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A NON-INTRUSIVE IDENTIFICATION OF HOME APPLIANCES USING ACTIVE POWER AND HARMONIC CURRENT

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Abstract. *In recent years, research on non-intrusive load monitoring has become very popular since it allows customers to better manage their energy use and reduce electrical consumption. The traditional non-intrusive load monitoring method, which uses active and reactive power as signatures, has poor performance in detecting small non-linear loads. This drawback has become more prominent because the use of nonlinear appliances has increased continuously during the last decades. To address this problem, we propose a NILM* method *that utilizes harmonic current in combination with the changes of real power. The advantages of the proposed method with respect to the existing frequency analysis based NILM methods are lower computational complexity and the use of only one feature to characterize the harmonic content of the current.*

Key words: *Non-intrusive load monitoring (NILM), load signature, energy management*

1. INTRODUCTION

The rapid growth in energy consumption and carbon emissions has generated interest in the deployment of efficient household energy management system. The system for home energy management enables consumers to control and manage their electrical consumption, according to the information of individual load consumptions [1, 2]. Therefore, in order to significantly reduce waste in residential energy consumption, it is necessary to use load monitoring system. Appliance load monitoring is not only useful in energy saving, but also in fault detection systems, remote monitoring systems and some residential applications such as in-home activity tracking [3, 4].

There are two methods for monitoring individual electrical loads: 1. distributed direct sensing or intrusive load monitoring and 2. single point sensing or non-intrusive load monitoring (NILM). The first approach requires complex instrumentation system to measure energy consumption of each device separately. This solution has many practical disadvantages such as: complex installation, low scalability, low reliability as well as high cost due to a large number of sensors and communication devices. A more practical solution for

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monitoring individual loads is NILM, that use only one sensor attached to the electric utility service entry. This method dis-aggregates the whole-house energy consumption into energy usage of individual appliances.

The most commonly used steady-state NILM method detects operation of individual loads from the step changes in real and reactive power [5]. This method works well for devices with two states of operation, but it is not suitable for extracting variable-loads and multi-state appliances. Another problem is the detection of loads that consume similar steady-state power since their two dimensional signatures overlap in the P-Q plane. It is especially difficult to distinguish low-power loads with small power consumption (lower than 150 W).

The current trends in electricity consumption show a rapid increase in the type and number of household appliances [6], most of which are not predictable or controlled. Consequently, the task of load identification becomes more challenging. An additional problem is the inability of previous NILM algorithms to detect low-power devices, which have become more numerous and diverse. A solution to this problem has been proposed in [7], through the use of the circuit-level instead of whole-house power measurements. This approach represents a trade-off between intrusive and non-intrusive load monitoring, which facilitate load disaggregation by the expense of the cost and complexity. In order to improve performance in detecting small non-linear loads several NILM methods have used current harmonics [8-11]. However, most of these techniques are not practical due to calculation of many harmonics in real time [12, 13].

In our previous works [14, 15], we have proposed the use of distortion power for appliance identification. The aim of these papers was to improve identification of small nonlinear loads by the analysis of three electrical quantities (active, reactive and distortion power), which is easy to obtain from metering devices. However, this method does not take into account the fact that the time variations of the voltage harmonics make the load identification imprecise. Namely, distortion power, which is used to characterize the nonlinear loads, mainly consists of cross-products of voltage and current harmonics of different orders. In this work we suggest the use of harmonic current instead of distorted power in order to improve the appliance disaggregation accuracy.

This paper proposes a NILM method based on the analysis of steady-state values of harmonic current and active power. The proposed approach uses only one feature to characterize the harmonic content of the current, as opposed to the previous NILM methods. We explore the effectiveness of the proposed electrical quantities in recognizing low-power loads.

The remainder of the paper is organized as follows: In the next section we review some of the commonly used NILM techniques. The proposed method for load monitoring is discussed in section 3. Section 4 presents the results of the application of the proposed NILM method on low power appliances. The conclusion is reported in section 5.

2. Background

The main stages of an NILM system are: a) the data acquisition b) the feature extraction and event detection c) the load identification. The purpose of the first stage is to gather the voltage and current measurements at an adequate sampling rate. The sampling frequency depends on the electrical characteristic used by the NILM method. Generally, the data acquisition for NILM can be classified in terms of the sampling rate as: high frequency and low frequency. The next step is to transform the raw data into a specific appliance feature, or load signature. In order to extract features it is necessary to first detect load events like switching on/off or changing state. The load signature can be derived from the steady-state signal component, which can be expressed as a finite number of sinusoids, or from the transient signal component [16-18]. Dong et. al. [19] studied non-intrusive extraction of load signatures and demonstrated their technique by using the smart meter data. The final step is the estimation of the appliance-specific states by using machine learning algorithms. There are two categories of load identification algorithms: supervised learning algorithm, which requires a training procedure, and unsupervised learning algorithms, which is able to directly recognize appliance operations.

The residential NILM systems usually use steady-states instead of transients load signatures. Transient load monitoring systems are not suitable for residential energy disaggregation since they require expensive hardware (high-frequency energy meters) that makes them impractical. In addition, turn-off events are very difficult to detect with transient signatures. Recently, Wang et. al. [20] developed a new NILM method which is not limited to transient or steady state analysis and categorize the appliances according to working style.

The most common method of NILM uses power measurement to characterize appliance [5]. Since the load signature of this method involves two electrical parameters, the steady-state changes in active and reactive power, they are mapped to a two-dimensional signature space (ΔP-ΔQ plane). An important characteristic of PQ signature is that it can be obtained by using data from the existing smart meters. The second advantage of the power change method is that it allows automatic identification of on-off appliances.

However, the method has some limitations. At first, it requires step changes in power level to identify loads. Therefore, there is a problem in detecting devices with variable power draw. Despite the fact that steady-state power level between two events of on-off devices is easy to detect, the method has a problem to distinguish these devices in some cases. False positive may occur when two or more devices change state at nearly the same time, since the sum of power consumptions of these devices may be associated with another load. Furthermore, different loads may exhibit overlapping of signatures in $\Delta P \Delta Q$ signature space, which become more prominent as the number of loads increases.

3. Non-intrusive Load Monitoring by Using Harmonic Current and Active Power

Nowadays, the number of non-linear household loads, such as energy efficient variable speed drives and switched mode power supplies, increases continuously. Since the nonlinear loads inject harmonic currents into the power system, it is promising to use harmonics as a load signature in the residential NILM. This kind of methods requires spectral analysis as opposed to the power based methods which use features directly derived from the raw current and voltage waveforms. Due to the presence of many linear loads in the residential buildings, it is not possible to use harmonic content as a unique load signature for load disaggregation.

Harmonic currents may be also caused by transients during shutdown and turn on events. The harmonic content of the transient waveforms varies with time and may have frequencies that are not related to the fundamental frequency. Some of the NILM methods are based on the frequency analysis of the transient waveforms [17, 18]. The problem with this approach is that transient detection is prone to errors. To overcome this problem some researchers have proposed the use of steady-state current harmonics to characterize the nonlinear loads [10, 11].

The online calculation of many current harmonics implies higher computational requirements [12]. Consequently, a practical harmonic based NILM system must use a limited number of harmonics. To solve this problem many researchers have proposed various NILM methods. Cole and Alike [21] have developed the first harmonic based NILM method which is based on a calculation of first eight odd harmonics. The authors of [22] have proposed the use of only 2nd and 3nd harmonic, while the authors of [23] have considered first sixteen odd harmonics. Recently, several authors [24] have proposed a method which used the first three odd harmonics.

The nonlinear loads can be characterized not only by harmonic components in the current signal, but also by the other quantities like total harmonic distortion of current, distortion power, harmonic current, crest factor, distortion power factor.

The focus of our research is on the identification of small non-linear loads. In the case when large loads are active smaller loads are difficult to identify due to the limited resolution of the data acquisition. Therefore, we need to consider the load signature that enables identification of low consuming appliance in the presence of high power devices.

In a typical household most of the existing load is still linear while nonlinear loads are small. Therefore the influence of small loads on the on the fundamental current harmonic is negligible. Each of the aforementioned electrical parameters (THD_i, D, DPF, K_I, and I_H) can be expressed in terms of the current and voltage harmonics. According to these equations only harmonic current, as opposed to the other quantities, is not mathematically related to the fundamental current harmonic. Therefore, we propose a novel approach in which non-linear loads are characterized by steady state harmonic current. The proposed method utilizes harmonic current in combination with the changes of real power.

The current signal can be represented as the sum of the fundamental and harmonic components, as follows:

$$I_{RMS}{}^2 = I_0^2 + I_1^2 + \sum_{h=2}^{\infty} I_h^2 = I_0^2 + I_1^2 + I_H^2 \tag{1}$$

where: I is a total RMS value of the current, I_1 is the RMS value of the fundamental harmonic, I_0 is the DC component of the current, I_h is the RMS value of the h-th harmonic component of the current signal.

Therefore, harmonic current can be simply expressed in terms of the effective current and fundamental harmonic of the current as follows:

$$I_H = \sqrt{I_{RMS}^2 - I_1^2 - I_0^2} \tag{2}$$

The effective current is usually calculated by using the root mean square method as:

$$I_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} i[n]^2} \tag{3}$$

where: n is the sample index, $i[n]$ is the current value measured at sampling point n and N is the number of samples taken during a full-wave of the current.

The standard method for calculation of the harmonic current and voltages is based on the use of the Discrete Fourier Transform (DFT). This method works well for estimation of periodic signal in stady state. The RMS value of the fundamental harmonic can be calculated using

$$I_1 = \sqrt{\frac{\mathrm{Re}\{\bar{I}_1\}^2 + \mathrm{Im}\{\bar{I}_1\}^2}{2}} \tag{4}$$

where $\bar{I}_1$ is the first harmonic current obtained by the discrete Fourier transform as:

$$\bar{I}_1 = \frac{1}{N}\sum_{n=1}^{N} i[n] e^{-j\frac{2\pi}{N}n} \tag{5}$$

According to (1-3), the calculation of the harmonic current is less computationally demanding than the calculation of harmonics. Therefore, we can claim that proposed method is more computationally effective than other approaches that use harmonic analysis.

To the best of our knowledge, the computational complexity of the harmonic-based NILM algorithms were not explicitly stated by researches. However, the computational cost of these methods can be determined according to the algorithm used to calculate DFT (Discrete Fourier Transform) and the number of frequencies required by the method. In the most NILM methods steady-state current harmonics are obtained by applying FFT [11, 21 ,22]. However, when only a few DFT frequencies are needed, as in the proposed method, it is more suitable to use the Goertzel's algorithm. The main advantage of the Goertzel algorithm over often used FFT algorithms is less mathematical operations required for harmonic analysis. Goertzel algorithm has linear complexity - for N data points and M applications (required harmonics) it is $O(MN)$, while FFT algorithms has $O(N\log_2 N)$ complexity. It is clear that for $M<\log_2 N$, Goertzel algorithm requires less operations.

We will now consider the number of arithmetic operations necessary to compute the harmonic current. According to (2), this quantity is calculated from the fundamental current harmonic and effective current. As was mentioned above, the fundamental current harmonic can be efficiently computed by using the Goertzel algorithm. The application of the Goertzel algorithm on a data set with N values requires for each DFT: $2N$+4 complex multiplications ($8N$+16 real multiplications and $4N$+8 real additions) and $4N$+4 complex additions/subtractions (8N+8 real additions). According to (3), the computation of the square of the effective current, I_{RMS}^2, involves N+1 real multiplications and N-1 real additions. Furthermore, there are N-1 real additions and two real multiplications required to compute the square of the DC component of the current. Consequently, the computation of the harmonic current requires $9N$+19 real multiplications and $14N$+16 real additions. We observe that the calculation of the harmonic current involves less arithmetic operations than the calculation of any combination of two or more current harmonics.

Another advantage of the proposed method is that it uses only one feature to characterize the harmonic content of the current, in contrast to the available NILM methods that use a set of harmonics. The number of electrical characteristics used for load dissagregation has a direct impact on the computational complexity of a NILM method [11]. The training and classification times increase as the number of appliance features increases [25], which can limit the applicability of the method. Therefore, in the case of methods that use harmonic analysis, the efficiency of the classification depends on the number of harmonics used for load disaggregation.

4. Experiments

The measurement system, described in details in [26-29], is based on a real time system for nonlinear load characterization and analysis. The system is implemented as virtual instrument, partially executing on real-time operating system (RTOS) keeping main advantage of traditional instruments – determinism in measurement. Data acquisition is performed by NI 9225 and NI 9227 acquisition modules connected to PXI-7813R FPGA card.

In order to evaluate our approach we did two experiments. In order to illustrate the effectiveness of using harmonic current in recognizing low powered loads we will consider a set of appliances given in table I. The group of selected residential appliances consists of small nonlinear loads such as energy efficient lighting devices, TV's, computers, monitors. The active power, reactive power and harmonic current have been measured for each load in steady state.

The steady-state quantities of all appliances are located in a three-dimensional signature space of real power, reactive power and harmonic current (P Q I_H). Figure 1 shows the projection onto the PQ coordinate plane and Fig. 2 shows the projection onto the PI_H coordinate plane. The considered loads are very close in PQ signature space. Therefore, it is very difficult to extract these loads by using only steady-state changes of active and reactive power. On the other hand the same set of appliances is well separated in PI_H signature space.

Table 1 Small nonlinear loads

Device	P[W]	Q[VAR]	I_{RMS}[A]	I_H [mA]
Incandescent bulb 75W	73.48	0.69	330	12.2
FL18W	11.33	-5.8	8	60.9
CFL bulb 20W	18.73	-9.58	140	110.9
LED bulb 15W	16.9	-3.87	157	136.4
Sound bar	17.3	14.85	109	79.78
CRT TV	31.44	-3.73	217	170.19
LED TV 1	27.36	-8.87	224	191.00
LED TV 2	95.61	-24.86	436	150.36
PC	55.83	-33.05	300	162.2
Laptop	16.58	-4.337	143	121.88
LCD Monitor 1	23.33	-7.06	180	146.26
LCD Monitor 2	40.28	-9.4	289	226.16
Printer StandBy	13.06	-5.01	120	102.29
Refrigerator	98.64	104.78	641	468.87

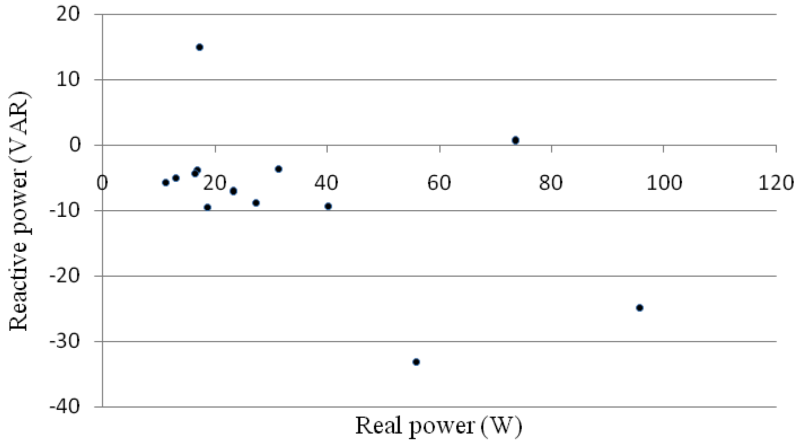

Fig. 1 Load distribution of the tested appliances in P-Q plane

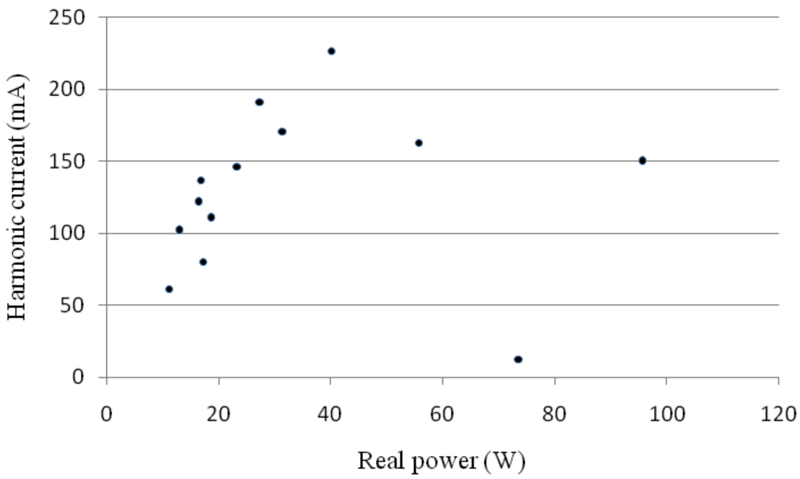

Fig. 2 Load distribution of the tested appliances in P-I_H plane

In the second experiment we consider three appliances with similar power consumption: a computer monitor, a PC and an incandescent bulb. We performed steady state measurements of active power (P) and harmonic current (I_H) with respect to each device combination. Table 2 shows average values and standard deviations derived from 100 measurements. The experimental results indicate *a small dispersion of* the feature values. Fig. 3 shows the distribution of device combinations in the P-I_H feature space. Each signature is represented by a point in the feature space.

Table 2 Average values and standard deviations of active power and harmonic current

Bul.	PC	Mon.	μ(P) [W]	σ(P) [W]	$\mu(I_H)$ [mA]	$\sigma(I_H)$ [mA]	Acurr. [%]
On	Off	Off	94.34	0.41	10.8	0.2	100
Off	On	Off	32.75	1.2	184.8	7.69	100
Off	Off	On	24.26	0.22	122.6	1.75	100
On	On	Off	126.14	3.25	194.8	13.7	98
On	Off	On	116.2	0.45	123.8	1.5	100
Off	On	On	57.25	0.5	312.1	4.9	100
On	On	On	150.23	2.22	307.9	11.5	100

The computed device features are analyzed by the naive Bayes classifier in order to to predict the state of the selected appliances. The naive Bayes classifier is a simple and efficient supervised machine learning algorithm. It requires an offline training stage to build the models of all the different combinations of appliances. The classifier must be trained for all possible combinations of the appliances since the harmonic current does not combine linearly. After training was completed, the classifier is tested by a set of measured data. The test data was collected for 700 minutes (one hundred for each device combination) at 1/60 Hz rate. Bayes classifier only two times does not recognize appliance specific states and that was in the case when PC and Bulb were turn on. The accuracy of the performed load disaggregation is shown in the last column of the Table 2. According to the experimental results, the proposed features show good performance for the identification of On/Off operation of small appliances.

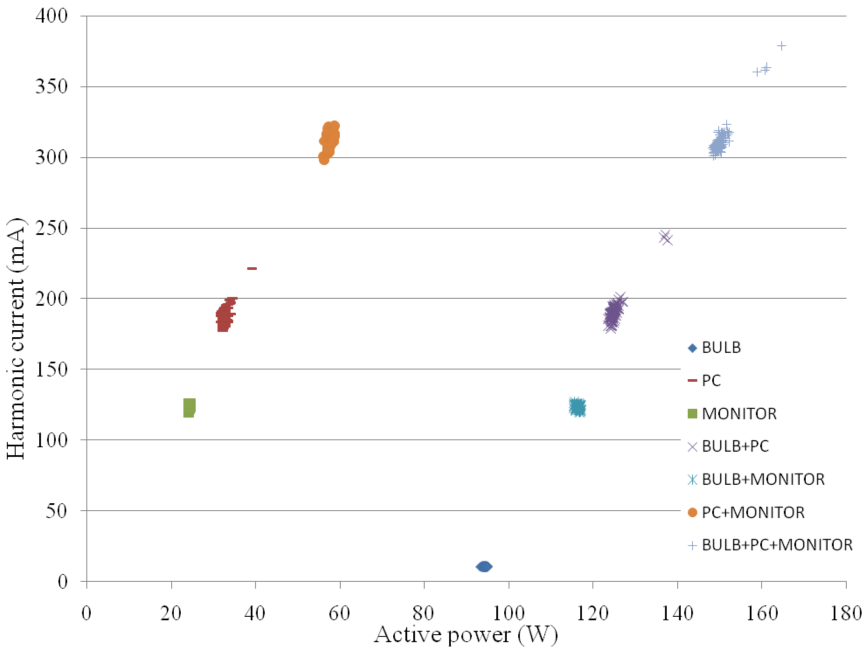

Fig. 3 Distribution of bulb, monitor and PC in the P-I_H feature space

5. Conclusion

In this paper, we present a NILM method that uses harmonic current in combination with the changes of active power. It has been shown that low-power nonlinear loads have clear separation of features in the two-dimensional feature space of real power and harmonic current (ΔP, I_H). Therefore, the proposed appliance signature enables a high load recognition accuracy.

The main advantage of the proposed method is its computational efficiency. The method requires a low sampling rate and use only one feature to characterize the harmonic content of the current. According to the experimental results, the proposed features show good performance for the identification of On/Off operation of small appliances.

In future work, the influence of voltage distortion on harmonic current should be studied. We also plan to further explore the potentials of the method by testing it on a larger set of devices and different classifier.

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