized that the dominant impedance used in the invasive method is a harmonic filter, tuned to the frequency under analysis.

Table 2 gives the mean value of the harmonic contribution for each one of the parts, before and after the filter activation, for the field case under analysis. As expected, the results obtained in the sharing of harmonic responsibilities by
**FIGURE 13**  Real and imaginary parts of fast and slow-varying components of voltage and current at the PCC. (A) Real part of harmonic voltage. (B) Imaginary part of harmonic voltage. (C) Real part of harmonic current source. (D) Imaginary part of harmonic current source.

**FIGURE 14**  Harmonic scalar contributions of 5th order for the case study.

**TABLE 2**  Results of responsibility-sharing for the case study under analysis

| Method    | Utility Filter Off | Utility Filter On | Consumer Filter Off | Consumer Filter On |
|-----------|--------------------|-------------------|----------------------|---------------------|
| DIM       | —                  | 93.06             | —                    | 0.97                |
| FastICA   | 96.33              | 98.70             | 3.67                 | 1.30                |
| RobustICA | 91.26              | 96.42             | 8.74                 | 3.58                |
| JADE      | 91.51              | 99.34             | 8.49                 | 0.66                |
| Covariance| 95.19              | 9.39              | 4.81                 | 90.62               |
the BSS method are highly consistent, with the utility being assigned as the main responsible for the observed harmonic distortion.

Therefore, as can be observed, different from the method based on the covariance characteristic of random vectors, the variation in the relationship between $|Z_c|/|Z_u|$, caused by the activation of the harmonic filter, did not negatively affect the performance of the BSS algorithms in the assignment of harmonic responsibilities. Furthermore, taking as a reference the DIM results, it is also verified that the evaluated algorithms presented satisfactory results even using a short measurement interval and were capable to detected even the slight improvement caused by the insertion of the harmonic filter.

6 | CONCLUSION

This paper presented the concept of BSS and evaluate how the variance of fast-varying components can affect the correct sharing of harmonic responsibility between the utility and the consumer at the PCC. Thus, at first, the performance of the BSS method was computationally evaluated for several harmonic sources of different variances, using a hypothetical system, with features typical of an EPS, and the obtained results compared with those provided by the method based on covariance characteristic of random vectors. Then, a case study with signals measured at the PCC of the federal university of Uberlandia was performed, and the results obtained using the BSS algorithms were also compared with those obtained from the invasive DIM.

Therefore, in light of the studies conducted until now, one notes that the BSS method is a relevant tool for promoting harmonic responsibility sharing, which does not require a knowledge of the network topology, does not need an installation of any additional component, and can easily be implemented in the power quality meters; However, through several computer simulations and a field case analysis, it can be seen that the results of the BSS technique are more sensitive to the level of variation of the fast-varying components and the amplitude of the harmonic sources than to the relationship between the harmonic impedances of the utility and the consumer.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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