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Experimental Investigation on the Load Signature Parameters for Non-Intrusive Load Monitoring

Abstract*. One of the most important design decisions in Non-Intrusive Load Monitoring (NILM) systems is choosing which electrical parameters will be used to define load signatures. In this paper, we present an experimental study where several electrical quantities of common home appliances were measured, in order to identify the most adequate to perform load disaggregation. It was found that active power, reactive power, rms voltage, and the first five odd harmonics of the current and voltage signals comprises the best set of parameters to define the signatures of residential loads.*

Streszczenie. *W artykule zaprezentowano eksperymentalne studium w którym zmierzono parametry typowych urządzeń elektrycznych w celu określenia i zestawienia obciążeń. Stwierdzono że moc czynna, moc bierna, napięcie skuteczne i pierwsze pięć nieparzystych harmonicznych prądu mogą stanowić podstawę do prognozowania obciążeń.* ***Badania parametrów urządzeń dla nieinwazyjnego monitorowania obciążeń.***

Keywords: load signature, power signature, non-intrusive load monitoring (NILM), harmonics.
Słowa kluczowe: monitorowanie obciążeń, znaczniki obciążeń..

Introduction

Over the last years, researches all around the world has been developing load monitoring systems, methodologies and algorithms to disaggregate the total energy consumption of a building. Despite the variety of techniques and technologies used, the disaggregation systems are divided in two main groups: intrusive and non-intrusive. Intrusive or decentralized systems, are those in which the power consumption is measured individually in each load. These systems are composed of several power meters, making them relatively expensive and difficult to install and maintain. The other way to disaggregate the energy consumption is through Non-Intrusive Load Monitoring (NILM). In this approach, only one power meter is required, usually installed at the utility service entrance. Systems which use the NILM methodology are cheaper and easier to install [1-5], but are more complex and unable to accurately identify the power consumption of appliances with multiple operating states, non-discrete changes in the power consumption or larger oscillations in the steady state, as some fluorescent lamps, refrigerators, AC variable speed drivers, and other non-linear loads [1-6].

NILM systems perform the load disaggregation based on the principle of power signature, which is defined as a set of electrical characteristics of a load that can uniquely identify it. Power signatures can be defined in several ways, the simplest is using power or current curves in the time domain, but almost all electrical parameters derived from voltage and current can be regarded as power signature. Active, reactive, and apparent powers, power factor, rms voltage, and current are quantities commonly used to define power signatures. These parameters can be represented either in time or frequency domain, or even mathematically in terms of wavelets, eigenvalues or singular value decomposition.

Regardless of the electrical parameters chosen to compose the power signatures, the recognition algorithm can operate using three different approaches: analyzing the transient characteristics (the period of time when the load is turned on or off), the steady state characteristics or a combination of both. It is worth to notice that steady state analysis requires a simpler hardware (since the sampling rate required is smaller than in transient analysis) [2], and the signatures of two or more loads are additive [7].

The choice of which electrical parameters are used to define load signatures is a critical factor of the performance of the NILM system [1]. The use of too few parameters can decrease the accuracy on the load identification, particularly for appliances which present a complex electronic behavior, as in personal computers where many internal loads are turned on and off with an unpredictable behavior (hard-disks, video graphic cards, sound cards, etc.). On the other hand, the use of too many parameters requires more complex algorithms and, therefore, more computational power, especially when a big number of appliances are monitored [1]. Since most commercial NILM systems are developed using embedded processors, the computational complexity to calculate the electrical parameters is a limiting factor in the development of these systems.

Although NILM has been studied for more than two decades, there is no consensus regarding which electrical quantities are the best for load disaggregation. In this work, we present the results of an experimental study performed with 12 common home appliances, which were measured and analyzed in order to determine the best set of electrical characteristics for development of NILM systems.

Non-Intrusive Load Monitoring

The first non-intrusive load disaggregation technique was proposed by Hart in the 1990's [8]. In this work the operating schedules of individual loads were determined by identifying instants that the power consumption changes from one steady state value to another. These steady-state changes, known as events, are characterized by the magnitude and sign of the active and reactive power values that is associated with a given load, which is being turning on/off. In this approach, only the information about steady state of the loads was used for its identification. A database containing the active and reactive power of every load is required to perform load disaggregation.

According to [10], this method fails in several cases: (i) when there are loads that overlap ambiguously in the ΔP-ΔQ plane (presents similar active and reactive power consumptions), (ii) when more than one load are switched on/off simultaneously, (iii) when the load is switched on/off faster than the power meters can capture, and (iv) when a new appliance, not registered in the database, is used.

In the 90's researchers started using transient information for load disaggregation. Leeb [3] proposed a prototype of a residential NILM system that uses transient characteristics in the real and reactive power space to distinguish loads. The paper in [11] presents a NILM for commercial buildings based on steady-state and transient load-detection algorithms. The developed prototype is able to differentiate appliances with near-simultaneous start-ups and similar power levels. Other techniques for load disaggregation based on transient were later proposed in [1,6,12-14].

Cole and Albicki [6] proposed a NILM system for three-phase environment that uses the first eight odd harmonics of the current signal for load disaggregation. Harmonic content proved to be very useful to distinguish loads that ambiguously overlap in the ΔP-ΔQ plane, as some non-linear loads. After the important work of Cole and Albicki, many systems which use harmonic analysis were proposed [1,5,12,15-18].
More information about NILM can be found in the reviews presented in [2,15].

Electrical Quantities Used to Define Power Signature

Although many non-intrusive load disaggregation methods have been recently proposed [1,5,12,19,20], a detailed study discussing which electrical parameters derived from voltage and current curves are more adequate for load identification has not yet been presented. According to [1], finding a meaningful set of electrical parameters to distinguish all appliances is one of the current challenges of load monitoring. Authors in recent publications clearly do not agree on the choice of these parameters. It is observed that, although active power and current are common to all works which perform identification based on load signatures, we see many different approaches, as the use of reactive power [4,5,12,16], power factor [21], and harmonic components in the current signal [1,5,6,12,16-18]. Analysis in the frequency domain has been shown to be promising; however, there is no consensus regarding which harmonics are appropriate for this purpose. In [1], the authors used the first three odd harmonics, in [6,16] the first eight odd harmonics, in [17] the sixteen first even and odd harmonics, whereas in [5] only the 2nd and 3rd harmonics were analyzed.

Considering the relatively high computational cost of the algorithms used to calculate the Discrete Fourier Transform (FFT [22], Goertzel [23], etc.), calculation of many harmonics at a high rate and in real time may become impractical. However, the use of too few harmonic will cause loss of important information for load disaggregation, especially for non-linear loads, resulting in misidentification.

Thus, the choice of an electrical parameter for defining load signature depends on two basic characteristics: it has to clearly present different values for different appliances, and also must require few computational resources to be calculated. In this paper we present an experimental study where the voltage and current signals from residential loads were measured and, from these data, commonly used parameters for load identification (rms current, active, reactive, and apparent powers, power factor, and the first harmonics of the current signal up to the 25th) and rms voltage were calculated. Based on the obtained data we indicate which are the best electrical parameters to be used in advanced load disaggregation algorithms.

Experimental Setup

To obtain the voltage and current waveforms we used a data acquisition module (DAQ) NI USB-621, a signal conditioning PCB, and a data acquisition software developed in LabVIEW.

The schematic of the signal conditioning board is presented in Fig. 1. The mains supply voltage was divided with a simple resistive voltage divider R1-R2, filtered by a 2nd order RC filter and sent in differential mode to the input of the NI USB-621, to be converted to a digital signal with 16 bits resolution. A current transformer with input/output ratio of 1000:1 and a maximum error of 1% was used as current sensor. The output voltage of the current transformer was also filtered by a 2nd order RC filter and fed into another differential channel of the data acquisition module and converted to digital with 16 bit resolution.

The two DAQ channels were configured with a conversion rate of 120 kS/s, and a full scale of ±200 mV. This configuration allowed us to measure voltages up to 230 V_{RMS} with 7 mV_{RMS} resolution and current up to 15 A_{RMS} with 458 μA_{RMS} resolution.

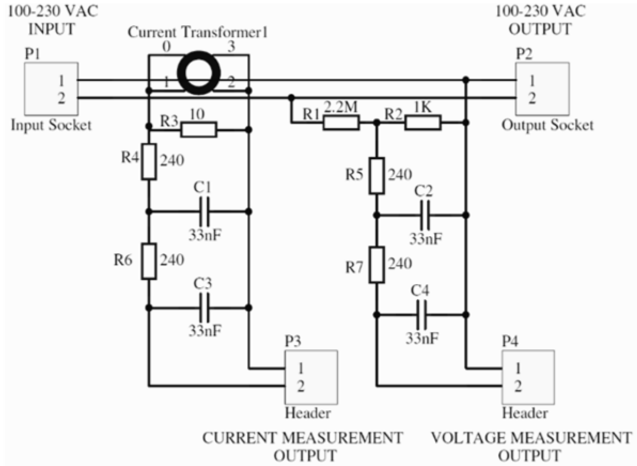

Fig. 1. Conditioning board used in the measurement of voltage and current.

A PC running a LabVIEW script was used to control the DAQ and store the measured data. After the data acquisition is finished, a MATLAB script was used to calculate the electrical parameters: rms voltage, rms current, active, reactive, and apparent powers, power factor, and the first harmonics of the current signal up to the 25th.

The effective voltage was calculated using the following equation:

$$V_{RMS} = G_v \sqrt{\sum_{n=1}^{N} \frac{v[n]^2}{N}} \tag{1}$$

where V_{RMS} is the rms voltage, G_v is the voltage gain, n is the sample index, $v[n]$ is the nth voltage sample and N the number of samples. The rms current is obtained by an analogous equation.

Eq. (2) was used to calculate the active power.

$$P = G_i * G_v \sum_{n=1}^{N} \frac{i[n] * v[n]}{N} \tag{2}$$

In this equation, P is the active power value and G_i and G_v are, respectively, the current and voltage gains.

The apparent power was calculated from the effective values of voltage and current using (3):

$$S = V_{RMS} * I_{RMS} \tag{3}$$

The reactive power was calculated from the active and apparent powers using (4):

$$Q = \sqrt{S^2 - P^2} \tag{4}$$

The power factor corresponds to the ratio of active power by the apparent power, as shown in (5):

$$PF = \frac{P}{S} \tag{5}$$

The effective values of the harmonic components of the current signal were calculated using a formula based on the classical equation of the Discrete Fourier Transform [22,23], presented in (6):

$$|I[k]_{RMS}| = \frac{\sqrt{Re\{I[k]\}^2 + Im\{I[k]\}^2}}{N} * G_i * \sqrt{2} \tag{6}$$

where k is the index of the harmonic component, $|I[k]_{RMS}|$ is the rms value of the module of the kth harmonic and $Re\{I[k]\}$ and $Im\{I[k]\}$ are, respectively, the real and imaginary parts of the kth harmonic component.

Eq. (7) and (8) present the formulas used to calculate $\mathrm{Re}\{\mathrm{I}[\mathrm{k}]\}$ and $\mathrm{Im}\{\mathrm{I}[\mathrm{k}]\}$.

$$Re\{\mathrm{I}[\mathrm{k}]\} = \sum_{n=1}^{N} \mathrm{i}[\mathrm{n}] * \cos\left(\frac{2\pi\mathrm{kn}}{\mathrm{N}}\right) \quad (7)$$

$$Im\{I[k]\} = \sum_{n=1}^{N} i[n] * sin\left(\frac{2\pi kn}{N}\right) \quad (8)$$

Experimental Procedure

A representative group of residential appliances was selected based on the taxonomy proposed in [24]. This taxonomy is based on the division of the appliances in groups of similar electrical behavior, that is, present similar current waveforms. So, from [24], the families and with their respective typical appliances are: a) Resistive Appliances - incandescent bulb lamps, clothes iron; b) Pump-Operated Appliances - refrigerators, cold water dispensers; c) Motor-Driven Appliances – fan; d) Electronic Appliances - microwave oven, LCD monitor, desktop computer, notebook computer, cell phone charger; e) Fluorescent Lightning - fluorescent lamps.

We performed only steady state measurements with all these appliances. Each device was turned on and during a window of one second; both voltage and current signals were acquired. From the acquired data we calculated the rms voltage, rms current, power factor, active power, reactive power, apparent power, and the 25 first harmonics of the current signal. The parameters were calculated for each 60 Hz AC cycle (as the mains frequency in Brazil is 60 Hz, 60 samples of each parameter were calculated per second).

Results and Discussion

Table 1 presents the measured results of rms voltage (V_{RMS}), rms current (I_{RMS}), Active Power, Reactive Power, Apparent Power, and the Power Factor. The results in Table 1 are the average value of 60 measurements taken of each parameter with their respective standard deviation; the low deviations of all parameters indicates that they keep constant in steady-state operation, a desirable characteristic for parameters used to define load signatures.

Table 1. Electrical parameters of the loads in steady state.

Electrical Parameters	V_{RMS} (V)	I_{RMS} (A)	Active Power (W)	Reactive Power (Var)	Aparent Power (Va)	Power Factor
Incandescent Lamp - 60 W	124.65 ± 0.07	0.49 ± 0.00	60.93 ± 0.06	2.01 ± 0.04	60.96 ± 0.06	1.00 ± 0.00
Fluorescent Lamp - 13 W	124.98 ± 0.23	0.18 ± 0.00	15.65 ± 0.04	15.79 ± 0.06	22.23 ± 0.07	0.70 ± 0.00
Fluorescent Lamp - 20 W	125.37 ± 0.06	0.30 ± 0.00	23.59 ± 0.16	29.69 ± 0.19	37.92 ± 0.21	0.62 ± 0.00
LCD Monitor	126.39 ± 0.13	0.41 ± 0.00	35.06 ± 0.27	37.40 ± 0.28	51.26 ± 0.24	0.68 ± 0.00
Desktop PC	125.85 ± 0.14	0.75 ± 0.01	60.44 ± 0.60	72.03 ± 0.58	94.02 ± 0.80	0.64 ± 0.00
Fan	126.90 ± 0.09	0.29 ± 0.00	36.72 ± 0.06	5.69 ± 0.03	37.16 ± 0.06	0.99 ± 0.00
Clothes Iron	116.06 ± 0.11	7.97 ± 0.01	924.06 ± 1.74	15.51 ± 0.24	924.19 ± 1.74	1.00 ± 0.00
Microwave Oven	114.19 ± 0.10	10.54 ± 0.02	1043.93 ± 2.96	601.27 ± 0.87	1204.70 ± 2.58	0.87 ± 0.00
Refrigerator	123.09 ± 0.15	1.55 ± 0.00	174.71 ± 0.30	77.72 ± 0.36	191.22 ± 0.28	0.91 ± 0.00
Water Cooler	125.54 ± 0.14	1.62 ± 0.00	116.57 ± 0.53	166.62 ± 0.37	203.35 ± 0.40	0.57 ± 0.00
Laptop	127.32 ± 0.10	0.37 ± 0.01	26.59 ± 0.99	38.64 ± 1.02	46.91 ± 1.39	0.57 ± 0.01
Cellphone (charging)	126.61 ± 0.09	0.09 ± 0.00	7.12 ± 0.06	8.87 ± 0.10	11.37 ± 0.09	0.63 ± 0.01

As can be seen in Table 1, the power factor is an extremely useful parameter in defining load signature, especially to distinguish resistive loads from the others. In many cases, two (or more) appliances drain practically the same current, as the fan and the 20 W compact fluorescent lamp shown in Table 1 (which drain 0.30 A_{RMS} and 0.29 A_{RMS} respectively). Nonetheless, these appliances present very different power factors (respectively 0.62 and 0.99) and, therefore, the power factor, together with the voltage, constitute the basic parameters of any NILM system. It is important to notice that since active power, reactive power, apparent power, and power factor are mathematically related through the power triangle, any pair of these quantities allows us to calculate the other two. Thus, only two of the four parameters are necessary in load recognition algorithms.

The voltage signal is usually not used as a parameter for load identification, it is assumed that the voltage variations are negligible and do not affect the identification results. However, this signal is not a constant sine wave, it contains many harmonics coexisting simultaneously with their amplitudes varying over time. The European Standard EN50160 [25], establishes that the voltage magnitude can differ from the nominal voltage up to ±10%. This standard also stipulates the maximum limits for the voltage harmonics, that is from 1,5% to 6% of the fundamental for the first seven odd harmonics [25]. In addition to the distortion present in the power grid, internal factors on the residential circuit also generate harmonics in the voltage signal. Nonlinear loads draw non-sinusoidal current causing distortion in the mains ac voltage; especially when high-power nonlinear loads are connected to the circuit. In our experiments, we observed significant voltage drops when high power loads, such as the cloth iron and microwave oven, was running, as can be observed in the first column Table 1. We also observed substantial voltage distortion caused by the microwave oven, as can be seen in Fig. 2 (a) and (b). The rms voltage variation and the presence of sporadic harmonics in the mains ac voltage changes the other the electrical parameters of all loads connected to the circuit, making difficult to identify their power signatures. Thus, the rms voltage and the harmonic content of the voltage signal must be measured to proper compensate this phenomenon.

Table 2 presents the calculated values of the odd harmonics up to the 9th of the current signal measured for all appliances in steady state. As in the case of the other electrical parameters, the presented results are average value and standard deviation obtained from 60 measurements.

Table 2. First five harmonics in the current signal in steady state.

Electric Current Harmonics	1st	3rd	5th	7th	9th
Incandescent Lamp - 60 W	0.489 ± 0.000	0.006 ± 0.000	0.010 ± 0.000	0.001 ± 0.000	0.002 ± 0.000
Fluorescent Lamp - 13 W	0.130 ± 0.000	0.085 ± 0.000	0.051 ± 0.000	0.040 ± 0.000	0.037 ± 0.000
Fluorescent Lamp - 20 W	0.199 ± 0.001	0.142 ± 0.001	0.093 ± 0.001	0.071 ± 0.001	0.070 ± 0.001
LCD Monitor	0.286 ± 0.002	0.222 ± 0.001	0.152 ± 0.002	0.081 ± 0.003	0.032 ± 0.003
Desktop PC	0.495 ± 0.005	0.413 ± 0.004	0.310 ± 0.002	0.197 ± 0.002	0.089 ± 0.003
Fan	0.292 ± 0.000	0.011 ± 0.000	0.015 ± 0.000	0.002 ± 0.000	0.002 ± 0.000
Clothes Iron	7.963 ± 0.008	0.132 ± 0.006	0.164 ± 0.005	0.023 ± 0.004	0.045 ± 0.003
Microwave Oven	9.534 ± 0.026	4.336 ± 0.022	0.772 ± 0.026	0.509 ± 0.012	0.148 ± 0.008

Refrigerator	1.537 ± 0.002	0.166 ± 0.004	0.116 ± 0.002	0.078 ± 0.001	0.030 ± 0.001
Water Cooler	1.617 ± 0.003	0.086 ± 0.004	0.047 ± 0.002	0.004 ± 0.001	0.015 ± 0.001
Laptop	0.216 ± 0.008	0.180 ± 0.007	0.154 ± 0.005	0.125 ± 0.003	0.093 ± 0.002
Cellphone (charging)	0.057 ± 0.001	0.030 ± 0.001	0.023 ± 0.001	0.014 ± 0.001	0.010 ± 0.001

We found distinct patterns in the frequency spectrum of the current signal of the analyzed loads that can be used for load identification. Fig. 2 presents the voltage and current curves of a microwave oven both in time and in frequency domain. Among all loads examined, the microwave oven was the only one that presented a high absolute value of third harmonic (4.34 A_{RMS}) in the current signal (see Fig. 2 (d)). This unique feature can be used for distinguish this appliance.

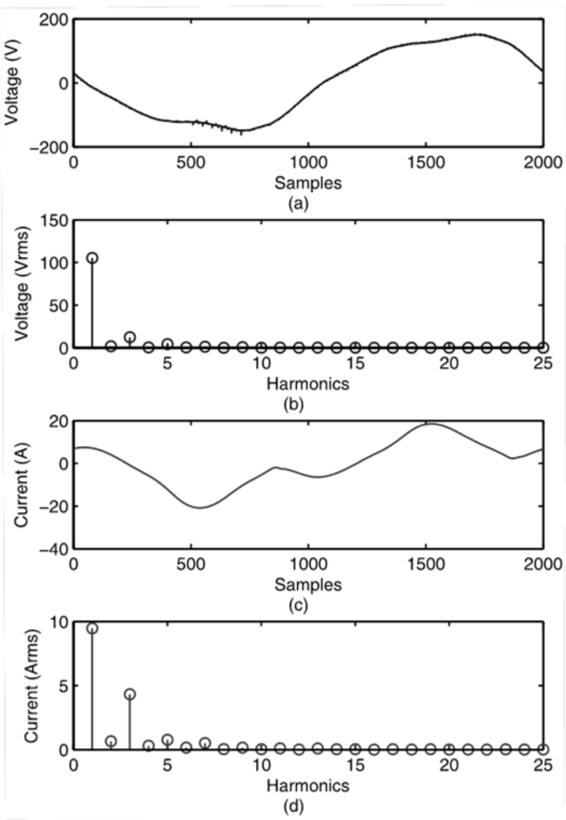

Fig. 2. Microwave oven voltage and current curves: (a) voltage in time domain (one cycle), (b) voltage in frequency domain, (c) current in time domain (one cycle) and (d) current in frequency domain.

Fig. 3 shows the frequency spectrum of the current signal of two fluorescent lamps with different powers and different brands.

Although the two lamps have slightly different signatures, both have similar patterns in frequency spectrum. Observe that in both graphics the 1st, 3rd and 5th harmonics fall almost linearly, decreasing the slope in the 7th and remaining almost constant until the 9th harmonic. This distinct pattern can be used to identifying compact fluorescent lamps.

As we can see in Fig. 4, the refrigerators also presented peculiar characteristics. Both appliances analyzed, a fridge and a water cooler presented 3rd and 5th harmonics with similar amplitude, much lower than the fundamental harmonic.

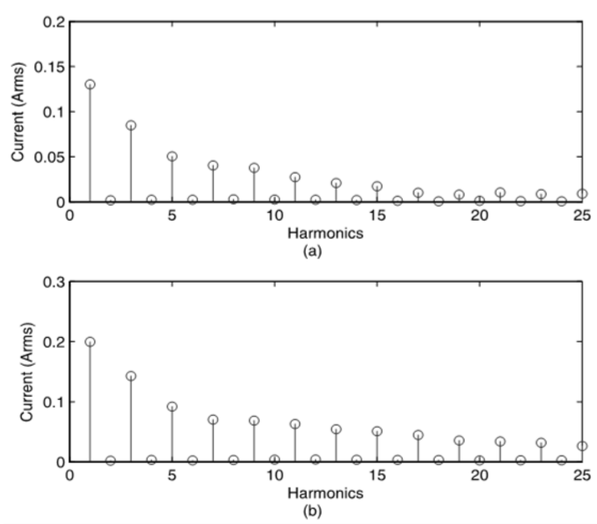

Fig. 3. Current spectrum of two different fluorescent lamps: (a) 13 W compact fluorescent lamp and (b) 20 W compact fluorescent lamp.

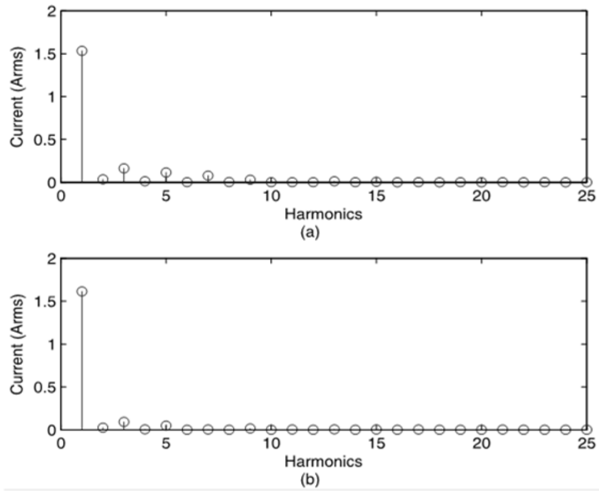

Fig. 4. Current spectrum of two different refrigerators: (a) fridge and (b) water cooler.

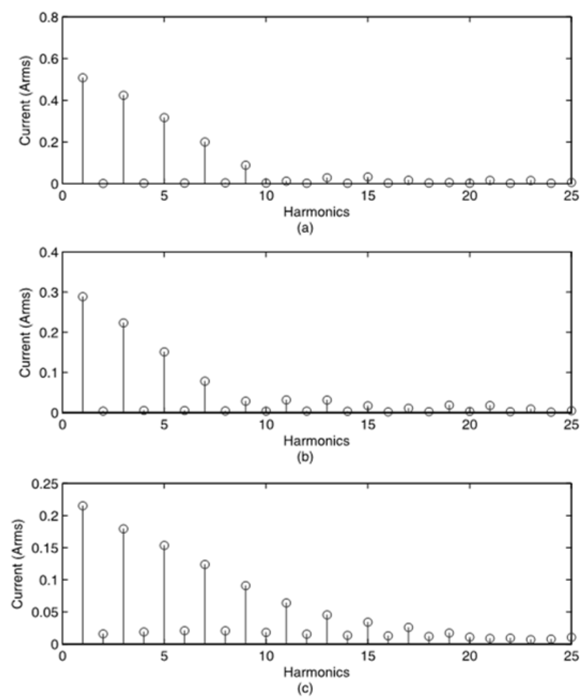

Fig.5. Current spectrum of: (a) a desktop computer, (b) a LCD monitor and (c) a laptop.

The LCD monitor, as well as the desktop PC presented very similar characteristics. In both loads, the first five odd harmonics have a downward linear behavior, as shown in Fig. 5. A similar characteristic was observed in the laptop but the downward linear behavior occurs with lower slope.

Analysis of the Fig. 2 – 5 indicates that the first five odd harmonics contain the major information in frequency domain useful for load disaggregation of residential loads. The use of harmonics higher than the ninth do not considerably improve the load identification, moreover implicates in more computational power requirements. In fact, the computational power available and the complexity of the algorithms used to perform the load disaggregation are the limit factors to the choice of the harmonics. We also observed that there is no significant amplitude in the even harmonics, except in the microwave oven, that presented a 0.620 A_{RMS} second harmonic. Since the microwave has a very distinct signature there is no need to take in account even harmonics for load identification.

Conclusion

Although the first studies with NILM systems have started two decades ago, there was still no consensus of which electrical quantities are the most adequate for load disaggregation. In this work, we presented an analysis of the most used electrical parameters and concluded which ones are the best for use in NILM.

We observed that the most useful information in the frequency domain for load identification is in the first five odd harmonics of the current signal. Using higher harmonics will not substantially increase the identification accuracy. Distinct patterns were identified on the current spectrum of some residential loads (microwave oven, fluorescent lamps, refrigerators, and personal computers), what confirms the potential use of spectrum analysis on load identification.

The voltage signal is usually not considered as a parameter for load identification since it is assumed that the voltage variations are negligible and do not affect the identification results. We verified in our experiments that it is not true. Variations on voltage signal and the presence of harmonics makes the load identification imprecise, especially for loads with similar signatures, as electronics, culminating in misidentification. Thus, we concluded that the voltage must be used as parameter to improve the accuracy and robustness of the load monitoring system.

Power factor, or optionally the active and reactive powers, shown to be good parameters to distinguish resistive loads from the others (capacitive, inductive and non-linear), so they should also be used in the load disaggregation.

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