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Application of Single Channel Blind Source Separation Based-EEMD- PCA and Improved FastICA algorithm on Non-intrusive Appliances Load identification

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Abstract: The deployment of NILM systems and others embedded systems in the residential sector provides a large amount of data to better understand the electricity consumption habits of occupants in order to provide energy optimization solutions. The Fast Fixed-Point Algorithm for Independent Component Analysis (FastICA) can be used in the identification of loads through the separation of aggregated current and voltage waveforms from devices in the operating conditions that ensure the time and/or frequency independence between the sources. However, in addition to being less suitable for under-determined systems, the FastICA algorithm is sensitive to the initial weight vector, which affects the convergence of the algorithm. In order to solve this problem, a combination of Signal processing methods has been proposed to extract individual current curves representing load profiles from the single channel observation. First, the current mixed signal was decomposed using the EEMD algorithm to obtain IMFs for use in the BSS. As the number of IMFs is very large, the PCA algorithm was used to reduce the number of IMFs from n to r. Selected principal components were whitened and an over-relaxation factor was incorporated into the iterative Newton algorithm to process the randomly generated initial weight vector. The improved FastICA algorithm was used to separate the source components, selected the best current source from the mixed observation. Finally, the individual current analyzes and compares to the original signal. The advantage of this approach lies in the fact that it applies perfectly to NILM applications where very often only one observation is available, which is the aggregated signal. Moreover, it reveals the importance of the data sampling frequency for an accurate characterization of the load profile.

Keywords: Desegregation, RobustICA, Non-intrusive Load Monitoring, Smart Grid, Bling Source Separation, FastICA, EEMD, PCA

1. Introduction

Conventional signal processing methods generally require prior knowledge of certain information from the signal to be processed or from the mathematical model of the signal mixing matrix, in order to estimate the original signals by filtering or transformation [11]. In practice, prior knowledge of the signal is not easy or even impossible in some cases to obtain. In this case, these conventional algorithms cannot solve the problem. The advantage of blind source separation is that it can use little prior knowledge to get the most information. However, the conventional blind separation algorithms only apply in a context where the number of observed signals is greater than the number of sources.

Its variants, which are the FastICA, the RobustICA algorithm, the second-order blind identification algorithm, diagonalization by joint approximation, etc., are all subject to this same constraint [6]. In case of an underdetermined condition, these algorithms cannot solve the problem. The sparse signal analysis, based on the time-frequency distribution, is the excellent method to solve this type of problem. The NILM problem, which lends itself better to the case of single-channel blind separation, i.e., relying only on single-channel observation to estimate source, does not lend itself to classical blind separation methods [9]. To overcome this limit, some researchers use wavelets to decompose the signal, the result of this decomposition is then applied to the FastICA algorithm, to finally obtain the source signals [1]. On the other hand, a spatial-temporal method has been proposed in [8], which consists in delaying the multichannel signals collected by the mixed signal, and then using the independent component analysis algorithm for the separation of the multiple mixed signals, thus allowing source separation or isolation. Wei Xu and al proposed in [4] an Algorithm Based on EEMD-PCA- RobustICA in Bearing Fault Diagnosis. In this work, we propose the EEMD algorithm associated with blind source separation methods to identify the electrical loads using aggregated and individual current curves from a real database. Several works in the literature proposed solutions aimed at identifying the loads in residential sector [10, 13, 14]. Most of these methods are based on machine learning and deep learning algorithms. However, the requirement of these methods in terms of volume of data and calculation speed confronted with the difficulties of acquiring real data does not always make it possible to obtain real models. Contrary to the existing work aroused based on machine learning techniques, the approach proposed in this article is based on the combination of classic signal processing methods already proven and less demanding as well in terms of computing power and in terms of the data needed to obtain the model. These algorithms make it possible to find the IMF components of the single observation signal, then an analysis of the found components is performed and they are then compared to the individual profiles to deduce the charges involved in the mixing. The objective of this work is simply to prove the feasibility of identifying loads in the residential sector on the basis of the analysis and observation of their pro- file, using simple and easy-to-implement techniques... The simulation results shows that the method can effectively identify the different loads in certain operational conditions. The article is organized as follows: section II highlights the interest of the method for NILM, then section III briefly describes the algorithms, followed by the presentation of the working hypotheses in section IV. Section V presents the results of the decomposition of the mixtures made from the profiles of the COOLL database followed by the interpretations. Finally, we conclude the article in section VI.

2. BSS Method Interest in Non-intrusive Load Identification

According to Kirchhoff's law, the sum of the currents entering a node is equal to the sum of the currents leaving this node. In the electrical circuits of modern buildings, all devices are connected in parallel. The main circuit breaker is a node where Kirchhoff's current law applies [14]. This results in the NILM equation on current:

$$I_{Total(t)} = \sum_{d\epsilon D} i_d(t) \quad (1)$$

$I_{Total(t)}$ is the current at the main breaker, d is the index of an electric device and D is the set of all the device in the electric network. All the devices on the network use the same voltage so the overall power can be express by:

$$P_{Total(t)} = \sum P_d(t) = \sum i_d \times V(t) \quad (2)$$

Time-frequency analysis disaggregate a signal into the time and frequency domain and is an important supporting technique for constructing energy analysis, such as noise cancellation in constructing load predictions based on the data [3]. Current methods for obtaining such information, for example surveys, are usually expensive and time-consuming [5]. The EEMD decomposition aims to decompose the signals contained in the aggregated curve into different modes having a good physical significance [12]. This means that knowledge of these modes makes it possible to intuitively understand the frequency content of the signal. Conventional methods decompose a signal using functions specific to the method, which are therefore independent of the signal studied. This is the case of the Fourier transform which breaks down a signal into a sum of sinusoids; The wavelet method, on the other hand, uses" wavelets" as basic functions, which are localized functions [7].

2.1. Problem Formulation

Individually identify loads connected to a network based on knowledge of their profile (current waveform). The proposed algorithm must be able to allow the identification of loads in a multi-function context (several devices in operation). This problem can be formulated differently, i.e. in terms of identifying the active devices at each time step [14]. In this case, from the actual measured power, we will estimate which de- vice is active in the house. Finally, the problem can also be formulated in terms of where the high frequency current and voltage measurements are used to estimate the actual electrical consumption in the house. For this last formulation of the problem, the current and voltage waveforms of different devices are estimated from the aggregate current and volt- age measurements acquired at the main circuit breaker of a house at a sampling frequency of 100 kHz (COOLL Data).

$$i_{\ Total}(t_k),\ u_{Total}\ (t_k)$$

$$P_d(t_k) = \frac{1}{T}\int_t^{T+1} i_d(\mu_d)dt \quad (3)$$

We have thus just shown that the problem of the NILI systems can be considered as a source separation problem. In such a problem, we mean to separate the unknown sources from the observed mixed signal. In our case, the unknown sources are the individual consumption (current) and the mixed observation is the total system consumption. By integrating that in the NILI context, the mixing process is simply the sum of the sources. The separation of the sources is said to be single- channel because only a single observation signal is available (corresponding to a mixing process). In its current form, the source separation problem is said to be blind since it is approached without knowledge of the number or type of sources.

2.2. Description of the Method

The method consists of the combination of the ensemble empirical mode decomposition (EEMD) with the PCA and FastICA algorithms to separate the current waveforms drawn by the individual load from the aggregate current. This is a single-channel blind separation, also known as the under-determined case, hence the use of empirical modes which make it possible, from a single signal, to obtain several intrinsic mode functions whose sum is equal to the signal of entry. This step allows reducing the problem to the over-determined case in order to make the application of blind source separation algorithms in particular FastICA possible. The number of IMFs being dependent on the size of the sample of the input signal, one can end up with a large number of intrinsic mode functions which would require a time and a higher computing power. The PCA algorithm is therefore used in order to reduce the number of input signals by choosing among the IMFs the main components, ie containing the greatest number of information from the aggregated signal. The IMFS retained by the PCA are then applied as source signals for the FastICA blind separation algorithm. The diagram below describes the steps of the process.

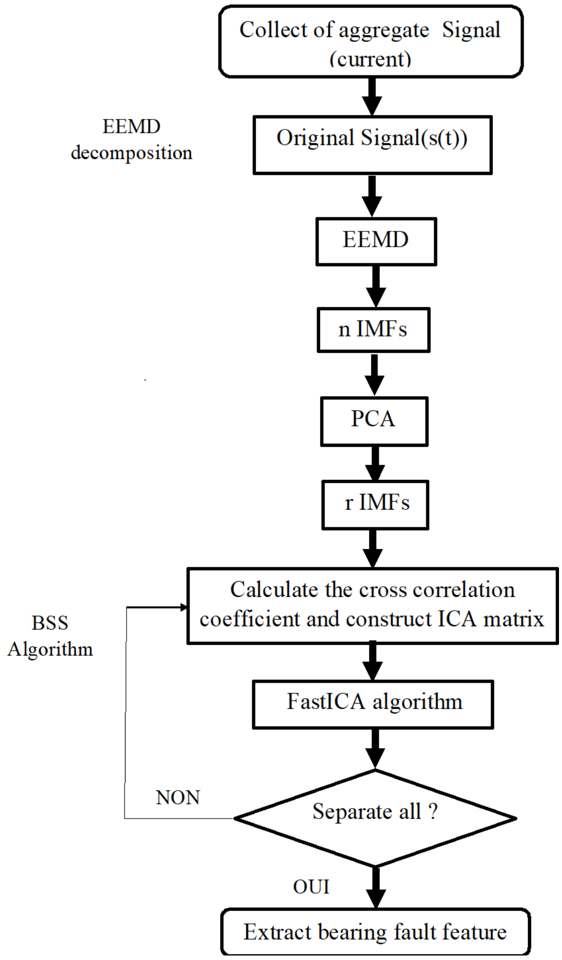

Figure 1. *Method's flowchart.*

3. Algorithms

3.1. EEMD Algorithm

The EEMD, as explained in [2], considers the oscillations of a signal at the local level. Over an interval separating two consecutive extrema, the signal is separated into a high frequency term and a low frequency term. First, the low frequency is eliminated (in the whole signal) to isolate the high frequency. A first mode is then extracted. Then we iterate over the residual. The low frequency term is equated to the average between the lower and upper envelopes of the signal. These envelopes are calculated by interpolation between the minima (for the lower envelope) or the maxima (for the upper envelope) of the signal [11]. This approach is obviously not sufficient and therefore to isolate the high frequency term, it is necessary to eliminate the average of the envelopes of the current signal until it becomes zero. Finally, the process is repeated on the signal, as it was before the elimination phase, devoid of the high frequency term. For one-dimensional current signals, the EEMD algorithm can be described as follows:

1) Initialization: $r = f, k = 1$.
2) Calculation of the average envelope e of r (i.e. the average of the envelope of the minima and the envelope of the maxima of r).
3) Extract intermediate functions $pi = r - e$ and define$r = e$.
4) As long as p_i is not an IMF (Intrinsic Mode Function) repeat the calculation of the mean envelope $ei$of pi, $pi + 1 = pi - ei - i = e + 1$.
5) dk = pi, r = r – dk.
6) If r is not monotone, go back to step 2 and set $k = k + 1$ otherwise the decomposition is complete. When the decomposition is complete, we can write x as:

$$\text{x(k)} = \sum_{i=1}^{N} s_i(k) + r(k) \tag{4}$$

Based on the model in Equation 4, we summarize the two-step approach, including:

7) The analysis step: In this step, a modal decomposition is applied to each output signal (current) in order to ex- tract all the harmonic or pseudo-harmonic components. This decomposition consists of the EEMD algorithm de- scribed above.
8) The synthesis step: In this step, the modal components corresponding to the same source signal are grouped together to reconstitute the original signal. This is done by a classification method based on the spatial direction of the components which is estimated by correlating them with the observed current wave.

This algorithm uses a particular noise instead of the Gaussian white noise which is added at each stage of the decomposition and obtains for each IMF with a unique residual.

3.2. PCA Algorithm

Our data is represented as an *np* matrix *X,* where n is the number of observations and p is the number of variables representing them. p is usually quite a large number, which can be up to several tens of thousands in some applications. This is the case of the signals from the COOLL database and used in this article. It will be a question of finding m variables, with $m < p$, which we will choose to use to construct a new matrix X' of dimension nm to represent our data [15]. If we can represent our data in a few dimensions, it also means less information to store, which reduces the cost of memory space. On the other hand, having fewer variables reduces the complexity of the learning algorithms that we can use, and therefore the computation times. Finally, if some variables are useless, it is not necessary to obtain them for new observations: this can reduce the cost of data acquisition. The goal of principal component analysis is to find a new orthogonal basis in which to represent our data, such that the variance of the data along these new axes is maximized. With p variables: each observation (IMF) is represented by a vector in R^p, and we have n observations gathered in a matrix $X \in Rpxn$.

We start by looking for a new direction, namely a vector w_1 R^p, of norm 1, such that the variance of our data projected on this direction is maximum. The projection of data X onto w is $z1 = WT\,X$. In sum the PCA algorithm can be describe by the steps below:

Step 1: Get the data. Take the 2 dimensional matrix of independent variables X. Rows represent data items and columns represent features. The number of columns is the number of dimensions.

Step 2: Give the data a structure.

Step 3: Standardize your data.

Step 4: Get Covariance of Z Covariance of $Z = Z_Z^T$.

Step 5: Calculate Eigen Vectors and Eigen Values. Calculate the eigenvectors and their corresponding eigen values of $Z^T\,Z$.

Step 6: Sort the Eigen Vectors Take the eigenvalues $\lambda 1, \lambda 2, ,., \lambda p$ and sort them from largest to smallest. In doing so, sort the eigenvectors in P accordingly.

Step 7: Calculate the new features.

Step 8: Drop unimportant features from the new set We need to determine which features from the new set we wish to keep for further study.

4. FastICA Algorithm

The FastICA algorithm is one of the most popular algorithms in the field of independent component analysis (ICA). There are two versions of FastICA: The one that deals with the case where the sample is of infinite size, and the other that deals with the concrete situation, where only a sample of finite size is available. In this article, we consider the finite size sample. FastICA, is a fixed-point algorithm intended to calculate the extremum of the kurtosis function of a probability density. The kurtosis is a contrast function for independent component analysis and when it is locally minimized to maximized after certain iterations by the linear combination $WT.x$ of the signals x which will be equal to the nearest signed to one of the independent components. The FastICA algorithm is based on this property to calculate the independent components and thus obtain the separation of the source signals [16, 17]. The iterative algorithm finds the direction of the weight vector w maximizing the non-Gaussianity of the protrusion w^T x for x. The $g(.)$ function is the derivative of a non-square function [18].

Step 1: Choose a weight from supports w.

Step 2: Is $w \leftarrow E\,[\,x\,g(wT\,x)] - E\,g''(wT\,x)w$.

Step 3: Is $w \leftarrow w\,/\|w^+\|$.

Step 4: If it did not converge, go back to step 2.

The maxima with respect to the approximation of the negentropy of wT x are obtained in correspondence with results of the optimization of the function $E\,G(wT\,x)$; according to the Karush-Kuhn-Tucker conditions, the Optimals of the function $E\,G(wT\,x)$ with constraint $E\,(wT\,x)2 = \|w^2\| = 1$ are obtained in the points where it occurs:

$$\mathrm{E}\,\mathrm{X}g(w^T\mathrm{X}) - \beta w = 0$$

The resolution of the equation with Newton’s methods allows to obtain the Jacobean’s matrix define as:

$$w^+ = w - \frac{[E\{Xg(w^TX)\} - \beta w]}{[E\{g''(w^TX)\} - \beta]}$$

In this case, convergence means the occurrence of the situation in which the values of w in step 2 referring to successive iterations point in the same direction. The optimum kurtosis contrast function given by the following expression:

$$\mu_{opt} = \arg max|K(w + \mu g)| \quad (5)$$

$$\mathrm{K(w)} = \frac{E|y|^4 - 2|E^2|y|^2 - E^2|y|^2|}{E^2|y|^2} \quad (6)$$

where the residue of the decomposition is noted r and s_i, the components, designating the intrinsic modes [1] and obtained by successive iterations, $si, \mathrm{i} = 1, \dots, \mathrm{n}$. Basically, it should be verified that the family of intrinsic modal functions s_i is complete and orthogonal. Completeness is ensured by definition while criteria exist to verify orthogonality properties [1]: 1. the difference between the number of extrema and the number of zeros of the function must be zero or at most equal to 1; 2. the average value of the sum of the upper envelopes, defined by the maxima, and lower, defined by the minima of the function, must be zero.

5. Hypotheses

The signals retained within the framework of this study are deterministic and therefore not Gaussian since it is the electric current drawn by different loads. However, blind separation is only applicable to random signals exhibiting time and/or frequency independence. The approach proposed in this work is therefore only valid under a certain number of hypotheses. First regarding the mixing criteria and then the algorithms themselves. We have therefore considered situations where:

The ON and the OFF of the two devices are close, which means that the two devices are started almost at the moment and it is the same for the stop. only after the start of one of the devices, the extinction of the other follows.

The second mix highlights the rapprochement of the ON instants of I2 with the OFF instants of I1.

Finally, the third scenario, the signals are mixed randomly. These scenarios allow us to create temporal independence between the original sources.

The random noise added during the decomposition converts our original sources from deterministic into random.

The results presented in the remainder of this document were produced using how individual and mixed currents signals loads such as the saw, the drill, the Fan and the Lamp from the COOLL database [9]. The charges retained in this study are those whose mixtures of signals go linearly and instantaneously, that means that the observations are written as linear combinations of the sources which are also one-dimensional signals $s_j(t)$ the mixture is written as:

$$x_i(t) = \sum_{j=1}^{N} a_{ij} s_j(t) \tag{7}$$

$i = 1,\ldots P$ where a_{ij} is a constant real which corresponds to the amplitude of the contribution of the source $s_j(t)$ on the sensor $s_j(t)$ and represents the elements of matrix A. In the context of non-intrusive energy disaggregation, we considered the mixture to be under-determined, i.e. the number of sources is greater than the number of observations. This scenario, al- though more complex to separate, allows better identification given that in reality it is not always possible to recognize certain loads, especially when large consumers operate simultaneously with small loads such as telephone chargers... From the COOLL database [9], we have chosen the current wave- forms corresponding to the following loads: Drill, Grinder, Fan and Lamp. The individual current curves of these two loads as well as that of the aggregate current are shown in figure 2.

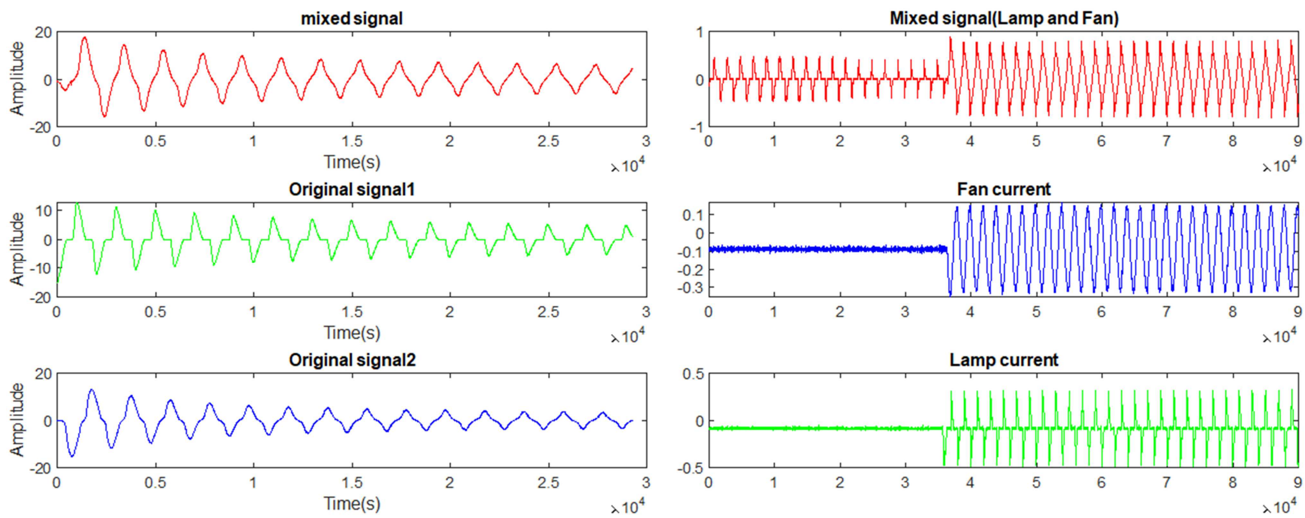

Figure 2. *Originals and Mixed signals drill and saw (a) and lamp/fan (b) with ONs/OFFs close to each other.*

Table 1. *Comparison between Original sources and estimations.*

Signals	Sample difference	Time difference
x1 and zfica1	8	0.0008
x1 and zfica2	231	0.231
x2 and zfica1	480	0.48
x2 and zfica2	5	0.0005
second couple of loads		
x1 and zfica1	0	0
x1 and zfica2	89184	
x2 and zfica1	-767	-0.0767
x2 and zfica2	-180	-0.018

6. Results

In this section we present the results of simulation carried out with the currents called by four loads: the drill, the saw, the lamp and the fan. Mixtures that have been made artificially.

One can observe beyond the approximation of the estimated waveforms (figure 4a, 4b, 4e and 4f) and the original curves (figures 4c, 4d, 4g and 4i) a significant difference in the amplitudes. This difference is due to the indeterminacies of the fastICA algorithm as well as the random display of the estimated curves. To reassure us that the estimates correspond or at least come close to the original signals, we use the metrics of analysis of similarities between the signals. The cross- correlation (figures 5a, 5b) allows also to calculate the difference of samples and time between these signals to better appreciate the rendering of the proposed approach.

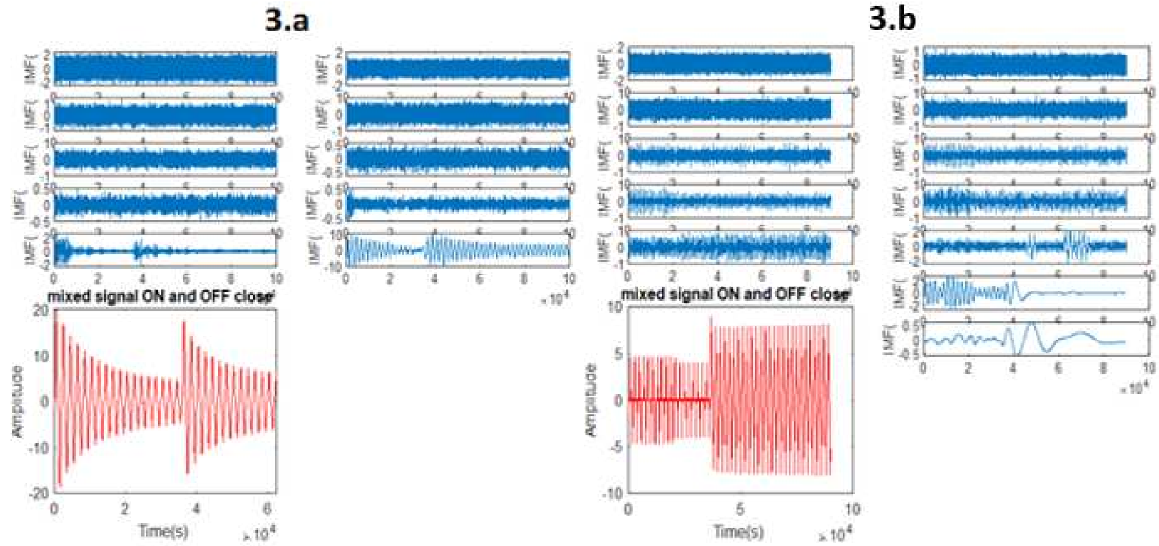

Figure 3. *Intrinsic modal functions (a) of the mixed signal (b) of Drill/Saw and Fan/Lamp Mixed current.*

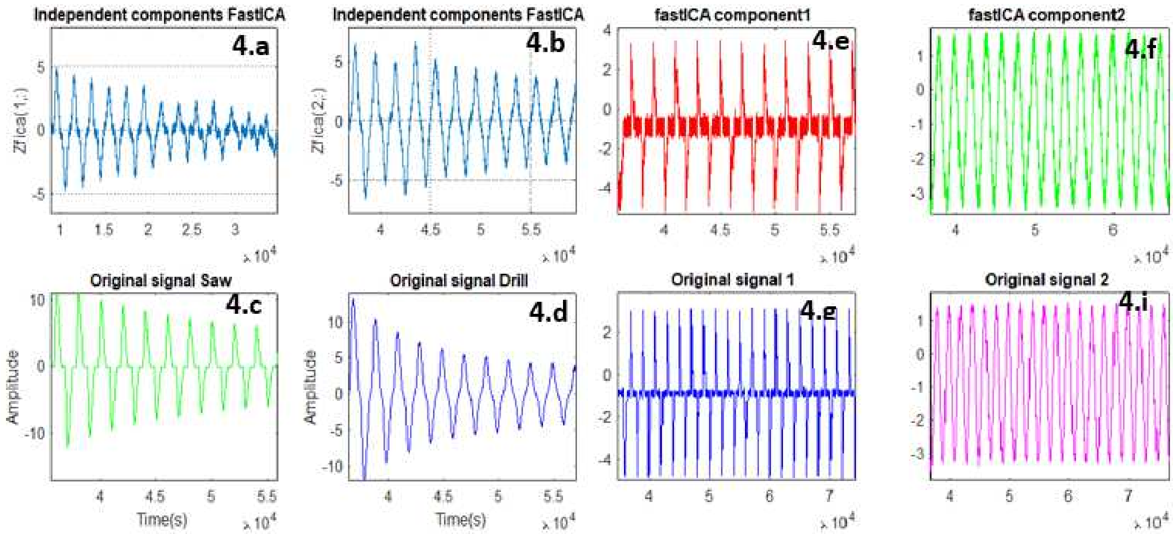

Figure 4. *Drill/Saw (a-d) Fan and Lamp (e-i) estimated signals and Original.*

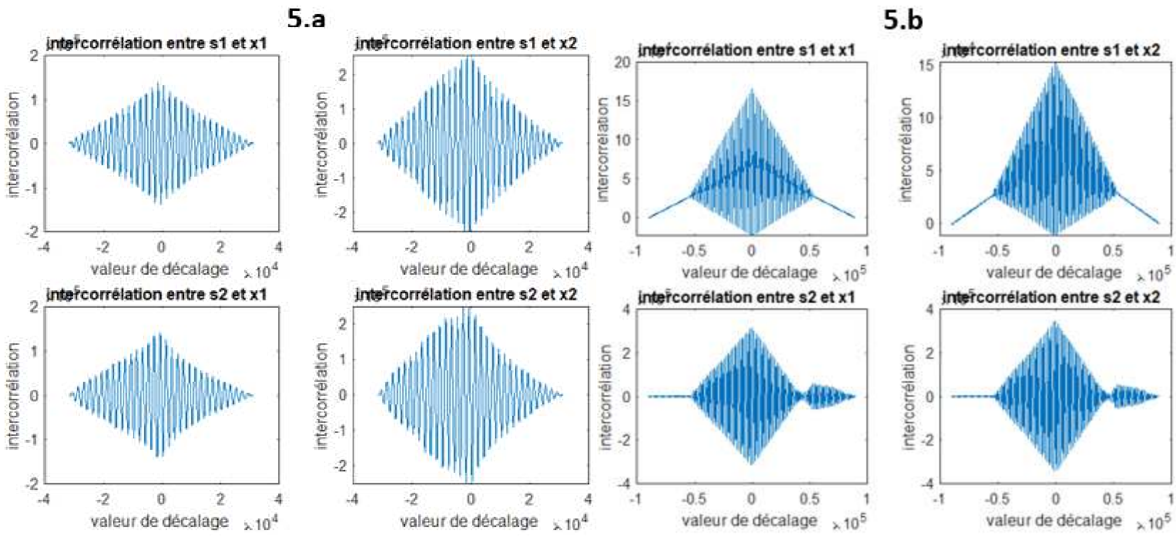

Figure 5. *Cross-correlation of Drill/Saw and Lamp/Fan current and estimations.*

7. Conclusion

In this article, the EEMD-PCA-FastICA method is proposed for the identification of electrical loads in a residential context. The signals used are currents measured on real loads from the COLL database. The mixtures were made artificially according to hypotheses making it possible to create a temporal independence between the signals. Although the various currents are deterministic, the addition of a random noise in the respect of the concepts of the algorithm EEMD allows the sources previously deterministic in random signals thus allowing the application of the algorithm of blind separation. The method is proposed in the context of a non-intrusive load monitoring and could make it possible to propose a solution to help diagnose the state of appliances in the residential sector thanks to spectral analysis of the oscillations resulting from the EEMD decomposition. The results from four charges prove the feasibility of our approach. However, FastICA-related indeterminacy lead to sample and temporal differences as shown in the table. These values can be used to synchronize the signals. The cross-correlation shows that the estimates are perfectly correlated to the original signals. In other words, the estimates do contain the original signals.

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