A fast event detection algorithm for residential loads within normal and disturbed operating conditions

Faten Mouelhi[1], **Houda Ben Attia Sethom**[1,2], **Ilhem Slama-Belkhodja**[1], **Laurence Miègeville**[3], **Patrick Guerin**[3]

1. Université de Tunis El Manar, Ecole Nationale d'Ingénieurs de Tunis, LR 11ES 15, Laboratoire des Systèmes Electriques

faten.mouelhi@gmail.com

2. Université de Carthage, Ecole Nationale d'Ingénieurs de Carthage 2035, Tunis, Tunisia

3. Université de Nantes, Institut de Recherche en Energie Electrique de Nantes Atlantique (IREENA), l'IREENA, EA 4642, Saint-Nazaire

ABSTRACT. *This paper deals with the classification and identification methods applied for the residential sector power management issue. A fast event detection algorithm is then proposed and applied to the identification of the load status changes occurred during a home facilities operation. Because the residential load current or the supply voltage can have harmonic components, the second idea developed by this paper is the consideration of the electrical grid harmonic disturbances that may affect the detection signals notifying the load status changes. Then the proposed event detection algorithm was applied to properly identify the status changes of a large variety of grid connected residential loads.*

RÉSUMÉ. *Ce travail porte sur la problématique d'identification et de classification des charges pour la gestion et la maîtrise de l'énergie électrique dans le secteur résidentiel. Un algorithme de détection d'événements rapide est alors proposé et appliqué à l'identification des changements d'état des charges dans une installation domestique. Le courant absorbé par les charges résidentielles ou la tension d'alimentation pouvant contenir des composantes harmoniques, la deuxième idée que développe cet article est la prise en compte de ces perturbations capables d'affecter la détection des évènements liés aux changements d'état des charges en question. L'algorithme de détection d'événements proposé a ensuite été appliqué pour identifier convenablement les changements d'état d'une grande variété de charges raccordées au réseau résidentiel en présence de perturbations harmoniques.*

KEYWORDS: *demand side management, event detection, steady and transient state, households, power quality, harmonic disturbances.*

MOTS-CLEFS : *maîtrise de la demande d'énergie, détection d'évènements, régimes transitoire et permanent, habitation résidentielle, qualité de l'énergie, perturbations harmoniques.*

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Nomenclature

DSM	Demand Side Management
HEMS	Home Energy Management Systems
DR	Demand Response
NILM	Non-Intrusive Load Monitoring
FSM	Finite State Machine
CVD	Continuously Variable Devices
MSC	Mean Shift Clustering method
KNN	K-Nearest Neighbor method
MCMC	Markov Chain Monte Carlo
PCM	Principal Components Method
TOU	Time Of Use
ILM	Intrusive Load Monitoring
EMI	Electromagnetic Interference
CDM	Committee Decision Mechanisms

1. Introduction

Due to the growth of electric end uses, the management of varying electric power demand has become essential. Several solutions are proposed, such as renewable energy and storage energy system integration and also Demand Side Management (DSM). Tremendous studies have been conducted in this field in order to reduce or to shift peak load demand from network supply side or to maintain balance between energy supply and demand in a building or residential sector equipped with renewable sources and storage systems (Chen *et al.*, 2013).

The main problems with DSM solutions are, on one hand, the uncertainty about customer’s demand and on the other hand, the intermittent and random nature of renewable sources. Loads monitoring becomes a key concern to tackle the Demand Response (DR) issue for household’s appliances (Mathieu *et al.*, 2012). Also studying loads in this context represents a key factor to insure the balance supply/demand in the low voltage network (Pipattanasomporn *et al.*, 2014).

Research in residential housing sector is not a recent topic. However the power issue is a more recent one to improve the management systems.

For such purposes, a great deal of research has been carried out on home appliances. Authors generally focus on classifying or categorizing, modeling and identifying or recognizing residential loads. Their work aims to establish a database for DSM program and then for Home Energy Management Systems (HEMS). The parameters, generally available in the database, are related to working style and consumer lifestyle. Data could be load power consumption profile, renewable sources produced energy, load currents in steady state and transient state, etc.

Historically, different methods of classification or categorization are reported in the literature. The widespread one corresponds to the most energy hogs such as electric water heaters, space cooling units, refrigerators, air conditioning systems, washers and dryers (Wang *et al.*, 2012; Kuzlu *et al.*, 2012; Nourbakhsh *et al.*, 2012). Household appliances classification is also performed to distinguish shiftable from non shiftable loads (Tasdighi *et al.*, 2014), in order to be able to turn on/turn off loads. In all these cases, the objective is to reduce or to shift the peak load demand.

It is to note that an increasing concern is reported nowadays in the literature for nonlinear loads since they play an important role in deteriorating the power quality. Thus, the excess of nonlinear loads leads to a significant impact on the electrical system. Several studies tackle this issue by focusing on the field of loads recognition (Pipattanasomporn *et al.*, 2012; Chaouch *et al.*, 2014).

Among the motivation for developing such a load model is the need of a tool to better predict, quantify and plan the future requirements in terms of power plants. Once database is available, identification works are carried out to identify or recognize working loads in order to turn them on or to shift them.

Load monitoring is based on three modules: classification, event detection and identification modules. Non-Intrusive Load Monitoring (NILM) methods are nowadays preferred for their accuracy. Although one sensor in the general electric board is required (Zoha *et al.*, 2012), they are still very expensive since they require high computing resources (Kong *et al.*, 2014). Moreover, due to the high number of loads and their variety, database requires huge storage capacity.

Thorough studies related to NILM approaches have focused on events detection methods, both in steady and transient states (Wang *et al.*, 2012).

A common research (Patel *et al.*, 2007) in residential and commercial sector has been carried out in order to develop inexpensive and easy to implement sensing systems in home. It was important to detail electric power consumption profiles of their customers to help level peak loads and plan future capacity. To deal with these concerns, utilities have sought a way of determining the operating history of an electrical load from measurements made solely at the utility service entry of a building.

Accordingly, the present work provides transient event detection for use in energy box in order to monitor loads.

To explore the idea of detecting and learning various electrical events in home, this present paper deals with an event detection method. A new fast and easy method for load event detection is proposed to mitigate the disadvantages of the previously published researches. This method uses the turn on transient state and traditional steady-state of the load current, and accordingly, it improves the recognition accuracy and reduces computational requirements. The proposed method has been applied for faulty sensor detection and isolation (Berriri *et al.*, 2012). Simulation and experimental results show that the proposed method is effective for load event detection and is also an efficient step to identify loads.

This paper is composed of five sections. Section II is a bibliographic review that handles the issue of loads analysis such as classification, modeling and identification. Section III explains the developed event detection algorithm in detail. Then, the effectiveness and the validity of the proposed method are checked by the practical experiment and simulation results given in Section IV. Finally, the findings and conclusions are addressed in Section V.

2. Survey and analysis of residential loads

2.1. Residential loads study for electrical management purposes

As the electricity demand is continuously increasing and in order to solve this problem, research is giving rise to the development of new and intelligent solutions such as HEMS in order to propose innovative solutions for energy control. In (Yi *et al.*, 2013) authors developed an algorithm to plan appliances' use according to the energy demand in order to control loads.

In addition, the growth of linear and non-linear loads in the residential sector leads to the harmonic resonance appearance, which could deteriorate the electrical distribution and increase the energy demand (Zoha *et al.*, 2012). As a result, the motivation for focusing residential loads is the energy quality improvement. Several studies such as (Munir *et al.*, 2013) have shown that the mechanism of distribution generator inverter of PV can efficiently compensate the residential system harmonics, thus improving energy quality.

Other reasons for investigating residential loads are on one hand, the control and management of the electric network and on the other hand, the study of varying load scenarios impacts on technical, demographic, behavioral and economical aspects.

Furthermore, studying loads could lead to the implementation of an optimal algorithm for providing bidirectional communication and real time pricing. In (Pipattanasomporn *et al.*, 2012; Kim *et al.*, 2014; Kwac *et al.*, 2014), authors have focused on the improvement of smart meter infrastructure which embeds intelligent control modules such as HEMS.

2.2. Load Classification methods

Against this background, it is worth monitoring and classifying loads into many classes. Before developing classifications strategies and research approaches in this field, it is important to start by enumerating the major energy hogs in homes such as electric water heaters, space cooling units, refrigerators, air conditioning systems, washers and dryers. In (Pipattanasomporn *et al.*, 2012; Najmeddine , 2009), authors classify all the household appliances into major appliances household, kitchen, sound and imaging, health and beauty appliances.

Domestic activities can imply the need of electricity without forcing it. That is the reason why the authors in (Wang *et al.*, 2012) have considered that appliance behavior is a feature to classify households such as induction coil (motor), heating resistance, electronic circuit and they have studied the events detection in steady state and transient state conditions. In (Richardson *et al.*, 2010), the authors have made connection between activities and the use of appliances. Another type of classification with power is considered in (Gerbec *et al.*, 2003), where the authors classify loads by using real and reactive powers using the P-Q plan.

In other works, researchers (Zoha *et al.*, 2012) have focused on the working style of different loads such as on/off machine, multistate appliances, Finite State Machine (FSM) and Continuously Variable Devices (CVD) that are appliances remaining active throughout weeks or days consuming energy. Other researchers (He, 2012) have tried to classify loads according to their energy consumption by dividing them into two categories, the first one including appliances with power above 30W and the second one including appliances with power level below 30 W.

These different classifications are based on methods such as Mean Shift Clustering method (MSC) (Gerbec *et al.*, 2003) and K-Nearest Neighbor method (KNN) (Kong *et al.*, 2014).

2.3. Load modeling

Once load classification is ready, a database is to be prepared for identifying loads. This database can be presented by a set of load models, either load profile models or electrical circuit models.

Load modeling is a relevant step for assessing power demand and investigating electrical consumption in order to decide the best strategy of load management. Various studies use a load curve model (Kong *et al.*, 2014; Tsagarakis *et al.*, 2012) to analyze or predict consumption, and they apply several methods such as the well-known bottom up and top down methods. In (Grandjean *et al.*, 2012) the authors have analyzed several techniques and methodologies. A hybrid method combining the both last techniques was selected, using other strategies of load modeling in order to improve domestic’s end-uses, consumer habits and behaviors. In those approaches the loads profile of each residential customer is transformed into a load curve which represents the electrical demand for a while. Authors in (Tsagarakis *et al.*, 2012) used Markov Chain Monte Carlo (MCMC) modeling technique to develop synthetic user profiles. This approach, validated for the UK region only, aims at reducing the energy bill in order to strike a balance between the utility and the customer’s needs.

According to the results of various surveys, authors have been applying the Principal Components (PC) method for a long time for modeling the load curves in order to contribute to a more rational employment of the hydrocarbon fuel in the case of surveys on environment and non renewable resources (Manera et Marzullo, 2005).

Another technique is to model the loads by an electrical circuit. In (Ghorbani *et al.*, 2011) residential appliances loads are modeled by a Norton equivalent model, which reproduces the same working style of an appliance. This approach enhances the process of monitoring appliances and controlling their electricity demand in terms of accuracy. Recently, in (Yi *et al.*, 2013) authors have replaced household appliances by a harmonic current source in parallel with fundamental impedance, in order to analyze harmonic distortions and compensation performances. Researchers in (Li et Wolfs, 2013) are striving to develop new approaches by using a hybrid model for residential electricity demand that focuses on low frequency aggregation behavior of loads and the higher frequency stochastic behavior. Also, in (Kim *et al.*, 2007) authors have started to analyze low frequency current ripples, then used load pattern to complete a residential load database working in fuel cells systems.

Currently, works such as (Ozturk *et al.*, 2013; Walker et Pokoski, 1985) focus on the load pattern and forecast the power demand based on the user's lifestyle in order to prevent load demand. In the context of the home energy management, they propose a solution using the Demand Response (DR) and the Time Of Use (TOU) of loads to reduce the energy bill and the electrical energy cost. Within the framework of smart grids, they developed an algorithm to schedule the operation of the appliance taking into account overall costs, climatic comfort level and timeliness. More precisely, Walker and Pokoski (Walker et Pokoski, 1985) are the first authors who have introduced the concept of Time Of Use, taking into account human behavior to reconstruct load curves so as to help the planning of new power plants.

2.4. Load characterization

The previous study devoted to the residential loads classification and modeling techniques emphasizes the interest in gathering loads information to build the broadest database.

The load database consists of load parameters or profiles signatures. The signatures are obtained from households' appliances operating characteristics such as power, voltage and current signals (Kim *et al.*, 2014). Among the methods for characterizing loads there are appliance load monitoring methods. So Non-Intrusive Load Monitoring (NILM) methods require only one sensor while Intrusive Load Monitoring (ILM) methods need one sensor for each appliance, which is more expensive.

Currently, a large part of research studies concerns NILM methods to improve identification systems and minimize the distortion phenomena (Wang *et al.*, 2012). In (Kong *et al.*, 2014) authors have shown that NILM-based system is an ideal platform for extracting useful information about any system that uses electromechanically devices. This leads to low cost installation by reducing the number of sensors.

Load characterization can be performed in both steady and transient states. In steady state, each appliance is identified by the time of operation changes. The analysis of steady state cannot identify nonlinear loads due to their frequency. Currently, further research is conducted on recognition accuracy using transient state data. Thereby the loads are identified by spectrum analysis, high frequency responses, wavelet transform, or neural network approaches (Kim *et al.*, 2014; Laughman *et al.*, 2003).

2.5. Events detection methods

In this subsection, the paper describes the most frequently employed load event detection methods, and provides examples of event detection applications in NILM methods, which are in turn divided into two categories (Basu *et al.*, 2015; Wong *et al.*, 2013), namely non-event-based and event-based methods.

A non-event-based NILM method is not based on edge detection schemes before the load event features classification step, but relies on performing inference for each aggregate power sample. Thanks to their advantages which are the non complexity of the mechanism in terms of cost and processing time, they are an interesting perspective in the field of residential load monitoring. Research works such as algorithms based on time series distance NILM approach (Basu *et al.*, 2015) or the algorithm using the Hidden Markov Models (HMM) are examples of these promising NILM methods.

An event-based NILM method starts with event detection by applying edge detection algorithms on the total power consumption curve. They are based on the detection of on/off load events. The classification of these load event features is then performed by the mean of Support Vector Machine (SVM) and the K-Nearest neighbor (K-NN).

The detection and recording of transients is important for purposes like protection, power quality assessment. For many researches such as in (Patel *et al.*, 2007) electrical event detection aims to recognize electrically noisy events such as turning on or off a particular light switch, television set, etc.

In addition, load identification by NILM methods is based on three steps. The first step is events detection using sampling of steady and transient analysis. Poisson Probabilistic model can be used for events detection (Wang *et al.*, 2012). Figure 1. presents different transient state current waveforms of appliances such as air-conditioner, a heating equipment, personal computer, microwave oven. In this work case, the event detection is applied to the rms current. The second step is to use the Mean Shift Clustering. The final step handles the identification of appliance by the mean of a multidimensional linear discriminate approach.

A recent research study uses the Electromagnetic Interference (EMI) noise to extend the range of identifiable events (Kim *et al.*, 2014).

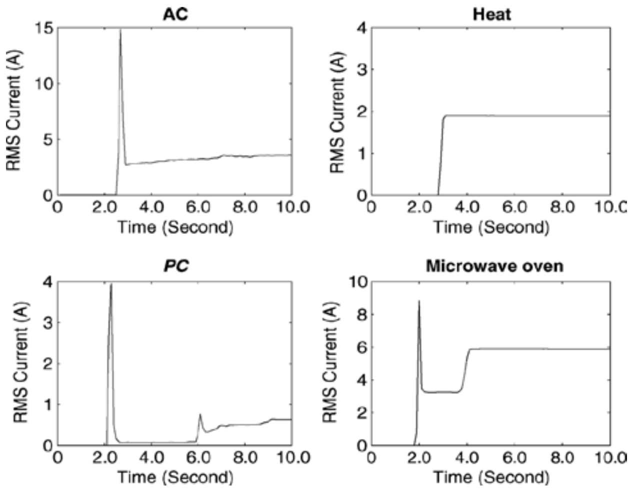


Figure 1. Examples of switching transient load currents, (Wang et al.*, 2012)*

Furthermore, in (Zeifman et Roth, 2011; Norford et Leeb, 1996; Berges *et al.*, 2011) several disaggregation and learning methods have been used to detect events for NILM which are based on signature analysis and Committee Decision Mechanisms (Liang *et al.*, 2010). They are more complicated and are calculation consumption.

Bearing in mind the cost of the solution, the steady state methods seem to be a more feasible approach because it requires low-cost hardware.

On the other hand, load disaggregation algorithms can incorporate transient features to improve the segregation of appliances with overlapping steady-state features, but at the cost of expensive hardware (Zoha *et al.*, 2012).

A wider evaluation and validation work in NILM methods has been conducted by (Duarte *et al.*, 2015) in order to improve detection event methods. The authors investigate transient event on/off detection from the voltage waveforms using mask trigger and harmonic filtering method. Switching transient voltage was introduced in the last decade as part of an initiative to develop easy-to-install NILM systems with a minimum number of sensors.

In this context, the present paper tackles the detecting events with a little storage space, and with an easy method to compute. In fact, the proposed method is based on the current transient state measurement of each appliance so as to detect on/off load event. The NILM method, as designed, is very fast and easier to implement in terms of computational resources, in contrast to methods reported in the literature which are space storage and time calculation consuming (Wong *et al.*, 2013; Basu *et al.*, 2015).

The authors are aware of the problems with the small datasets which could not be very accurate to detect the event.

3. Algorithm implementation for load event detection

3.1. Detection algorithm principle

The proposed algorithm is based on the parity space approach used for fault detection and isolation problems (Berriri *et al.*, 2012). The method relies on temporal redundancies of measurements performed with a given acquisition period T_a. Variation between two consecutive measurements $\delta(k)$ is calculated each kT_a as expressed in (1) and then, the difference between two consecutive variations is processed in (2), giving as a result the residual value r_k in (3).

$$\delta(k) = \left|I_1(k) - I_1(k-1)\right| \tag{1}$$

$$\delta(k-1) = \left|I_1(k-1) - I_1(k-2)\right| \tag{2}$$

$$r_k = \left|\delta(k) - \delta(k-1)\right| \tag{3}$$

In order to avoid noise measurements, variations are evaluated considering R_k defined by (4)

$$R_k = r_k + r_{k-1} + r_{-2} \tag{4}$$

In normal cases, variations between consecutive measurements remain below a threshold (e.g. R_k). The threshold value can be evaluated experimentally or analytically if a mathematical model is available. When an abrupt deviation occurs, variations between consecutive measurements will increase and exceed the threshold. Basic applications of the space parity approach require a linear model of the system under study and lead to heavy calculations. Nevertheless, when acquisitions are performed in a very fast way (largely faster than the system time constant), approximations are derived and lead to a simple algorithm detecting abnormal or abrupt variations.

This approach has been detailed and experimentally validated for faulty current sensor detection and isolation in AC drives (Berriri *et al.*, 2012). In this work, this algorithm was applied for residential load turning on or off detection. In previous developments presented in (Berriri *et al.*, 2012), acquisitions were performed each 5µs, on sinusoidal signals and new R_k value outputted each 15µs. In the present work, loads are more often nonlinear and analytic models are generally not available, so a threshold value associated with normal operating conditions should be established based on experimental data to provide with a suitable database. Furthermore, R_k variation could be computed off-line after several acquisitions, since the current waveform period is 20ms (which is corresponding to the network frequency, 50Hz). This requires more storage resources but less severe requirements in terms of time execution, which is more adapted to target applications, like energy box devices.

Figure 2 illustrates this method: A sinus waveform simulation is carried out under MATLAB® software environment using 5µs sample time calculation, and results are stored in a data file. The residual R_k is calculated with different acquisition periods. Simulation results give the residual shape, in Figure 2a for T_a =200µs, and in Figure 2b for T_a =1ms. Bigger is T_a, higher is the peak of residual. In Figure 2c, the variation rate has been mitigated with smaller T_a.

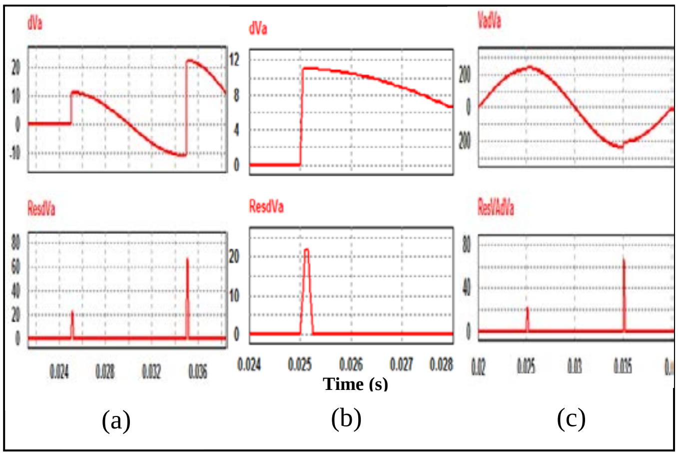


Figure 2. Residual of Sinus wave abrupt changes (a), (b), (c)

3.2. Application to the load detection in normal operating conditions

3.2.1. System description

Experimental results aim at studying some residential loads including the most often used ones in homes like kettles, lights LED and light lamps.

First, the proposed method has been tested on both the light board and the kettle as shown in Figure 3. The experimental set-up is composed of light bulbs (n°1), a kettle (n°2), an oscilloscope (n°3) for data acquisition, a MATLAB® simulator (n°4), a current probe (n°5), and a current measurement instrument (n°6).

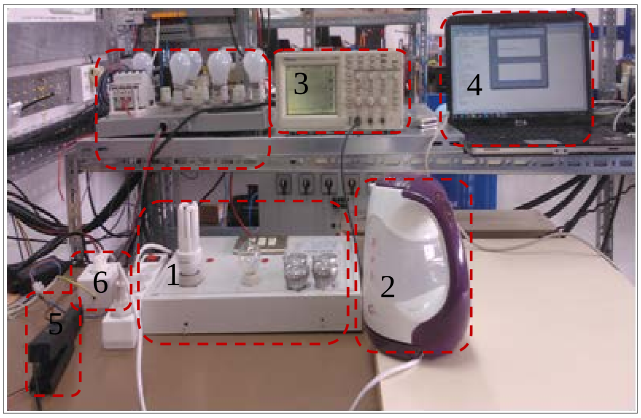


Figure 3. Experimental set-up

The light board consists of Compact Fluorescent Light lamp (CFL), LED bulbs, and incandescent bulbs.

To establish communication with the TDS210 Series Digital Storage Oscilloscope, MATLAB® software space has been used. The test and measurement tools in MATLAB® enable a very fast data transfer between the oscilloscope and the PC.

3.2.2. Experimental Results

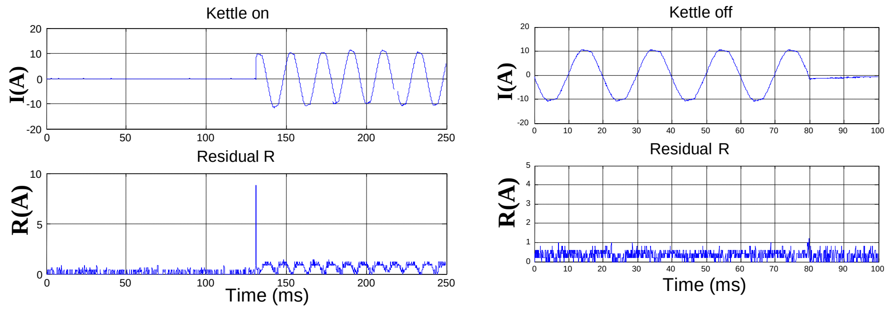
The test results obtained from the proposed method for home appliances are presented as follows.

The first test concerns with the kettle in steady state operating conditions. Both switching on and switching off transient currents were recorded in order to analyze the current waveforms and extract unique appliance specific features as shown respectively in Figure 4a, The LED bulbs (on/off) are presented in Figure 5b. Other appliances are investigated in this paper in order to compare between linear and nonlinear lighting loads such as CFL (on/off), as shown in Figure 5a and the transient current of incandescent lamp (on/off) in Figure 4c. The fan has been detected in spite of its low current as shown in Figure 4b.

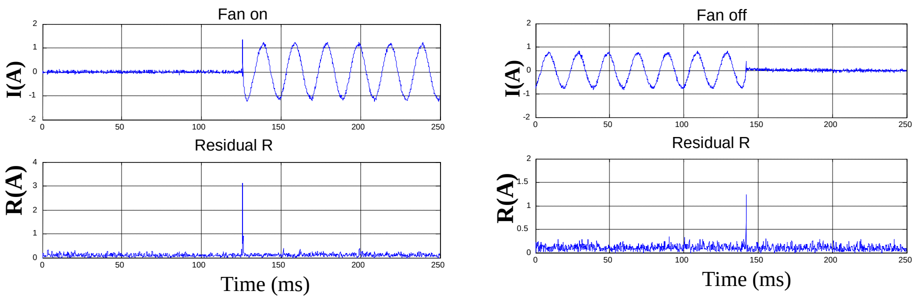
As a result, Figures 4 and 5 depict, for each tested appliance, its switching-on/off behavior; the event detection is then observed by the peak value noted by R. Thanks to the detection event algorithm, it becomes possible to detect the occurrence of load current abrupt variation. This allows monitoring changes i.e. once an event occurs, consumers could control remotely their appliances. Also the signature of any appliance can be analyzed in the database module in order to identify which appliance is working or turning off.

In order to validate event detection method for several loads, two approaches have been applied. In the first approach, each appliance has been tested separately. In the second approach, two events of two loads have been tested in the same time. Therefore CFL and LED bulbs have been chosen to perform the tests. As a result, the detection of the on/off switching is shown in Figure 6. The procedure firstly consists in turning on the CFL bulb and turning on the LED bulbs afterward. Then, it can be checked that two events can be detected when starting off, like shown by the two different residual R values. The former corresponds to the CFL switching, and the latter is the LED switching event (Figure 6a). This result justifies the existence of two events despite the non-linearity of the loads.

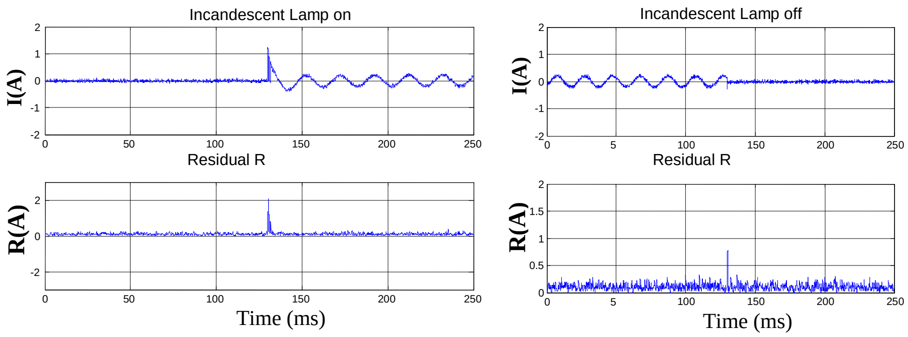
Then, the sum of residential loads events has been performed by using the MATLAB® simulator in order to validate this approach. The same experimentations of CFL and LED bulbs have been carried out, i.e. the addition of the two load profiles leads to a new one as shown in Figure 6b. In addition, the event detection algorithm has been tested on this new profile. Actually, the economic lamp was turned on while the LED bulbs were working. Accordingly, the occurrence of an event characterized by a residual value was observed when switching on the lamp.



(a)

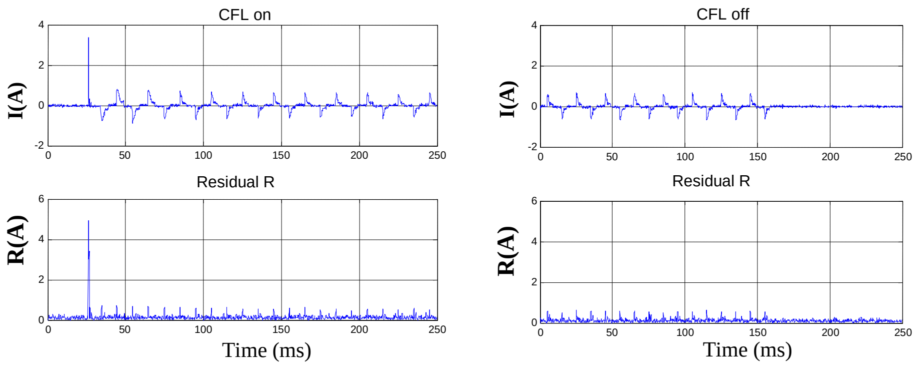


(b)

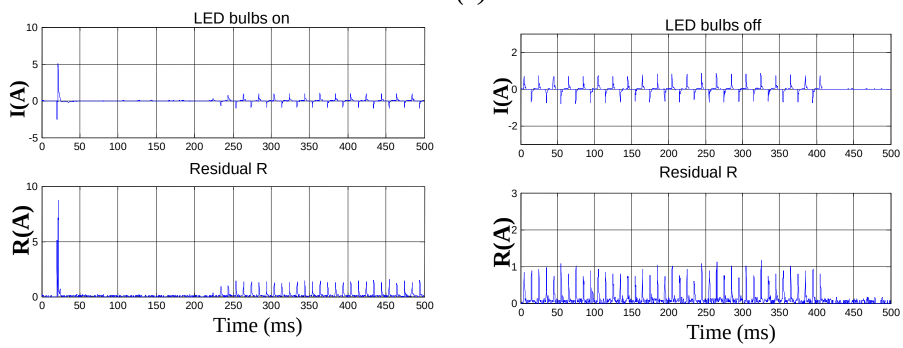


(c)

Figure 4. Linear load switching on/off events (a) kettle, (b) fan, (c) incandescent lamp



(a)



(b)

Figure 5. Non Linear load switching on/off events, (a) CFL, (b) LED bulbs

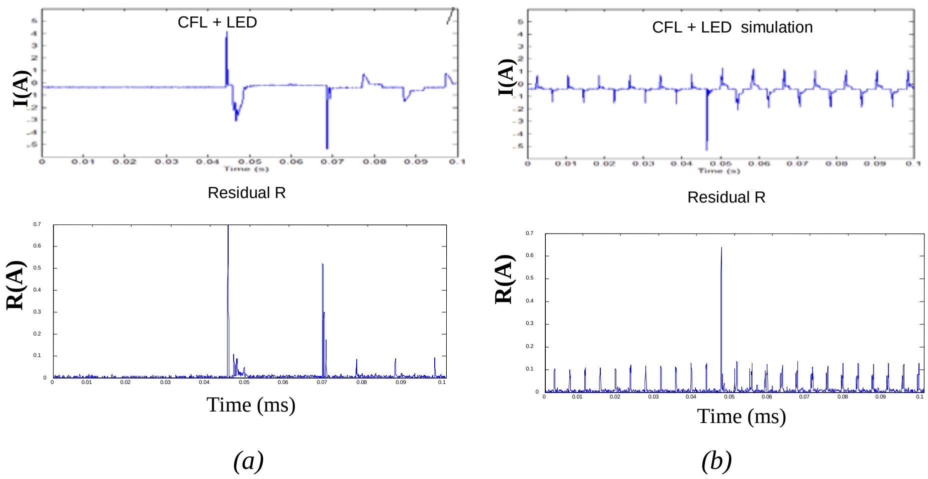


Figure 6. CFL and bulbs on/off event detection a) Switching on event successively applied to each load (experimental results); b) Switching on event applied to LED bulbs during CFL operation (signals sum)

The existence of this residual value proves the detection of the turning on of the CFL even though there are other loads turned on.

Furthermore, working on a set of same-type devices, the approach can be appropriate in the case of buildings so as to identify appliances switching on/off. Moreover, its application to a set of five LED bulbs highlights a proper matching between experimental and simulation results.

3.3. Event detection in disturbed network

3.3.1. Introduction of the power quality issue in the residential sector

The purpose of this subsection is to deal with the load identification within disturbed operating conditions. Indeed, classification and identification methods of residential loads have to take account of the voltage and current distortion introduced by the emergent use of modern electronic devices.

Although the appliances and electric devices connected to the public mains are designed to operate with a sinusoidal voltage at rated power, many of them are of non linear type and draw currents with a distorted sine waveform. Examples of non linear loads in homes and residential sectors are electronic office equipment (like personal computers or printers), audiovisual materials (like television sets, stereo systems, or videotape recorders), energy-efficient lighting (with fluorescent tube with electronic ballast and compact fluorescent lamps), uninterrupted power supply and any other equipment powered by switched-mode power supply unit. As the number of harmonic-producing loads in residences hasn't stopped increasing over the years, power quality of distribution networks is severely affected. Among the concerns caused by the harmonic distortion in residential power systems: overheating of security transformers, resonance in smoothing capacitors for the devices power supply, control system disturbances, unjustified tripping of circuit breakers, excessive heat in some appliances, increased power consumption, decreased system efficiency (Singh and Singh, 2010).

Nowadays, the widespread uptake of local electricity generation technologies such as solar photovoltaic or wind turbines also makes power quality concerns worse with more undesirable voltage swings in electricity distribution networks. It therefore underlines the interest in considering for our research purposes the matter of load classification and identification under distorted power supply.

3.3.2. Harmonic distortion indicators

Various computation techniques and estimation methods are today available to provide information on the harmonic distortion generated by non linear loads.
The most simple calculation tool is the crest factor, IEEE Std 519 (IEEE Std 519, 1992): Crest Factor = $\frac{\text{Peak}}{\text{True rms}}$.

Any deviation from $\sqrt{2}$ which defines the crest factor of a perfect sine wave, characterizes the degree of distortion.
Another common method is based on the calculation of the individual harmonic components. According to the type of sensitive equipment, it may be necessary to use a weighted combination of the different harmonic values, which leads to the following proposed criteria:

– individual harmonic percentages $c_h^* = 100 \frac{c_h}{c_1}$ (%);

– weighted sum of individual harmonic components $S_h = \sum_{h=2}^{\infty} k_h \frac{c_h}{c_1}$;

– total harmonic distortion (THD), defined by the ratio of the rms value of the harmonics to the rms value of the fundamental, which provides a measure of the additional harmonic contribution to the total rms value $THD = 100 \frac{\sqrt{\sum_{h=2}^{\infty} c_h^2}}{c_1}$ (%);

Power supply standards (EN50160, 2010) have set the upper voltage THD limit for public networks at 8%.

3.3.3. Simulation results

In order to reflect realistic operating conditions, a case study was conducted on several loads of linear and non linear type supplied under non sinusoidal voltage waveforms. The purpose was to simulate a state transition resulting from an on/off load switches and to check the proper identification of the status changes by the proposed fast load event detection algorithm.

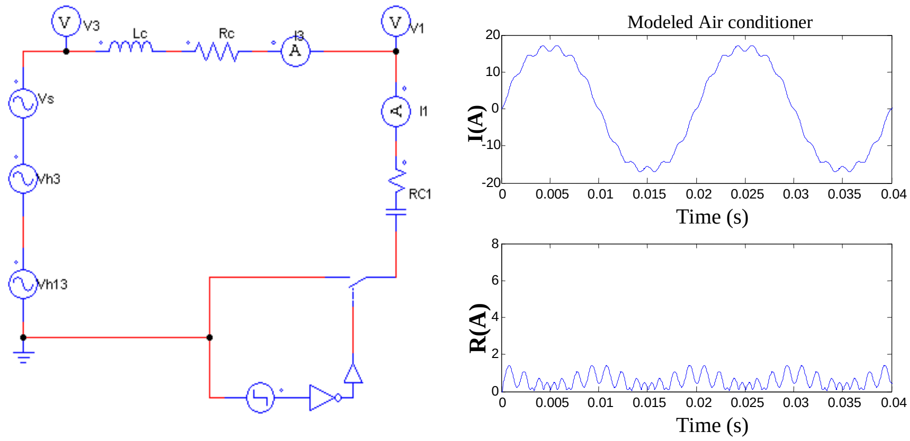
So as to take account of the load diversity, several kinds of load have been considered and simulated under PSIM. The first one was a huge energy consuming load consisting of an air conditioner (Figure 9) whose parameters are given in Table 1. It was modeled under PSIM environment (Figure 7a) by a RC circuit as proposed by (Kim *et al.*, 2007) in order to simulate its switching on/off events under distorted operating conditions. The cable parameters are taken into account and modeled by a resistance and an inductance (Table 1).

Then, the simulations were conducted under a non sinusoidal input voltage waveform constructed by adding together a series of sine wave frequencies: 5% of order 3 and 5% of order 13. The wave distortion observed on the load current and depicted in Figure 7 highlights rapid current variations and sometimes a double zero-crossing signal resulting from the presence of a 13^{th} harmonic order in the non sinusoidal voltage source. Tested on the new profile, the proposed event detection algorithm can successfully detect the state transition of the load when it is turned on (Figure 9a) or turned off (Figure 9b). Then, the event occurrence is marked by an emerging residual value easily recognisable from a sequence of repetitive residual values of lower magnitude generated from the variations of the current introduced by the distorted input voltage source.

The same approach was performed on a personal computer (PC), modelled by a diode bridge rectifier with smoothing capacitor. The model's parameters are defined in Table 1. and the simulation results are displayed in Figure 8. The load behaviour shows a typical waveform with a strong harmonic content recognisable by a sequence of repetitive current peaks over each half-period.

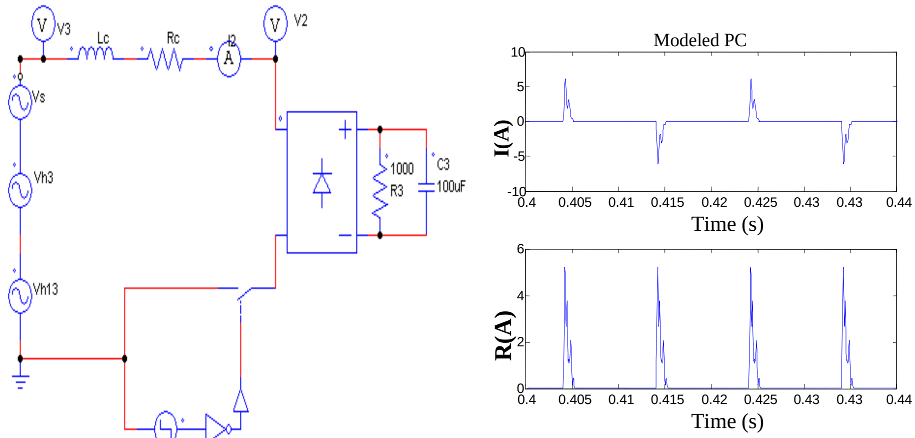
When switching on the PC (Figure 10a), the occurrence of an event characterised by an emerging residual value is observed. Then, the following sequence composed of repetitive residuals of lower magnitude associated with the current peaks of each half-period can be a useful way to characterise the non linear nature of the load. Indeed, compared to the results provided with another load of linear type like a coffee maker modelled by a pure resistance (Figure 11), the event detection algorithm leads to a different shape of residuals. When the linear load is switched on or switched off, the event detection algorithm identifies a sole residual value associated with the observed status change.

As a conclusion, the proposed approach based on the fast load event detection algorithm is interesting for discriminating between a linear and a non linear load. In the first case, it helps to characterise the linear nature of the load and to know its status 'on' or 'off', while in the second case, the repetitive sequence of the residual values returned by the fast event detection algorithm is the typical electrical signature of a non linear load.



a) *b)*

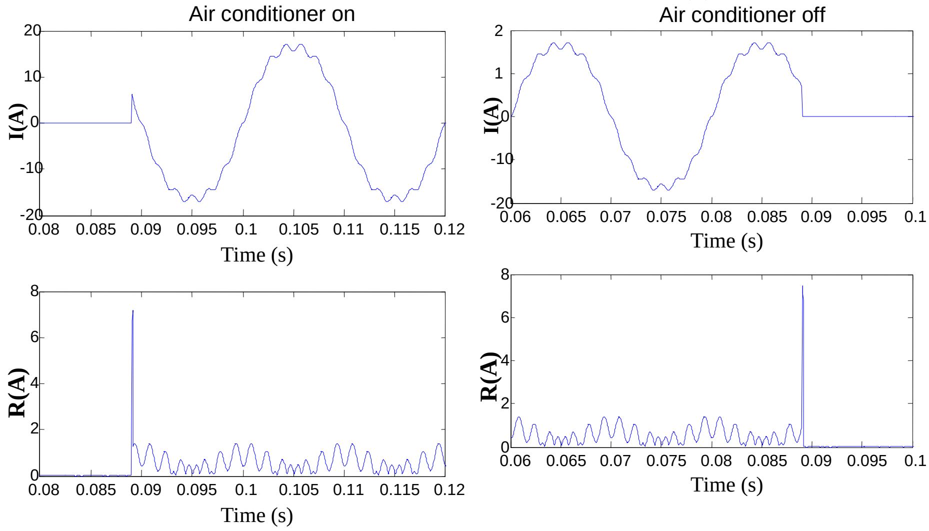
Figure 7. Air conditioner: (a) circuit model, (b) Simulated current under PSIM environment



(a) *(b)*

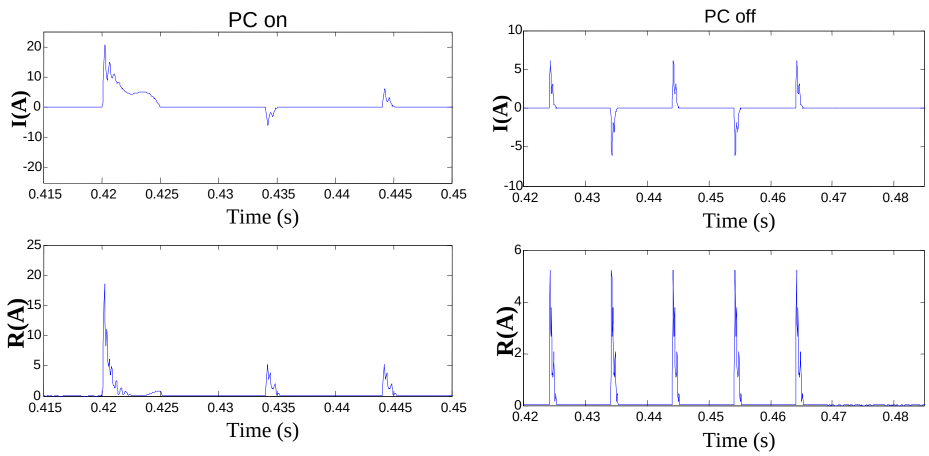
Figure 8. PC case study: (a) Circuit model, (b) Simulated current and related residual

(b)



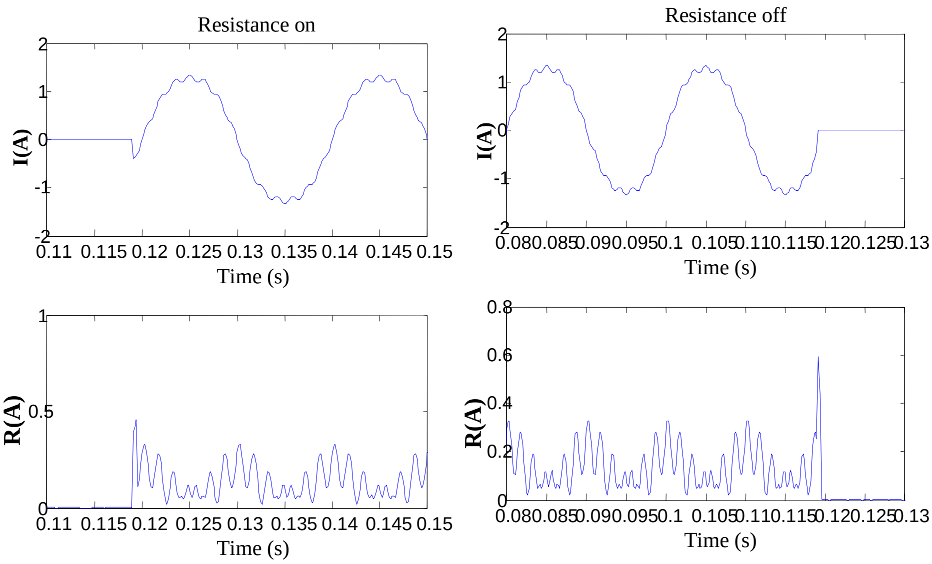
(a) *(b)*

Figure 9. Air conditioner switching (a) on (b) off event in presence of 3rd and 13th harmonics



(a) *(b)*

Figure 10. PC switching (a) on (b) off event in the presence of 3rdand 13th harmonics



(a) *(b)*

Figure 11. Resistance switching (a) on (b) off event in the presence of 3rd and 13th harmonics

Table 1. Load's parameters

Load	R(Ω)	C(μF)	L(μH)
Air conditioner	18.62	680	
PC	1000	100	
R	242		
Cable	0.14		38

4. Conclusion

This paper argues the main reasons that make residential loads an important topic to investigate for home energy management purposes. Based on a summary and a comparative survey of the existing methods for load classification, identification and modelling, the idea was to identify the advantages and drawbacks of each one and to suggest a new approach more efficient which can take account of that interest.

The purpose was also to develop methodological tools that give consumers a way to monitor and control their own energy costs and to have access to the exact power level used in real time. Within this context, this paper proposes an efficient method based on the analysis of the load current waveform to detect transient event occurrences when appliances are switched on/off. Owing to the emergent use of modern electronic devices, harmonic currents generation raises a new problem of power quality that increasingly affects electricity consumers at all levels of usage. Hence the motivations for taking it into consideration when applying load identification methods. Based upon experiments conducted so far, the proposed event detection algorithm was successfully applied and validated on several domestic loads working in normal operating conditions. The approach was also validated by simulation on some huge consuming loads working in a distribution network affected by harmonic disturbances. Rapidity, ease of implementation and scalability are the major advantages of this approach, with little required storage space.

Future works will be interested in the sensitivity study of the proposed load event detector both in normal and disturbed operating conditions in order to avoid false alarms. The user behaviour according to the acceptance of introducing such a load monitoring method and the method practical implementation cost in the home smart meter are very interesting issues that will be prospected.

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