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Nonintrusive identification of residential appliances using harmonic analysis

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Abstract: The role of nonintrusive load monitoring (NILM) is to identify the operating schedules of individual appliances and their power consumption from single-point electrical measurements. This paper discusses appliance load monitoring based on the harmonic analysis of the steady-state current, which is specifically suited for identification of nonlinear appliances. The existing harmonic-based NILM methods have limited applicability due to the fact that their complexity increases exponentially with the number of target appliances. In order to overcome this problem, this study suggests the use of the step changes of current harmonic phasors as a feature for appliance detection. The key benefit of the proposed method is that only individual appliance signatures are needed to identify load activities, as opposed to the previous NILM methods that require load signatures with respect to all possible appliance combinations.

Key words: Nonintrusive load monitoring, load signature, power harmonics

1. Introduction

Several studies have found that energy consumption can be significantly reduced by providing customers information about their electricity usage [1,2]. Household electricity data enable consumers to modify their usage behavior and thereby control their electricity consumption. The potential energy savings are larger if the available usage data include information on how much power each individual appliance consumes.

Different load monitoring methods have been developed to determine individual appliances' electrical loads during operation. Nowadays, appliance load monitoring is commonly performed using information from a single sensor at the utility service entry of a house. This is a highly reliable, low-cost approach known as nonintrusive load monitoring (NILM).

NILM systems provide information that is valuable not only to residential energy users but also to utilities. The real-time appliance recognition allows the demand-side management and control actions [3]. Another application of NILM is monitoring the state of electrical devices for appliance failure analysis [4]. The operation of individual loads can be related to domestic activities [5]. Hence, NILM systems are ideal platforms for activity sensing which have many applications like health care, home automation, and in-home activity tracking.

Nonintrusive appliance load monitoring has become a challenge because of the rapid increase in the number and diversity of small power loads in residential settings in the last few decades. The other effect of the increase in low-power devices is the degradation of power quality, since most modern devices are nonlinear [6]. Therefore, effective detection of the activity of small nonlinear loads is important for two reasons: to

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characterize the harmonic emission of nonlinear loads and to provide insight into the influence of low-power appliances on the total household consumption.

Nonlinear appliances can be uniquely characterized by their steady-state current harmonics. The use of the harmonic current content for load disaggregation has been explored in various ways by many researchers [7–14]. Common to all these works is the use of harmonic current amplitudes as a feature for appliance detection (load signature). Although the existing harmonic-based NILM methods achieved high load identification accuracy, their applicability is limited. The main drawback of this approach is that it requires harmonic current signatures with respect to all possible combinations of devices. Consequently, the complexity of this method increases exponentially with the number of electrical devices.

The aim of this study is to explore the possibility of using harmonic current phasors as load signatures in appliance load monitoring. This paper is organized as follows. The next section gives an overview of the NILM methods with special emphasis on the methods based on using current harmonic signatures. A new method is outlined in the third section. The fourth section presents experimental results that validate the proposed method. Finally, the conclusion is drawn in the last section.

2. NILM by using harmonic content of the current signal

NILM systems identify appliance operations from the composite electrical consumption waveforms in three main steps. The first step is a measurement of the voltage and aggregate current at an adequate rate. In the next step, the raw data are processed in order to extract the load signatures, electrical parameters that uniquely characterize an individual device during operation. In the final step, a classifier maps the extracted load signatures to appliance-specific states.

The different types of load signatures used in NILM methods could be categorized as steady-state, transient, and ambient environmental (nontraditional). Steady-state signatures are derived from the steady-state changes of the electrical signal. They are usually easily exploitable features that require minimal hardware requirements. On the other hand, transient signatures describe the electrical behavior of an appliance during the turn-on event. They are usually used as an additional feature to improve the recognition of appliances with overlapping steady-state features. The main drawbacks of transient methods are high sampling rate requirement and poor repeatability of the transient events.

The most frequently used electrical parameters (appliance features) in NILM systems are the step changes in steady-state real and reactive power. An important advantage of the power-based approach is that it has minimal hardware requirements. However, typical residential appliances often have similar power consumption, which is difficult to discern in the signature space. This problem is especially noticeable among the low-power devices.

In order to solve the problem of overlapping signatures in the power-based method, many researchers have proposed the use of various appliance features in addition to the steady-state power draw. Several studies, for example [15–17], explored the use of power factors to distinguish different appliances with similar power usages. Another solution, described in [18], suggests the use of power factor, root mean square current, and voltage, as well as the phase difference.

One possible solution to improve the disaggregation accuracy of power-based methods is to include current harmonics in the appliance signature. For this purpose, the harmonic content of the aggregate current can be analyzed in the steady state as well as in the transient state. Initial works on this topic focused on the usage of a transient signal for harmonic analysis [7–9], as it is generally more computationally efficient than the usage of a steady-state signal. Cole et al. [19] demonstrated that the current harmonics in the steady state had a lower standard deviation than current harmonics in the transient state. Srinivasan et al. validated the approach based on the harmonics of steady signal in [10].

The main drawback of the methods based on the harmonic analysis of the steady-state current is that their complexity increases exponentially with the number of target appliances [20]. This is a consequence of the fact that the methods require harmonic signatures corresponding to all possible combinations of devices, which limits the applicability of this method. In a typical household, the number of various appliance combinations as well as the computational demand of the method and the complexity of the training procedure are extremely large.

Several researchers have addressed the scalability problem of NILM methods based on steady-state harmonics. In order to reduce the number of appliances that need to be disaggregated, the authors in [21] suggested the use of multipoint sensing instead of using a single point of measurement. A different solution was proposed in [12], where the load-monitoring technique has a virtual signature library. Namely, in this method, the load signatures are determined in two phases. First, each individual appliance's signature is obtained by measuring amplitudes of the first five odd current harmonics. Thereafter, any appliance combination signature is created by summing corresponding individual appliance's signatures.

One way to improve the computational performance of the disaggregation process is to reduce the dimensionality of the feature vector. For this purpose, some authors used the principal component analysis method [22] to reduce the number of features in the NILM method based on harmonic current analysis [11].

3. Developing the load signature of harmonic current phasors

The NILM methods based on the use of harmonic current magnitudes have proven to be inefficient. The complexity of these methods is a consequence of the fact that the extracted features are not additive [20]. As opposed to the additive features, the harmonic current magnitudes of a composite load are not possible to relate to the same load signature of individual appliances. In this section, we will further explore the features based on the frequency representation of the current signal in an attempt to introduce a load signature that meets a feature-additive criterion.

NILM is based on the analysis of the voltage and current waveforms obtained at the point of common coupling (PCC). Considering that electrical devices are connected in parallel, applying Kirchhoff's current law at the PCC implies:

$$i\,(t) = \sum_{k=1}^{n} i_k\,(t), \tag{1}$$

where i_k is the steady-state current of individual appliances and n is the number of appliances in operation.

The aggregate current as well as currents of the individual appliances can be expressed by Fourier series as follows:

$$i\,(t) = \sum_{h=1}^{\infty} I_h \cdot \sin\left(h \cdot 2\pi \cdot f_l \cdot t + \Theta_h\right), \tag{2a}$$

$$i_k\,(t) = \sum_{h=1}^{\infty} I_h^k \cdot \sin\left(h \cdot 2\pi \cdot f_l \cdot t + \Theta_h^k\right), \tag{2b}$$

$k = 1,2,...,n$,

where I_h^k is the harmonic current amplitude of order h for the kth appliance, Θ_h^k is the hth harmonic current phase angle with respect to the fundamental voltage, and f_l is the fundamental frequency (i.e. 50 or 60 Hz).

From Eqs. (1) and (2) follow the relations between harmonic components of the aggregate current and harmonic components of the individual appliance's current:

$$I_h \cdot \sin\left(h \cdot 2\pi \cdot f_l \cdot t + \Theta_h\right) = \sum_{k=1}^{n} I_h^k \cdot \sin\left(h \cdot 2\pi \cdot f_l \cdot t + \Theta_h^k\right), \tag{3}$$

$h = 1, 2, ..., n.$

In the sinusoidal steady state, the total current i as well as the current drawn by an individual device, i_k, can be represented by corresponding phasors as follows:

$$\bar{I}_h = \sum_{k=1}^{n} \bar{I}_h^k, \tag{4}$$

h = 1,2,3...,

where $\bar{I}_h = \left|\bar{I}_h\right| \angle\Theta_h$ represents the phasors of the total current and $\bar{I}_h^k = \left|\bar{I}_h^k\right| \angle\Theta_h^k$ represents the harmonic current phasor of device k.

Separating Eq. (4) into real and imaginary parts, we get:

$$I_{hr} = \sum_{k=1}^{n} Re\left\{\bar{I}_h^k\right\} \quad I_{hi} = \sum_{k=1}^{n} Im\left\{\bar{I}_h^k\right\}. \tag{5}$$

The current drawn by nonlinear loads is caused by the fundamental and higher harmonic voltages. However, a satisfactory approximation of the current signal can be obtained by taking into account only the influence of the voltage fundamental frequency, as stated in [23]. This statement is in agreement with the standards that set the limits for voltage distortion at the PCC. Power supply standard IEEE 519 sets limits on the harmonic content of voltage waveforms. According to this standard, the total harmonic distortion of voltage should be less than 5%, while individual harmonic voltages should not exceed 3% of the fundamental voltage.

We can accept that the current through an electrical device is the same whether it operates individually or simultaneously with other household devices. According to Eq. (5), the harmonic current phasors have an additive property. Therefore, changes in the harmonic current phasors can be used as a load signature of the nonlinear appliances. The proposed method is event-based and uses the frequency features from the current signal to identify when a device turns on or off. Many signal processing techniques have been used for event detection [24,25]. Some of them are suitable for the proposed method since they efficiently recognize the state transitions of low-power devices [26].

The proposed load signature has an additive property, as opposed to the harmonic current magnitudes that were used in the previous methods. The key benefit of the proposed method is that only individual appliance signatures are needed to identify the operating states of the appliances.

4. Experimental procedure

This section describes the experiment that was conducted to validate the proposed method. The objective of this experiment is twofold. One aim is to test the appliance recognition accuracy of the proposed method. The second aim is to test whether the proposed load signature meets the future-additive criterion. The proposed method is tested on a representative group of four household electrical devices. In the experimental setup, we use an LCD monitor, fluorescent lamp, halogen lamp, and desktop PC.

To perform the data acquisition, we use a Fluke 435 II energy analyzer. The analyzer offers a powerful set of measurements to check the power distribution system. Both the voltage measurement signal and current measurement signal are digitized with a sampling frequency of 200 kS/s on each channel simultaneously and 16 bits of resolution. The harmonic content (amplitude and phase) of the current waveform is calculated through fast Fourier transform. The acquired steady-state data are analyzed and statistically processed by MATLAB.

The schematic of the appliance identification system is illustrated in Figure 1. For single-phase measurements, the ground, a neutral line, and a phase line are connected to the corresponding input voltage terminals of the power analyzer. Current measurements are obtained using a two-current transducer (i430flex), put around the conductors of a phase and neutral.

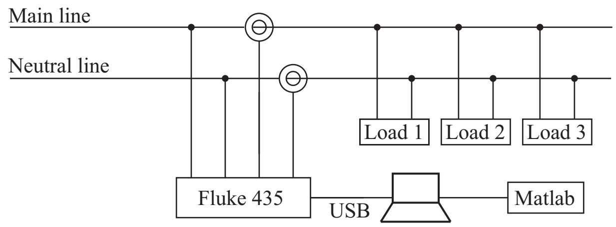


Figure 1. The schematic of the experimental setup.

A photo of the experimental setup is shown in Figure 2a. As the figure depicts, the experimental setup includes a Fluke 435 power analyzer with its connections to the power socket, current sensors, and connection of the loads. Figure 2b shows the power analyzer screen of a current waveform.

Fluke generates a text file that contains all specified quantities. The measured data are stored on a computer for further offline processing. The proposed load signature represents a difference between harmonic current phasors before and after an appliance is turned on. In order to avoid transients in the current waveform, each measurement trial is broken into two analysis windows, one before and one after the event. These two windows are extracted offline by using an event table, which is generated from the power analyzer and contains the time and duration of each calculated quantity. We make use of the naive Bayes algorithm to detect the most likely states of the appliances. The naive Bayes classifier is a suitable classification algorithm for load monitoring because of its simplicity and efficiency. In addition, it requires a small amount of training data to classify efficiently. The classifier uses the training data to create a distribution with respect to each appliance. According to these distributions, the classifier calculates the probability that a given change in the feature vector corresponds to an appliance state transition.

The current through each individual device was sampled for 100 s. Thereafter, the first three odd harmonic current phasors were extracted from each second of the acquired data. In the Bayes algorithm training data contain the mean and standard deviation of each variable. In this case, the variables are the magnitudes and phase angles of the first three current harmonic phasors. The load signatures of the target appliance are represented in Table 1.

Table 2 lists the values of the 1st, 3rd, and 5th current harmonics when different combinations of two devices are in operation. The quantities given in Tables 1 and 2 are the average values and standard deviations of the measurements taken over the period of the experiment.

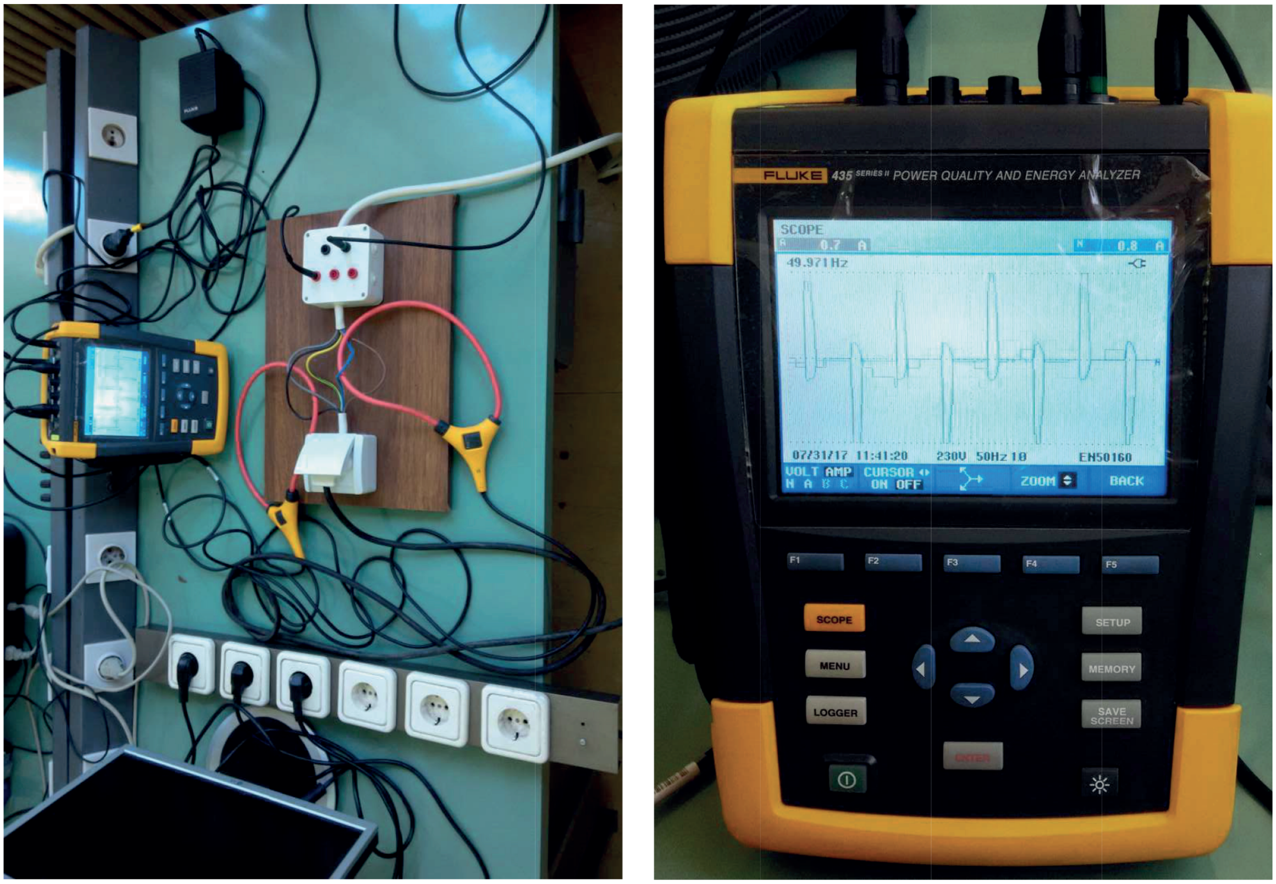
Figure 3 depicts the frequency spectrum of the current for some of the appliances in the experimental setup. According to the harmonic content of the consumed currents, we can conclude which of the harmonics contain the most useful information for load disaggregation. It can be observed that the first four odd harmonics

Table 1. The average values of the odd harmonics of the current signal with their respective standard deviations.

Appliance	Current harmonic					
	1st		3rd		5th	
	Mag. [A]	Phase [rad]	Mag. [A]	Phase [rad]	Mag. [A]	Phase [rad]
Desktop PC	0.3333 ±0.0250	4.5212 ±0.0122	0.3814 ±0.0029	3.4571 ±0.0376	0.2623 ±0.0063	2.642 ±0.0648
LCD monitor	0.3143 ±0.0293	4.7272 ±0.0108	0.0833 ±0.00054	3.0094 ±0.0110	0.0661 ±0.00051	1.6867 ±0.1252
Fluorescent lamp 4 × 18 W	0.6498 ±0.0530	3.3997 ±0.0198	0.0797 ±0.00084	5.4757 ±0.0263	0.019402 ±0.00049	5.3782 ±0.0702
Halogen lamp 3 × 40 W	0.6507 ±0.0499	4.4393 ±0.0047	0.0199 ±0.00086	3.8397 ±0.0605	0.0143 ±0.0007	6.6918 ±0.0597

Table 2. The test data when different combinations of two devices were in operation.

Appliances	Current harmonic					
	1st		3rd		5th	
	Mag. [A]	Phase [rad]	Mag. [A]	Phase [rad]	Mag. [A]	Phase [rad]
Hal. lamp + fluo. lamp	1.0552 ±0.0491	3.7767 ±0.0147	0.0718 ±0.0008	5.3888 ±0.0301	0.0252 ±0.0008	6.1183 ±0.0546
Hal. lamp + monitor	0.7776 ±0.0291	4.3789 ±0.0048	0.1237 ±0.0008	3.2177 ±0.0271	0.096 ±0.0007	1.6386 ±0.0493
Hal. lamp + PC	0.9841 ±0.009	4.3809 ±0.0047	0.3325 ±0.0009	3.4194 ±0.0183	0.2224 ±0.0022	2.5391 ±0.0322
Flu. lamp + monitor	0.7229 ±0.0477	3.5776 ±0.0057	0.0710 ±0.0023	3.586 ±0.0429	0.0929 ±0.0008	1.5571 ±0.0567
Flu. lamp + PC	0.8966 ±0.0087	3.7209 ±0.0109	0.3052 ±0.0016	3.6402 ±0.0083	0.2244 ±0.0013	2.5978 ±0.0112
Monitor + PC	0.4539 ±0.0176	4.5085 ±0.0108	0.3959 ±0.002	3.2579 ±0.0253	0.2651 ±0.0042	2.2667 ±0.0393



a) b)

Figure 2. a) Photo of the experimental setup, b) power analyzer.

are the most adequate for load disaggregation. It can also be seen that the PC and monitor produce high levels of 3rd and 5th harmonic currents. This is a consequence of the fact that they are powered by switch-mode power supplies.

The harmonic voltage distortion and fluctuations of the voltage amplitude are usually neglected in nonintrusive load disaggregation. However, this information can be used to improve the accuracy of the load monitoring system. Over the period of the experiments, the mean value of the voltage amplitude was 221.28 V and its standard deviation was 0.27 V. We also calculated the voltage distortion from the measurements taken during the experiments. The voltage total harmonic distortion at the point of common coupling was 2.45%.

In the proposed method, the feature vector contains the magnitude and phase angle of the current phasors. Therefore, it is most suitable to express the current phasor in polar form. Figures 4a and 4b illustrate, respectively, the 1st and the 3rd current harmonic in the polar plot for all considered electrical devices. From this figure, it can be seen that the amplitude of the harmonics decreases with the harmonic order. Each current harmonic is represented by a point in the feature space. The selected residential appliances are well separated in the signature space, which indicates that they can be easily identified. On the other hand, it is very difficult to extract these loads using only the magnitude of the harmonic currents (for example, a fluorescent lamp and halogen lamp).

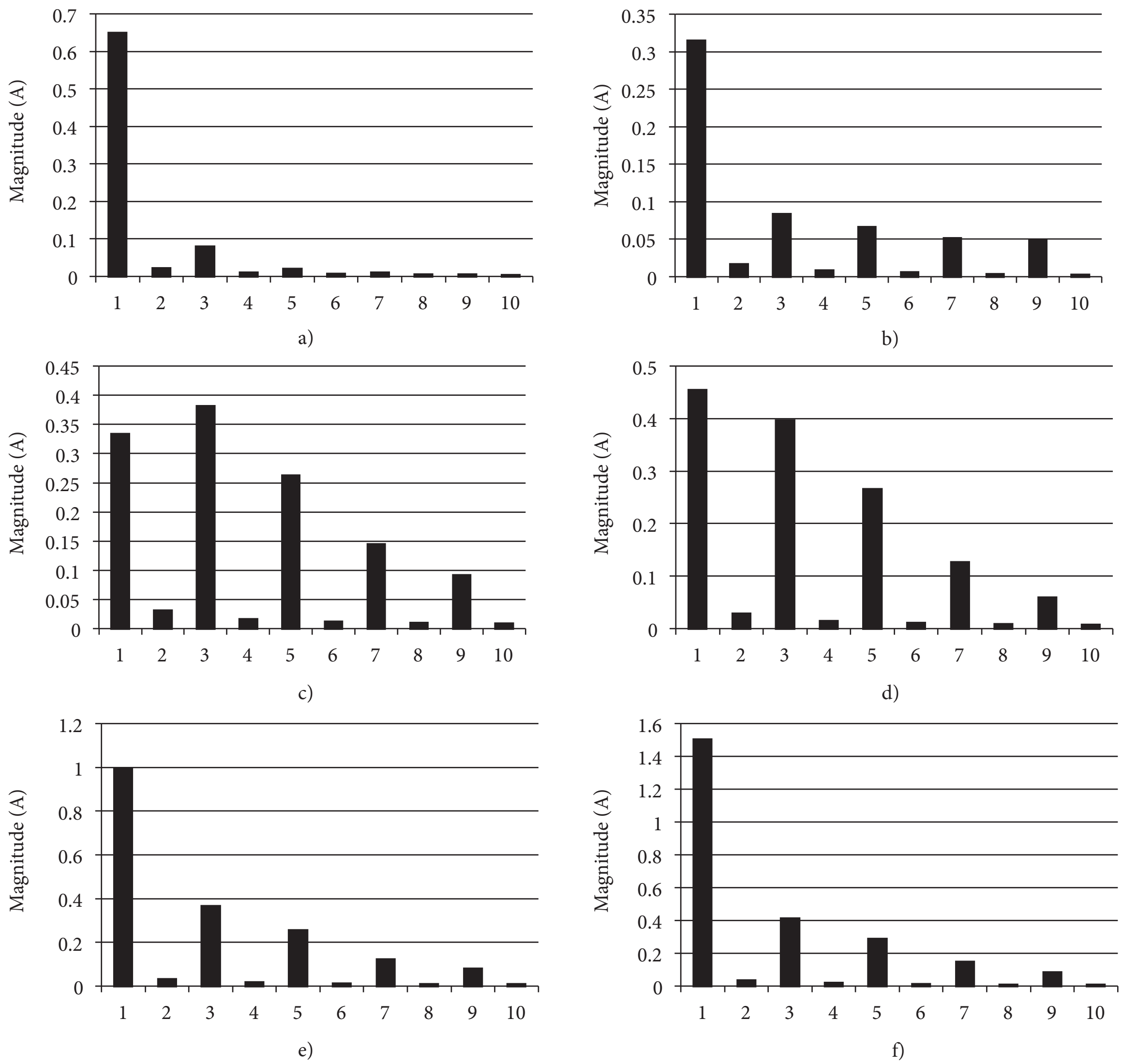


Figure 3. Current harmonic spectrum of a) fluorescent lamp; b) LCD monitor; c) PC; d) monitor and PC; e) monitor, PC, and fluorescent lamp; f) monitor, PC, and fluorescent and halogen lamps.

Figure 5 illustrates the first three odd current harmonics for the simultaneous operation of the fluorescent lamp and PC. This figure comparatively shows the measured current harmonics and those calculated by Eq. (4). In this way, we illustrate the additivity of the proposed load signature. The orders of the current harmonics are labeled by the appropriate numbers in Figure 5. The complex numbers obtained by adding two phasors of the same order are denoted by asterisks, while the measured current phasors are denoted by circles. Ideally, these two complex numbers should overlap. However, the obtained deviations are acceptable and will not significantly affect the classification of the devices.

The proposed method is based on the assumption that when an event occurs, one electrical appliance is being turned on or turned off. In order to test whether the proposed load signature meets the feature-additive criterion, we took a set of measurements. In these measurements, one of the three devices is turned on while a selected group of the remaining three appliances was operating simultaneously. The appliance under test

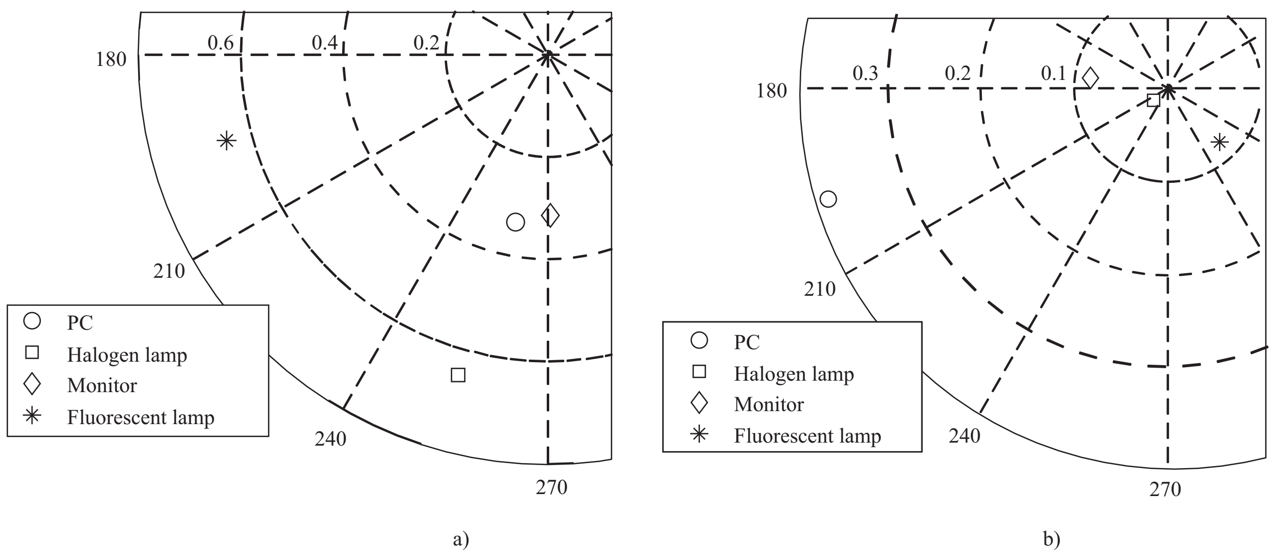


Figure 4. Polar plot of the harmonic currents: a) first harmonic, b) third harmonic.

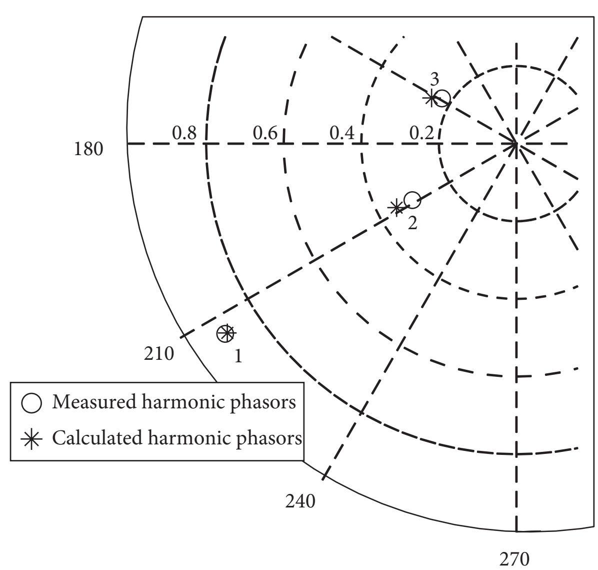


Figure 5. Polar plot of the first three odd current harmonics for the simultaneous operation of the fluorescent lamp and PC.

was switched ON while various different combinations of appliances were operating in steady state. For each event, there were two analysis windows with a time length of 1 s, one before the device was turned on and the second after the appliance had gone through a state transition (5 s after the event). In order to establish the load signature, the first three odd harmonic phasors of the current were calculated with respect to both analysis windows. Thereafter, the feature vector associated with the event was obtained by subtracting the corresponding harmonic current phasors of the two analysis windows:

$$\Delta \bar{I}_h = \bar{I}_h(t + \Delta t) - \bar{I}_h(t), \tag{6}$$

$$h = 1, 3, 5,$$

where $\bar{I}_h(t) = \left|\bar{I}_h(t)\right| \angle\Theta_h(t)$ represents the phasors of the total current before the device was turned on and $\bar{I}_h(t+\Delta t) = \left|\bar{I}_h(t+\Delta t)\right| \angle\Theta_h(t+\Delta t)$ represents the phasors of the total current after the event has ended.

The feature vector contains six elements, the magnitude and phase angle of the three complex numbers $\Delta\bar{I}_1$, $\Delta\bar{I}_2$, and $\Delta\bar{I}_3$. Tables 3 and 4 show the classification confusion matrix for identification of target appliances. Both tables list the classification accuracy when one appliance is switched ON. Table 3 lists the classification accuracy in the case where one appliance is operated continuously. On the other hand, Table 4 gives classification accuracy in the case where two devices are operated continuously. The first column corresponds to the appliances operated at that time while the second column corresponds to the device that changes state. The last column indicates the recognition accuracy for the given appliance combination (measurement trial). In the case where two appliances operate simultaneously (Table 3), the mean classification accuracy is 97.4%.

Table 3. Classification confusion matrix for identification of electrical devices.

Active load	Load that is turned on	Predicted load				Accuracy (%)
		Hal. lamp	Fluo. lamp	Monitor	PC	
Hal. lamp	Fluo. lamp		93		7	93
	Monitor		4	95	1	95
	PC				100	100
Fluo. lamp	Hal. lamp	100				100
	Monitor		98		2	98
	PC				100	100
Monitor	Hal. lamp	99		1		99
	Fluo. lamp		99		1	99
	PC				100	100
PC	Hal. lamp	99			1	99
	Fluo. lamp		100			100
	Monitor	14		86		86

5. Conclusion

This paper considers the problem of NILM of small nonlinear loads. It has been shown that nonlinear appliances can easily be detected by frequency analysis of the current waveforms. This paper investigates the use of the harmonic current phasors to uniquely define an appliance activity. The main benefit of the proposed method is low computational complexity. The complexity of the proposed load identification algorithm is proportional to the number of devices, N, as opposed to the previous methods based on the harmonic content of the current, whose complexity is proportional to 2^N. Therefore, the NILM method presented in this paper is able to operate in a monitoring system with a large number of appliances. The experimental results have indicated that harmonic current phasors showed good performance in the identification of small nonlinear appliances.

In addition to load monitoring, the method is also applicable to harmonic source identification. In this study, we have neglected voltage variations since they do not affect the identification of nonlinear loads. However, linear loads are characterized only by fundamental current harmonics, while higher current harmonics depend on the harmonic content of the voltage. In future work, we will consider the incorporation of the voltage spectrum to the method in order to improve the segregation of linear appliances.

Table 4. Classification confusion matrix for identification of electrical devices.

Active loads	Load that is turned on	Predicted load			
		Hal. lamp	Fluo. lamp	Monitor	PC
Hal. lamp + fluo. lamp	Monitor			100	
	PC				100
Hal. lamp + monitor	Fluo. lamp		100		
	PC				100
Hal. lamp + PC	Fluo. lamp		100		
	Monitor			100	
Fluo. lamp + monitor	Hal. lamp	100			
	PC				100
Fluo. lamp + PC	Hal. lamp	100			
	Monitor			100	
Monitor + PC	Hal. lamp	100			
	Fluo. lamp		100		

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