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Steady state signatures in the time domain for nonintrusive appliance identification

Firmas estacionarias en el dominio del tiempo para identificación no intrusiva de aparatos

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ABSTRACT

Smart Grid paradigm promotes advanced load monitoring applications to support demand side management and energy savings. Recently, considerable attention has been paid to Non-Intrusive Load Monitoring to estimate the individual operation and power consumption of the residential appliances, from single point electrical measurements. This approach takes advantage of signal processing in order to reduce the hardware effort associated to systems with multiple dedicated sensors. Discriminative characteristics of the appliances, namely load signatures, could be extracted from the transient or steady state electrical signals. In this paper the effect of impact factors that can affect the steady state load signatures under realistic conditions are investigated: the voltage supply distortion, the network impedance and the sampling frequency of the metering equipment. For this purpose, electrical measurements of several residential appliances were acquired and processed to obtain some indices in the time domain. Results include the comparison of distinct scenarios, and the evaluation of the suitability and discrimination capacity of the steady state information.

Keywords: Nonintrusive load monitoring, load signatures, appliance identification, demand side management.

RESUMEN

El paradigma de las redes inteligentes promueve aplicaciones de monitorización avanzada de carga para apoyar la gestión de la demanda y los ahorros energéticos. La monitorización no intrusiva de carga ha generado un creciente interés para estimar la operación y el consumo individual de potencia de los aparatos residenciales, a partir de mediciones eléctricas en un solo punto. Este enfoque aprovecha las ventajas del procesamiento de señales para reducir los esfuerzos de hardware asociados a los sistemas con múltiples sensores dedicados. Algunas características distintivas de los aparatos, llamadas firmas de carga, pueden ser extraídas de señales en estado transitorio o estable. En este artículo se investiga el efecto de algunos factores que pueden afectar las firmas estacionarias de carga bajo condiciones reales: distorsión en la tensión de suministro, impedancia de la red y frecuencia de muestreo del equipo de medida. Para tal fin, se adquirieron y procesaron mediciones eléctricas de diferentes aparatos residenciales para obtener algunos índices en el dominio del tiempo. Los resultados incluyen comparaciones entre distintos escenarios y evaluación de la idoneidad y la capacidad de discriminación de la información del estado estable.

Palabras clave: Monitorización no intrusiva de carga, firmas de carga, identificación de aparatos, gestión de la demanda.

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Introduction

Smart Grid paradigm promotes advanced load monitoring applications to support demand side management decisions such as demand response (direct load control or voluntary price-based load management), energy saving practices or energy efficient technologies. Studies report that users who receive detailed and frequent feedback about their electricity consumption are prone to modify their consumption behaviors resulting in savings of up to 15 % (Electric Power Research Institute, 2009).

Although a feedback about the residential energy consumption comes usually with the monthly bill, demand side management strategies require more detailed and disaggregated information about the individual appliance consumption. Historic information e.g. surveys and manual registers are often considered for load monitoring, but automatic methods gain interest for the sake of laboriousness and accuracy. A simple approach is to install one dedicated sensor per appliance (electrical meters or sometimes indirectly through microphones, accelerometers

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and video cameras). Nevertheless, the high costs associated with installation and maintenance of multiple sensors and communication platforms discourage this approach (Tsai & Lin, 2012).

On the other hand, electrical measurements can be acquired at one point, for example, at the metering point of a customer, and the individual appliance operation and consumption can be estimated through mathematical post-processing of the measured data (Hart, 1992). Recently considerable attention has been paid to this so-called Non-Intrusive Load Monitoring (NILM) approach since it demands less hardware effort by taking advantage of the signal processing advances. Despite the growing literature on the area, no complete solutions have been formulated yet (Burbano, 2015). For instance, relevant characteristics extracted from the electrical signals to distinguish the appliance that most likely caused a switching on or off, namely load signatures, are still investigated. Indices of transient state and/or stationary state might be used for NILM systems (Zoha, Gluhak, Imran & Rajasegarar, 2012). In general, transient state analysis characterizes the switching, while steady state analysis is dedicated to the quasi-stationary operation of the appliances.

This paper is devoted to the study and empirical investigation on steady state load signatures of individual residential appliances. Some of these signatures were presented in previous works for NILM (Liang, Kendall & Cheng, 2010), (Hassan, Javed & Arshad, 2014). However, several practical questions arise. One of the main questions is: how do factors related to realistic supply conditions affect the robustness of load signatures for suitable residential appliance identification? Some of these factors are: the voltage supply distortion, the network impedance and the sampling frequency of the metering equipment. In (Jimenez et al., 2015) the effect of those factors was analyzed for current switching transients of individual residential appliances. As both transient as well as quasi-stationary indices shall be applied for non-intrusive load identification throughout the further research, this paper discusses the impact of these factors on the discrimination of individual residential appliances based on steady state indices. The results for individual appliances provide the basis for the analysis of the index performance in case of multiple, parallel operated appliances. This will be part of future research and is not in the focus of this paper.

The methodology includes acquiring electrical measurements of residential appliances belonging to several categories, and afterwards processing the signals to obtain some indices from time domain and evaluating the capacity of steady state signals to provide information for appliance identification under different conditions. The extraction of indices from frequency domain is contemplated for further work.

This paper is organized as follows. At first, a general classification of appliances and the different types of stationary signatures are presented. Secondly, the appliances and the measurement setup of this study are described. Thirdly, the stationary indices are explained. Then, the effect of the impact factors for individual operation is discussed. Finally, the conclusion wraps up the paper.

Background

Types of appliances

Appliances can be separated in several categories according to their circuit components, which determine their electrical behavior:

- Non-electronic: they can be resistive (in phase), inductive (lagging phase), capacitive (leading phase) or their combination (Jimenez et al., 2015).
- Electronic: they can be distinguished according to the power factor correction (PFC) in three categories: no PFC, passive PFC and active PFC (Blanco, Yanchenko, Meyer & Schegner, 2013).

Stationary signatures

Each appliance could be distinguished from others through a set of particular attributes exhibited in the electrical signals, namely load signatures, which can help the identification of the appliances. Stationary signatures are characteristics or indices computed from the signals during the operation of the appliances, in contrast to the transient signatures that describe the behavior of the signals at the switching instant. Some time domain stationary signatures in scientific literature are detailed as follows:

Current based: Indices from the time domain waveforms of the currents (Tsai & Lin, 2012).

Power based: The values of the active and reactive power even plotted in a plane, or the power factor (Liang et al., 2010).

Voltage-Current based: Indices that relate the currents and the voltages (Hassan et al., 2014).

Measurement framework

Data were acquired in the laboratory. The measurement setup is shown in Figure 1. The equipment under test (EUT) is connected to a power source that simulates the 120V/60 Hz supply. A manual switch is used for switching the appliances (sometimes the equipment includes its own switch). A data acquisition system connected to a computer controls the power source and allows to simultaneously take voltage and current measurements at a sampling frequency of 2 MHz. IEC 60725 (International Eletrotechnical Commission [IEC], 2012) provides typical values of the network impedance in public low voltage grids with 230 V/50 Hz supply. Based on this impedance a value for 120 V/60 Hz was derived with $Z = (0.2 + j0.125)\ \Omega$. This impedance is shown as a dotted box in Figure 1.

Table 1 shows the list of the EUT used in the laboratory and their power ratings. Figure 2 presents the characteristic waveforms of the currents drawn by the appliances under a non-distorted 120V/60 Hz voltage supply for a fundamental period. These appliances have a nearly constant operating state. Meaurements with only one appliance in operation were performed. Subsequently, the samples of the electrical signals are processed off-line in Matlab® in order to extract the stationary signatures.

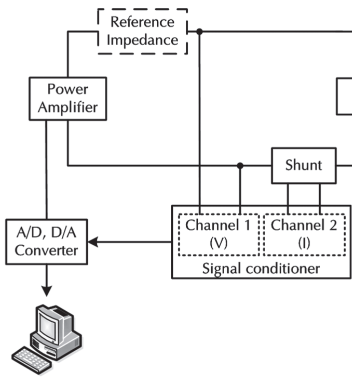

Figure 1. Measurement setup.

Table 1. Equipment under test.

Category		Appliance	Rated Power
Non-electronic	Resistive	Halogen Lamp	53W
	Resistive	Hair Dryer	1875W
Electronic	No PFC	CFL	18W
		Laptop charger	50W
	Passive PFC	LED lamp	1.2W
	Active PFC	PC power supply 1	400W
		PC power supply 2	430W

Calculation of stationary indices

As the steady state signals are periodical, a couple of cycles is enough to describe the behavior of equipment with constant operating states. These cycles should be located after the switching transient has finished and before the occurrence of another event (e.g. switching off). The similarity of the consecutive cycles has been verified during the pre-processing of the measurement data. The indices from these sections of the signals are calculated to explore the discrimination capacity of the steady state signals of current, voltage and power.

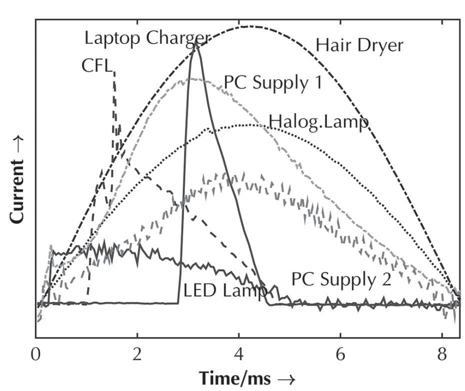

Figure 2. Characteristic waveforms of the currents carried by the appliances in half a cycle. Scales are modified to better visualization.

Current based: The following statistical measures from the time domain waveforms of the current can characterize the loads. *Mean* in Equation (1) is the dc value of the current. *Rms* or effective current in Equation (2) is the equivalent DC value that yields the same average power. *Crest factor* in Equation (3) indicates how pointed is the signal with respect to the RMS value. *Standard deviation* in Equation (4) describes the variability or dispersion including the mean. *Skewness* in Equation (5) and *kurtosis* in Equation (6) are measures of the shape of the waveform. Finally, *entropy* in Equation (7) measures the randomness of the waveform.

$$\bar{I} = \frac{1}{N}\sum_{k=1}^{N} i_k \tag{1}$$

$$|i|_{rms} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} |\, i_k \,|^2} \tag{2}$$

$$cf = \frac{|\mathbf{i}|_{\max}}{|\mathbf{i}\,|_{rms}} \tag{3}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{k=1}^{N} (i_k - \bar{I})^2} \tag{4}$$

$$\gamma = \frac{1}{\sigma^3}\sqrt{\frac{1}{N}\sum_{k=1}^{N} (i_k - \bar{I})^3} \tag{5}$$

$$\kappa = \frac{1}{\sigma^4}\sqrt{\frac{1}{N}\sum_{k=1}^{N} (i_k - \bar{I})^4} \tag{6}$$

$$\varepsilon = \sum h_k \log_2 h_k \tag{7}$$

Where i_k is the kth sample of the vector of the instantaneous current, $\mathbf{i}$. Moreover, $|\mathbf{i}|_{max}$ is the peak value and N is the length of **i,** and h_k is the kth element of the vector **h** which comprises the counts of the histogram for the vector **i.**

Voltage-Current based: Geometrical properties of the V-I curves are considered because a polygon whose vertices are the currents and voltage points can be visualized. Two embedded straight lines are created for the V vs. I plot of each appliance. Then the following indices are calculated: *slope 1* is the slope of the line that connects the extreme points of the voltage; and *slope 2* is the slope of the line that connects the extreme points of the current. The other index is the *area* of the polygon. Figure 3 shows that appliances from the same category exhibit similar shapes for the V vs. I curves.

Power based: This classical approach intends to distinguish the appliances through the active and reactive power in Equations (8) and (9), respectively.

$$P = \frac{1}{N}\sum_{k=1}^{N} i_k v_k \tag{8}$$

$$Q \;=\; \sqrt{|\mathbf{v}|_{rms}\,|\mathbf{i}|_{rms} - P^2} \tag{9}$$

where v_k is the kth th sample and $|\mathbf{v}|_{max}$ is the *rms* value of the voltage, and N is the length of the section of the signals considered in the analysis. Figure 4 shows the results for the analyzed equipment in a P - Q diagram. Here some clusters that correspond to the appliances can be identified. The true power factor in Equation (10) is also used to identify the appliances.

$$PF = \frac{P}{|\mathbf{v}|_{rms}|\mathbf{i}|_{rms}} \tag{10}$$

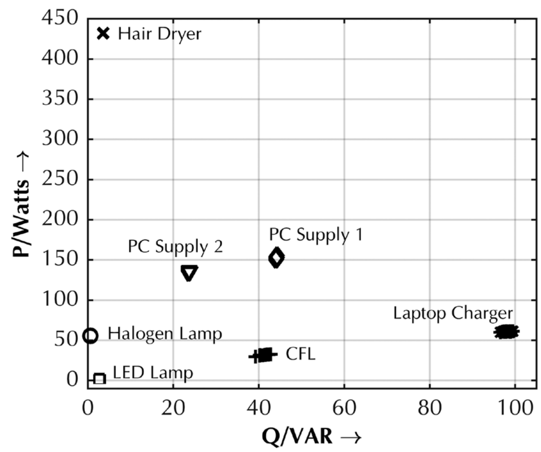

Figure 3. $P-Q$ plots of the appliances in Table I. Each point represents one measurement (several points are stacked).

Effect of the impact factors

The stationary indices are used to assess the robustness of the identification in terms of impact factors that can occur under realistic conditions such as the supply voltage distortion, the network impedance and the sampling rate of the metering equipment. The scenarios for the analysis are shown in Table 2.

Table 2. Scenarios for the analysis of impact factors.

Scenario	Supply Voltage	Reference Impedance	Downsampling
1	Sine	*0*	No
2	Flat-top	*0*	No
3	Sine	$Z=(0.2+j0.125)\,\Omega$	No
4	Flat-top	$Z=(0.2+j0.125)\,\Omega$	No
5	Sine	*0*	Yes

The discrimination capacity of the stationary indices is derived for each appliance by examining how distinguishable one appliance is from the others by each index. For this purpose, some *matrices of separability* where introduced. Each entry of the matrices indicates the linear separability of an index with respect to the same index of the rest of the appliances. For the case of a minimum overlap between the indices, a penalty is applied through a weighting factor of 0.9**.** More details about the algorithm are provided in (Jimenez et al., 2015).

Reference case

Scenario 1 is considered the reference case, so it is compared to scenarios 2, 3, 4 and 5 for the analysis of the impact factors. Tables 3 and 4 present the separability matrices for Scenario 1. For instance, the first row has a value of 1.0 at the first entry and 6.0 at the second one, which implies that the *mean* of the current of the Halogen Lamp allows discriminating itself from only one other appliance, while its *rms* value provides separation from all the other appliances.

Most of the indices are promising for Scenario 1, except the *mean* and the *skewness* of the currents and the *slope 2* of the polygon drawn by the V-I curves. The summation of all the values in Table 3 and 4 indicates a total discrimination capacity of 447.8 points for Scenario 1. These are the accumulated points for all the indices of the complete set of appliances.

Table 3. Current based indices for Scenario I.

Appliance	$\bar{I}$	$\|i\|_{max}$	cf	σ	ε	Υ	κ
Halogen Lamp	1.0	6.0	5.9	6.0	6.0	0.0	6.0
Hair Dryer	2.0	6.0	5.9	6.0	6.0	0.0	6.0
CFL	0.0	6.0	5.0	6.0	6.0	0.0	6.0
Laptop Charger	0.0	6.0	5.0	6.0	6.0	0.0	6.0
LED lamp	1.0	6.0	6.0	6.0	6.0	0.0	6.0
Power Supply 1	0.0	6.0	6.0	6.0	6.0	0.0	6.0
Power Supply 2	0.0	6.0	6.0	6.0	6.0	0.0	6.0

Table 4. Power and Voltage - Current based indices for Scenario I.

Appliance	P	Q	PF	Slope1	Slope2	Area
Halogen Lamp	6.0	6.0	6.0	5.0	5.0	6.0
Hair Dryer	6.0	6.0	6.0	6.0	5.0	6.0
CFL	6.0	6.0	6.0	6,0	4,0	6,0
Laptop Charger	6.0	6.0	6.0	5.0	5.0	6.0
LED lamp	6.0	6.0	6.0	6.0	0.0	6.0
Power Supply 1	6.0	6.0	6.0	6.0	5.0	6.0
Power Supply 2	6.0	6.0	6.0	6.0	4.0	6.0

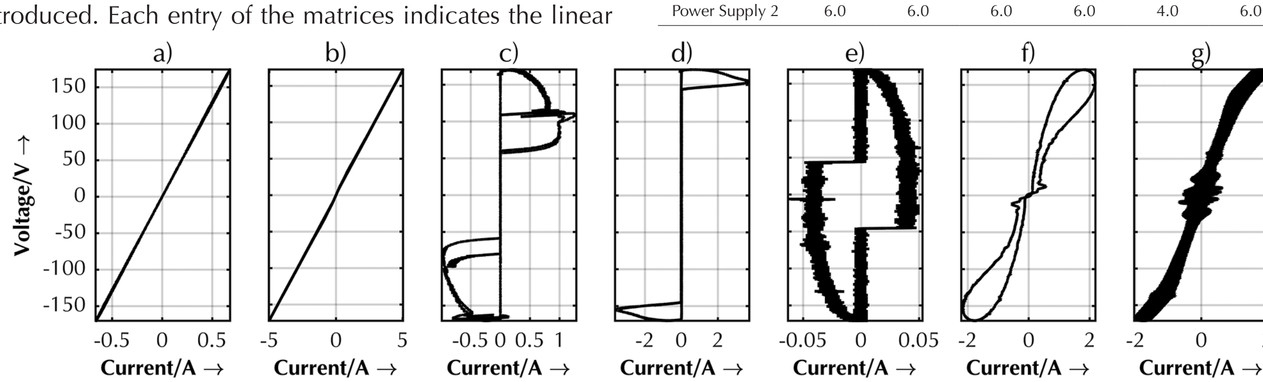

Figure 4. Examples of polygons provided by V-I curves of a) Halogen Lamp, b) Hair Dryer, c) CFL, d) Laptop charger, e) LED Lamp, f) PC power supply 1 and g) PC power supply 2.

Impact of supply voltage distortion

Generally, residential LV grids show a flat-top voltage due to the mass use of single-phase rectifiers. The effect of such voltage distortion on the steady state signatures is analyzed by comparison with the non-distorted condition (Scenario 1).

Tables 5 and 6 depict the separability matrices for Scenario 2. Similarly to Scenario 1, most of the indices are promising for appliance identification, except the mean and the skewness of the currents. The summation of all the values is 445.8 for Scenario 2, which is very similar to the value of Scenario 1, i.e. only a slight reduction is observed. The impact of the flat-top distortion on the discrimination capacity is low.

Table 5. Current based indices for Scenario 2.

Appliance	$\bar{I}$	$\|i\|_{max}$	cf	σ	ε	ϒ	κ
Halogen Lamp	0.9	5.0	5.0	5.0	6.0	0.0	6.0
Hair Dryer	0.0	6.0	5.0	6.0	6.0	0.0	6.0
CFL	0.0	5.0	4.0	5.0	6.0	0.0	5.0
Laptop Charger	0.0	6.0	5.0	6.0	6.0	0.0	6.0
LED lamp	0.0	6.0	5.0	6.0	6.0	0.0	5.0
Power Supply 1	0.0	6.0	6.0	6.0	6.0	0.0	6.0
Power Supply 2	0.9	6.0	6.0	6.0	6.0	0.0	6.0

Table 6. Power and Voltage-Current based indices for Scenario 2.

Appliance	P	Q	PF	Slope1	Slope2	Area
Halogen Lamp	6.0	6.0	5.0	6.0	5.0	6.0
Hair Dryer	6.0	6.0	5.0	6.0	6.0	6.0
CFL	6.0	6.0	6.0	6.0	6.0	6.0
Laptop Charger	6.0	6.0	6.0	6.0	6.0	6.0
LED lamp	6.0	6.0	6.0	6.0	5.0	6.0
Power Supply 1	6.0	5.0	6.0	6.0	6.0	6.0
Power Supply 2	6.0	5.0	6.0	6.0	6.0	6.0

Impact of network impedance

The equipment current flowing through a finite network impedance generates a voltage drop and subsequently a distortion of the supply voltage, which can change the steady state load signatures. The recommended values of reference impedance in (IEC, 2012) are adapted to 120 V/60 Hz systems and the possible impacts on the signatures are examined.

Tables 7 and 8 present the separability matrices when supply impedance is connected to the appliances. Most of the indices have potential for appliance identification. Again, the *mean* and the *skewness* of the currents exhibit low ability to distinguish the appliances. The summation of all the values for Scenario 3 is 437.8. In conclusion, a slightly higher reduction of the discrimination capacity for appliance identification is yielded.

Table 7. Current based indices for Scenario 3.

Appliance	$\bar{I}$	$\|i\|_{max}$	cf	σ	ε	ϒ	κ
Halogen Lamp	2.0	6.0	5.0	6.0	6.0	0.0	6.0
Hair Dryer	0.0	6.0	5.0	6.0	6.0	0.0	6.0
CFL	0.0	6.0	6.0	6.0	5.0	0.0	5.0
Laptop Charger	0.0	6.0	5.0	6.0	5.0	0.0	6.0
LED lamp	2.0	6.0	5.0	6.0	6.0	0.0	5.0
Power Supply 1	0.0	6.0	6.0	6.0	5.0	0.0	6.0
Power Supply 2	2.0	6.0	6.0	6.0	5.0	0.0	6.0

Table 8. Power and Voltage-Current based indices for Scenario 3.

Appliance	P	Q	PF	Slope1	Slope2	Area
Halogen Lamp	6.0	6.0	6.0	5.0	4.9	6.0
Hair Dryer	6.0	6.0	6.0	6.0	5.0	6.0
CFL	6.0	6.0	6.0	6.0	4.0	5.0
Laptop Charger	6.0	6.0	6.0	5.0	5.0	5.0
LED lamp	6.0	6.0	6.0	6.0	0.0	6.0
Power Supply 1	6.0	6.0	6.0	5.0	4.0	6.0
Power Supply 2	6.0	6.0	6.0	5.0	4.9	6.0

Joint impact of supply voltage distortion and network impedance

The combined effect of the presence of supply voltage distortion and a finite network impedance is analyzed as Scenario 4, which is the closest to the real conditions in a public network.

Tables 9 and 10 present the separability matrices corresponding to such Scenario. Most of the indices have the potential for appliance identification. The low efficiency of the *mean* and the *skewness* of the currents to discriminate the appliance is even more evident in this case, while several indices still exhibit good scores. The summation of all the values of the indices of the separability matrices for Scenario 4 is 424. In summary, the effects of the distortion and the network impedance are combined to reduce the discrimination ability for appliance identification slightly more.

Table 9. Current based indices for Scenario 4.

Appliance	$\bar{I}$	$\|i\|_{max}$	cf	σ	ε	ϒ	κ
Halogen Lamp	0,0	6,0	5,0	6,0	6,0	0,0	6,0
Hair Dryer	0,0	6,0	5,0	6,0	6,0	0,0	6,0
CFL	0,0	6,0	6,0	6,0	4,0	0,0	6,0
Laptop Charger	0,0	5,0	6,0	5,0	4,0	0,0	5,0
LED lamp	0,0	6,0	6,0	6,0	6,0	0,0	5,0
Power Supply 1	0,0	5,0	6,0	5,0	3,0	0,0	6,0
Power Supply 2	0,0	4,0	6,0	4,0	3,0	0,0	6,0

Table 10. Power and Voltage - Current based indices for Scenario 4.

Appliance	P	Q	PF	Slope1	Slope2	Area
Halogen Lamp	6,0	6,0	6,0	6,0	5,0	6,0
Hair Dryer	6,0	6,0	6,0	6,0	5,0	6,0
CFL	6,0	6,0	6,0	6,0	5,0	4,0
Laptop Charger	6,0	6,0	6,0	6,0	6,0	6,0
LED lamp	6,0	6,0	6,0	6,0	5,0	6,0
Power Supply 1	5,0	6,0	6,0	5,0	5,0	4,0
Power Supply 2	5,0	6,0	6,0	5,0	5,0	4,0

Impact of sampling frequency

The best details of the waveforms are obtained when the sampling frequency of the metering equipment is high, but the processing and storage requirement and even the cost of the equipment rise. In this paper, the decrease of the discrimination capacity of the signatures is evaluated when the sampling frequency diminishes.

Several down-sampling factors were applied to the primary signals (current and voltage) to investigate the effect of having lower sampling frequencies than 2 MHz. These results are summarized in Table 11, where the summations of separability matrices are presented. As was expected, the lower the sampling frequency, the lower the discrimination ability.

Table 11. Discrimination capacity for different sampling frequencies.

Sampling frequency	200 Hz	2 kHz	20 kHz	200 kHz	2 MHz
Summation of the separability matrix entries	352	434	442	441.6	447,7

For example, Tables 12 and 13 show separability matrices for the 2 kHz case, and Tables 14 and 15 present the 200 Hz case. Despite the discrimination capacity reduction, columns of these Tables depict some indices with perfect scores for all the appliances such as the *rms* value and the *standard deviation* of the current. This indicates that the identification is still possible when the sampling frequency of the metering equipment is lower.

Table 12. Current based indices at 2 kHz sampling frequency.

Appliance	$\bar{I}$	$\lvert i\rvert_{max}$	cf	σ	ε	ϒ	κ
Halogen Lamp	0.0	6.0	5.0	6.0	6.0	0.0	6.0
Hair Dryer	0.0	6.0	5.0	6.0	6.0	0.0	6.0
CFL	0.0	6.0	6.0	6.0	4.0	0.0	6.0
Laptop Charger	0.0	6.0	6.0	6.0	3.0	0.0	6.0
LED lamp	0.0	6.0	6.0	6.0	6.0	0.0	6.0
Power Supply 1	0.0	6.0	6.0	6.0	4.0	0.0	6.0
Power Supply 2	0.0	6.0	6.0	6.0	5.0	0.0	6.0

Table 13. Power and Voltage-Current based indices for 2 kHz sampling frequency

Appliance	P	Q	PF	Slope1	Slope2	Area
Halogen Lamp	5.0	6.0	6.0	5.0	6.0	6.0
Hair Dryer	6.0	6.0	6.0	6.0	5.0	6.0
CFL	6.0	6.0	6.0	6.0	4.0	6.0
Laptop Charger	5.0	6.0	6.0	5.0	5.0	6.0
LED lamp	6.0	6.0	6.0	6.0	1.0	6.0
Power Supply 1	6.0	6.0	6.0	5.0	5.0	6.0
Power Supply 2	6.0	6.0	6.0	5.0	4.0	6.0

Table 14. Current based indices for 200 Hz sampling frequency.

Appliance	$\bar{I}$	$\lvert i\rvert_{max}$	cf	σ	ε	ϒ	κ
Halogen Lamp	0.0	6.0	1.0	6.0	3.0	0.0	2.0
Hair Dryer	0.0	6.0	1.0	6.0	3.0	0.0	2.0
CFL	0.0	6.0	4.0	6.0	3.0	0.0	4.0
Laptop Charger	0.0	6.0	0.0	6.0	3.0	0.0	5.0
LED lamp	0.0	6.0	0.0	6.0	0.0	0.0	1.0
Power Supply 1	0.0	6.0	1.0	6.0	0.0	0.0	2.0
Power Supply 2	0.0	6.0	1.0	6.0	0.0	0.0	2.0

Table 15. Power and Voltage-Current based indices for 200 Hz sampling frequency.

Appliance	P	Q	PF	Slope1	Slope2	Area
Halogen Lamp	5.0	6.0	6.0	6.0	5.0	6.0
Hair Dryer	6.0	6.0	6.0	6.0	6.0	6.0
CFL	6.0	4.0	5.0	6.0	4.0	4.0
Laptop Charger	5.0	4.0	5.0	6.0	5.0	5.0
LED lamp	6.0	6.0	6.0	6.0	6.0	6.0
Power Supply 1	5.0	4.0	6.0	5.0	6.0	5.0
Power Supply 2	5.0	6.0	6.0	5.0	6.0	6.0

Conclusion

This paper discusses the ability of time-domain indices derived from steady state signals to discriminate between typical individual electronic and non-electronic household appliances. The analysis of steady state signals in time domain requires less computing power and can be easily implemented into smart meters. The study presents promising results for the discrimination of the selected set of appliances. Several indices based on current and voltage signals were computed to evaluate the suitability of appliance identification. Table 16 summarizes the indices with good and bad performance in terms of their discrimination ability and robustness under different measurement conditions.

Suitability of steady state indices for appliance identification slightly decreases when voltage distortion and network impedance are considered in the set-up. The effect of the network impedance is larger than the effect of the supply voltage distortion, due to the coupling between the appliance circuit and the impedance. Few indices are still able to discriminate between the different devices, which demonstrates their suitability for typical conditions in the public LV networks.

Table 16. Performance of indices for appliance identification.

Type of index	Recommended	Not recommended
Current based	*Rms, standard deviation, kurtosis.*	*Mean* and *skewness*.
Power based	*Active Power, Reactive Power, Power Factor.*	
Voltage-Current based	*Area*	*Slope 2*

The reduction of the sampling frequency also decreases the level of discrimination because fewer signal details are considered in the analysis. Nevertheless, for low sampling frequencies such as 200 Hz and 2 kHz, some of the current based indices have been identified as robust. This suggests that the available sampling rates in the present metering generation are well enough for appliance identification based on stationary signatures in time-domain.

The use of the proposed methodology for monitoring residential customer behavior is expected to have less additional costs compared to other methods described in the Introduction. First, neither multiple sensors nor communication platforms between them are needed. Secondly, less sophisticated meters are required. Finally, the computation is not intensive because simple statistics are computed from few cycles of the electrical waveform.

Future work is dedicated to the study of suitable indices of steady-state signals in frequency domain, e.g. the harmonics. After validating the suitability of selected indices in a field study, an identification strategy based on the combination of transient an steady state indices will be developed. This also includes the simultaneous operation of multiple appliances at the same measurement time, as in a realistic household.

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