Harmonic Signal Seperation in Domestic Loads through Blind Source Technique

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Abstract— **The harmonic signals measured at the main power supply that contains various unknown original independent harmonics are analysed using an enhanced Fast ICA algorithm using Blind Source Separation Technique. Using the FastICA the harmonics signals are separated by the differentiating factor of the power loads and are analyzed. The mixed signal is measured with a current sensor and goes through the existing FastICA unction and cross-correlation of signals that are developed to separate and identify multiple unknown type of appliance.**

Keywords-blind source separation, harmonic analysis, domestic loads

I. INTRODUCTION

With the proliferation of highly inductive loads for various applications the harmonic mitigation is a challenging aspect in the power system area. In the domestic and commercial appliance such as the personal computers, printers, fax machines, telephone systems and any other equipment powered are major culprit as they are operated through switched-mode power supply [1-2]. Power analysis focuses on these electrical power harmonics. Harmonics is considered a threat as it is a perturbuted unwanted signal that causes the loss of energy and damaging the load appliance [3]. Low quality power source produce output electrical waveform of non-sinusoidal that comprises the fundamental frequency and non-fundamental frequency altogether. The paper presents the mitigation strategy used in the domestic inductive load through a proposed fast separation of harmonic signals through cross-correlation function. The implication of the use of this enhanced algorithm can be used for any harmonic signal separation.

II. METHODOLOGY

A. Blind Source Seperation

Blind Source Separation also known as blind signal separation, as most of the sources are made up of signals, is the separation of a set of signals from a set of mixed signal, without aid of information or with very little information about the source signals or the mixing process [4]. The Blind source separation (BSS) is a technique for recovering source signal solely from their mixtures [5]. BSS has been widely used since the year 1997 [6].

Blind Source Signal is used in every aspect as long as the sources are of: sounds, images, biomedical or financial data, and of course for this work the source of current and voltage waveforms. Some of the common use includes principal Component Analysis (PCA)[7], Singular value decomposition [8], Independent Component Analysis (ICA) [9], Dependent Component Analysis (DCA)[10], Non-negative matrix factorization [11], Low-complexity coding and decoding [12], Stationary subspace analysis (SSA) [13], Common Spatial Pattern [14]. BSS is very time consuming especially when the number of sources are large, this is mainly because the permutation problem of frequency-domain BSS is difficult to solve when there are many sources [15][16]. In some cases it is related to Independent component analysis, Multichannel Blind De-convolution, or Blind Signal Extraction.

B. Independent Component Analysis

For this work itself, a fixed-point algorithm is used for Independent Component Analysis (ICA). BSS sources be as non-Gaussian as possible and because ICA functions in a way of Kurtosis, Gaussian graphs kurtosis give no value. Kurtosis is the 4th order cumulated, as kurtosis measures the non-Gaussianity. Kurtosis in mathematical form is stated as in Equation (1).

$$kurt(y) = E\{y^4\} - 3(E\{y^2\})^2 \qquad [1]$$

As shown above the kurtosis form, the 4th moment is stated as $E\{y^4\}$, while $3(E\{y^2\})^2$ states the Gaussian of the fourth moment. And so if the 4th moment $E\{y^4\}$ is Gaussian , the answer is zero as it subtract the Gaussian that is available in the statistics [49]. To give a deeper understanding of Kurtosis, it go through the moment and central moment as Kurtosis revolves around statistical properties [15]. For a first moment it is also be known as the Ensemble Mean or Ensemble average, or simply mean [16]. For a mathematical formulation for n number of moment is as in Equation (2).

$$\overline{x^n} = \int_{-\infty}^{\infty} x^n p_x(x) dx \qquad [2]$$

According to the formulation above $p_x(x)$ mean the probability amplitude which is 0 to 100 in percentage in a Probability distribution function. Another formulation that represents the standard variation is the central moment which give a formulation as in Equation (3).

$$\overline{(x - \overline{x})^n} = \int_{-\infty}^{\infty} (x - \overline{x})^n p_x(x) dx \qquad [3]$$

As shown the central moment is centered around the mean the 2nd central moment eventually be the variance. By understanding the above two equations which is the moment and central moment the skewness which is an order lower than kurtosis which is in the 4th order is given in Equation (4).

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$$\text{kurt}(\propto x_1) = \propto^4 \text{kurt}(x_1) \qquad [4]$$

From the above equation $\propto$ is the scalar constant, this equation proves that the amplitude is not taken into consideration during the process of kurtosis is given in Equation (5).

$$\text{kurt}(x1 + x2) = \text{kurt}(x1) + \text{kurt}(x2) \qquad [5]$$

As stated above x1 and x2 are two independent random variables. From the above equation it seen kurtosis happens on individual independent components. Skewness gives information on the amount of relatively high values or low values. As an example, if a set of numbers consist more high value numbers, the peak of the distribution graph is inclined towards right, also it is known as negative skew. If the set of numbers contain more low value numbers, the peak is relatively slanting to the left, also known as positive skew [16]. As seen the skewness, kurtosis is of the 4th order which is $\frac{\text{4th Central Moment}}{\text{standard deviation power of 4}}$. By dividing the 4th central moment kurtosis give us a specific position of the value that is most not random in a set of number [15]. Thus using the formulation of kurtosis give us an independent component. Kurtosis may not be robust in the measure of non-gaussian because kurtosis is sensitive to outliers, as its value only depend on a few observation in the tails of a statistic distribution, which is at the most left or most right of a statistics waveform [15]. And so another formulation has to come in place to fulfill the lacks of kurtosis in the measure of non-gaussian.

C. System Design

The brief methodology of the working of the harmonic separation is shown in Figure 1 and the block diagram with the data acquisition interface is as shown in Figure 2. The hardware design of the universal test bench is as shown in Figure 3. A current sensor is used to sense and capture the current and through the data acquisition it is captured for analysis in the MATLAB environment. Three different domestic loads are used for the analysis. The operational addition of the loads affect the current from the source and the variations in the power signals are captured through the

current sensor and the DAQ. The acquired data are separated using programming from the MATLAB interface using cross-correlation technique. The software used for simulation is Matlab software. To be able to deal with real time signals, the user defined signals are put in so that the main objectives is solved foremost. In a real time signal, there are lot of factors that affect the outcome, such as the noise that consists inside of the signals. By using self-defined signals, an ideal situation to minimize complexity is simulated. In this work a mixed signal originated from the connections of loads around a house to its main grid is simulated. The connections of these appliances are in parallel, and every load is directed to one main power supply just like every house. The purpose of parallel connection is that current is supplied separately towards each and every load that is connected in parallel. Let us assume the loads are connected in series, and when one load is in open circuit state, other loads do not get voltage flowing through as well. And so the signals that goes into account are assemble in rows as shown below.

```
sig(1,:)=sin(v/2); %sinusoid
sig(2,:)=((rem(v,23)-11)/9).^5; %funny curve
sig(3,:)=((rem(v,27)-13)/9); %saw-tooth
sig(4,:)=((rand(1,N)<.5)*2-1).*log(rand(1,N));
%impulsive noise
```

As shown in the above coding, signals are assembled in row as the function sig(N,:) sets a variable in the Nth row as shown in Equation (6) .

```
mix1=0.2*x+0.3*y+0.5*z;
mix2=0.5*x+0.2*y+0.3*z;
mix3=0.3*x+0.5*y+0.2*z;                        (6)
```

As shown above, x, y, z represents independent signals. The constants represent the percentage that each independent signal is assigned of. To create a differentiating factor for the usage of FastICA algorithm, the amount of mixed signal that is developed must be the same as the amount of signals that is originally available.
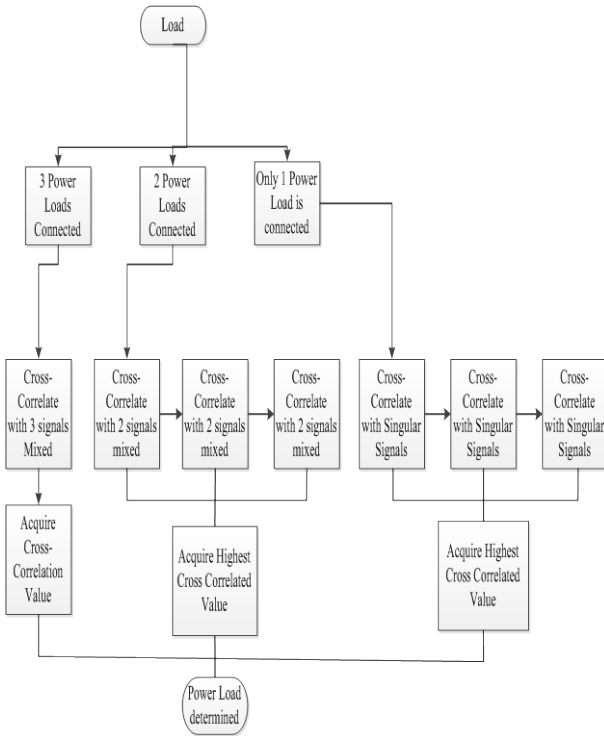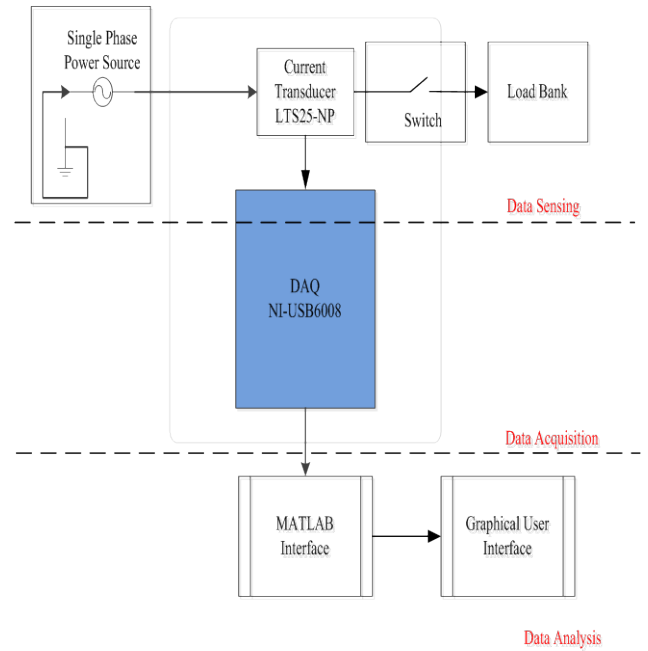
Figure 1. Power Harmonic Signal Analysis
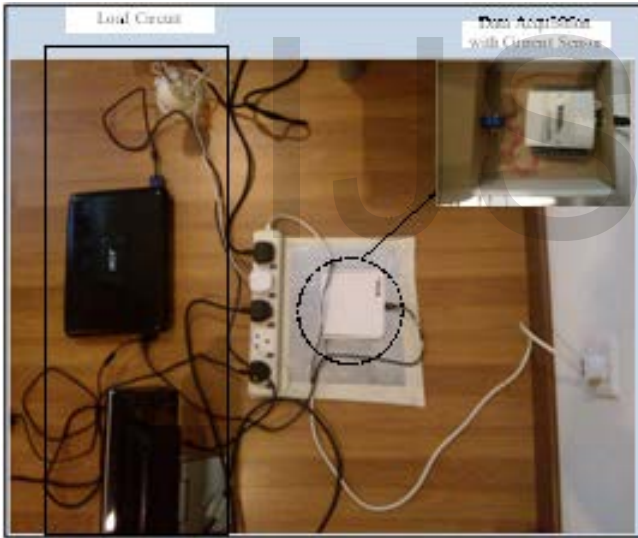

Figure 2. Measurement System Integration

Figure 3. Data Acquisition System

III. RESULTS AND DISCUSSIONS

The signals are mixed in a simple way as shown in Equation (7).

mix1=0.2*(y1)+0.3*(y2)+0.5*(y3);
mix2=0.5*(y1)+0.2*(y2)+0.3*(y3);
mix3=0.3*(y1)+0.5*(y2)+0.2*(y3);
mix4=0.5*(y1)+0.5*(y2);
mix5=0.5*(y1)+0.5*(y3);
mix6=0.5*(y2)+0.5*(y3);
(7)

mix1, mix2 and mix3 are actually the mixing of 3 signals. We may use one of the mix in cross correlating. Mix 4 is the mixing of stand light and display monitor signals. Mix5 is the mixing of stand light and laptop signals. Mix6 is the mixing of

display monitor and laptop signals. Once the signals are cross correlated the commands in Matlab editor to display the cross correlation value are as follows:

```
d1=max(abs(D1));
disp('light and monitor signals')
disp(d2);
```

Figure 4 shows the choice on the load using the graphical editor and the real time signal is shown in the window. Figure 5 shows the three loads used in these investigations. The three signals from the display monitor, laptop and the stand lamp representing the inductive load are captured in the real time through the data acquisition system and are reconstructed through the coding in the MATLAB environment for analysis. TABLE 1 shows the various sources of signal and the magnitude results.
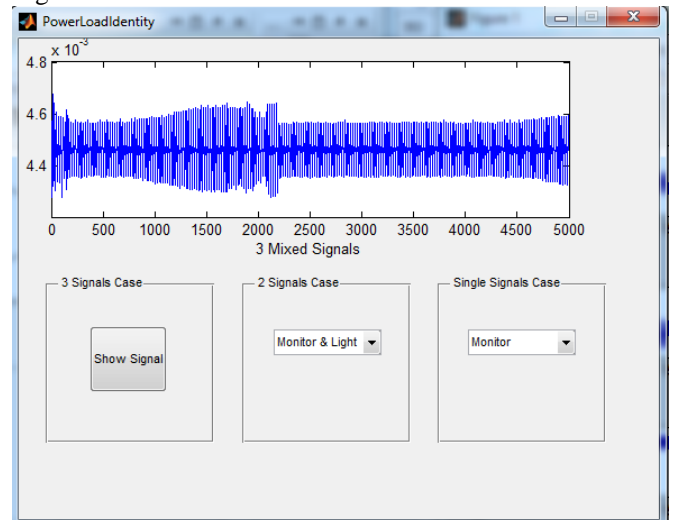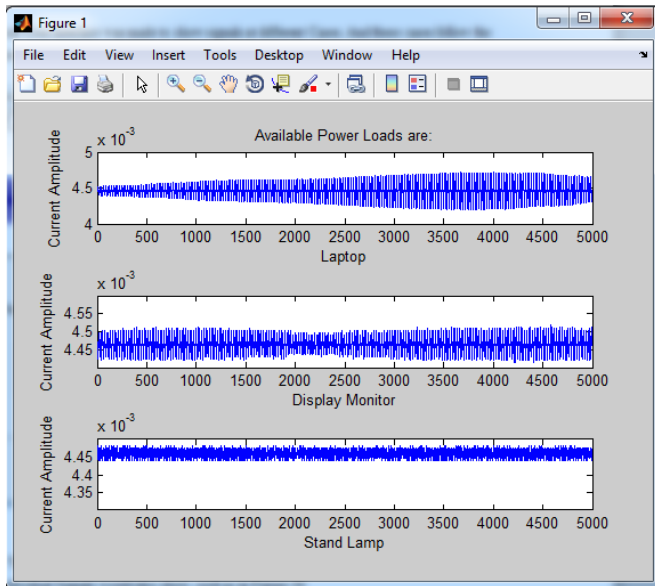

Figure 4. Data Acquisition System

Figure 5. Data Acquisition System

TABLE 1. Results of non-mixed and two mixed signal

Item	Non-Mixed Signal	Two Mixed Signal
All three signals	0.9999	0.9568
Light and Monitor	0.6960	0.6866
Light and Iron	0.999	0.9565
Monitor and Iron	0.999	0.9567
Light	0.9545	0.9296
Monitor	0.4637	0.4726
Iron	1.0000	0.9564

IV. CONCLUSIONS

Direct FastICA implementation in this work is not possible, or rather defeats the purpose of separating blind source signal. Initially the FastICAfuctions as follows in the Blind Source Separation by saving the three independent components, as three separate data and then they are mixed into one signal and then use the Fast ICA to three independent components again. The approach could be used for any number of signal mixing to understand the signal separation through cross-correlation technique. With the help of the USB 6008 the acquiring of the data in real time is possible. The current sensor captures the variations with respect to the changes in the load and the captured data are used for analysis in the MATLAB environment. This setup makes it a platform for measurement and analysis power signals in real time.

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