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A new approach of electrical appliance identification in residential buildings

Marwa Hamdi*, Hassani Messaoud, Nasreddine Bouguila

Electrical Engineering Department, Laboratory of Automatic Signal and Image Processing, National Engineering School of Monastir, University of Monastir, Monastir, Tunisia

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ABSTRACT

This paper proposes a simple algorithm about non-intrusive appliance load monitoring (NIALM) method. The main objective is to analyze the overall power consumption of a given building and to identify the different operating appliances. This approach aims to reduce the overall energy expense of maintaining a specified level of comfort. In our approach, we firstly replace the main signal by a shorter form in order to reduce computing time. This criterion is important to guarantee real-time operation mode. Furthermore, we can classify the operating devices through their type and the mean electrical power consumed. Finally, for identification, we use the template's waveform matching to identify the individual energy consumption with an optimized manner. To validate the proposed algorithm, satisfactory simulation results showing the reliability of the proposed NIALM method are found.

1. Introduction

1.1. NIALM development technology

Nowadays, intelligent power consumption is one of the most innovative criterions for Home Energy Management Systems (HEMS) [1,2]. It is used in the smart grid buildings [3]. This technology can reduce CO_2 emissions and prevent high energy costs by integrating renewable energy resources. It also provides customer satisfaction in terms of comfort and ensures the utility in terms of energy saving [4–6]. HEMS can also be used for hybrid energy systems and OFF grid power systems [7,8]. The emergence of HEMS technology in smart grid buildings leads to a larger use of the appliance load monitoring (ALM) technique which can be Intrusive ALM (IALM) or non-intrusive ALM (NIALM) [9].

Indeed, because of the expensive and difficult installation of sensors on different electrical devices and the security problems of the customers' privacy, the intrusive approach is discouraged from the academic and industrial point of view [10,11].

In fact, NIALM technology is used by utilities to study the specific uses of electrical energy in different types of buildings using a single sensor installed on the main electricity meter. It is considered as an inexpensive alternative to attaching individual monitors on each device. However, it might raise concerns about privacy.

In general, linking residents' behavior to energy use can improve energy efficiency and thus reduce electricity consumption during peak hours.

Until now, the accuracy and capability of NIALM technology are still under development and they are not perfectly reliable in real time, so the complete information is accumulated and analyzed over periods ranging from minutes to hours.

NIALM was developed for the first time by Hart [12]. His study was based on a general analysis of active and reactive power to detect the intervals between ON and OFF change of state (events) and then estimate the individual energy consumptions by examining only the steady state case. In fact, active power was used to identify energy-intensive appliances and ignores those with low energy consumption [13,14]. Event detection technology, used for the first time in a steady state, has been developed and improved in the field of research. It is now considered an essential step in the identification process of electrical equipment [15].

Since its first development by Hart in 1992, several NIALM approaches have been reported in the literature. However, these approaches haven't been yet considered as a reliable solution [4,16]. Generally, the NIALM approach follows a routing algorithm based on four steps: event detection, feature extraction, device classification and estimation of the individual energy consumptions. Despite its importance to determining the schedule of appliances operation, the event detection technique, in several types of research, has been ignored and the focus was on appliance features extraction as the first step of the general electrical appliance identification process [17,18]. The most reliable NIALM algorithms were based on multi-label classification

* Corresponding author.
E-mail addresses: marwa.hamdi1990@gmail.com (M. Hamdi), hassani.messaoud@enim.rnu.tn (H. Messaoud), nasreddine.bouguila@gmail.com (N. Bouguila).

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technique which decomposes the main problem into several sub-problems and forms a classifier for each subset [19].

1.2. Contribution and organization of the proposed research

The contributions of this article are a review of the NIALM background from which we extract the issues about the environment, public data availability and technical concerns. We also present three combined techniques to achieve a practical NILM approach that allows the identification of individual energy consumptions. We discuss some initial results that we have obtained from the simulation of the algorithms using open source ECO dataset [11]. We present real-time experimental results based on our own database using a dSpace-based test bench. We also discuss several critical issues related to NILM performance problems.

The organization of this paper is as follows. Section 2 presents the NIALM method background. Section 3 provides the limitations of achieving a practical NIALM algorithm.

This article will present, in the coming sections, two main contributions of the research. The first one is proposing a reliable disaggregation algorithm for individual electrical appliance identification using the NIALM technology presented in Section 4. This algorithm will handle the pre-processing, the event detection process, the feature extraction technique, the shape matching and the energy estimation of appliances. This strategy can detect transients, classify usage by type, identify appliance operation time and estimate its electrical consumption.

The second contribution is presented in Section 5 as a methodology to develop a real-time NIALM system. The proposed approach is based on using dSpace real-time Interface (RTI) and Matlab. Results given to illustrate the performance of the proposed electrical appliance identification approach are discussed in Section 6. Lastly, in Section 7 conclusion and future research work will be presented.

2. NIALM background

The NIALM process diagram, shown in Fig. 1, presents the steps of a general classification of individual electrical appliances in residential buildings.

Determining the power consumption of each appliance in such a system relies on several monitoring devices for data acquisition, feature extraction, device classification, and power consumption optimization detailed in the following.

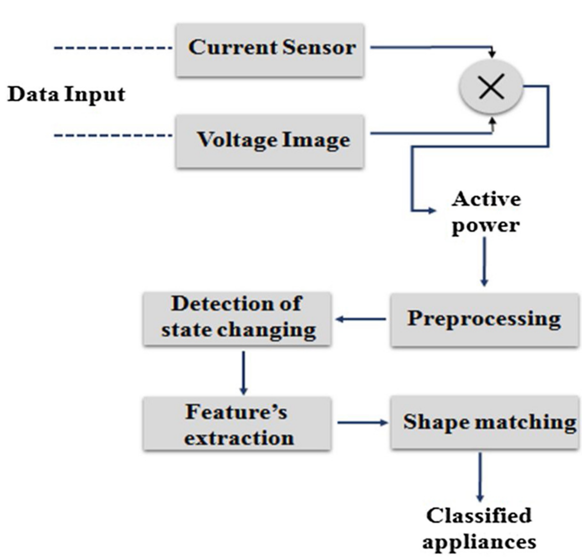

Fig. 1. Diagram of NIALM process.

2.1. Data acquisition devices

These devices measure the inputs required for the monitoring system. They can be current or voltage sensors, smart meters, etc… They must be directly connected to the main counter input.

2.2. Features extraction devices

This type of devices is divided into two categories: communication tools and recognition devices.

2.2.1. Communication devices

These are tools used to ensure the transmission of data between the different equipment of the monitoring system. They constitute a flexible and less complex wireless network such as Wi-Fi, Bluetooth, and Zigbee in order to facilitate load monitoring and automation.

2.2.2. Recognition devices

These are tools used by the monitoring algorithm to recognize the different operating appliances in the building. They utilize the collected data to extract features about it. The recognition devices can be laptops, microcontrollers or desktop computers.

2.3. Classification devices

Appliance classification processes are choosing regarding occupant's behavior and appliances specifications according to the four following categories: Customer preferred devices (Appliances most used by the client), operation mode (two-state, multi-state, continuously variable and permanent devices), waveform features (parameters that characterize the current or voltage waveforms) and user interface (user-activated or self-activated appliances) [20,21]. The classification process can also be reliable in the energy management field.

Indeed, the classification technique is based on the following types of devices: The main electrical energy consumers (their operation mode cannot be deferred such as a refrigerator) and the devices characterized by a deferrable operation mode relying on peak hours [9].

2.4. Optimization devices

The optimization concept is based on the correlation and matching of the extracted signatures with a possible load combination pre-recorded in a database. It allows the reduction of the correspondence error using algorithms executed by computer programming software.

As shown in Fig. 2, and in comparison to the conventional method, NIALM is a reliable method of individual appliances energy consumptions identification using only one sensor at the main meter input [22,23]. It is based on the analysis of the overall consumed power (or current) in a building. The analyzed signatures are classified into two complementary categories: traditional signatures (steady state and transient) and non-traditional signatures. The analysis of any type of those signatures allows the extraction of several features [24]. The extracted features in case of traditional signatures are the real power, the reactive power, the current, the voltage and the harmonics [25]. In the other case, features are temperature, light sensing, the instant of state changes and peak hours.

3. Issues to achieve a practical NIALM algorithm

There are several issues that have not been discussed clearly in the literature. These concerns can affect both the users of the NILM interface as well as the execution results of the NILM algorithm. A practical and useful NILM algorithm should take into account the different issues discussed in the following.

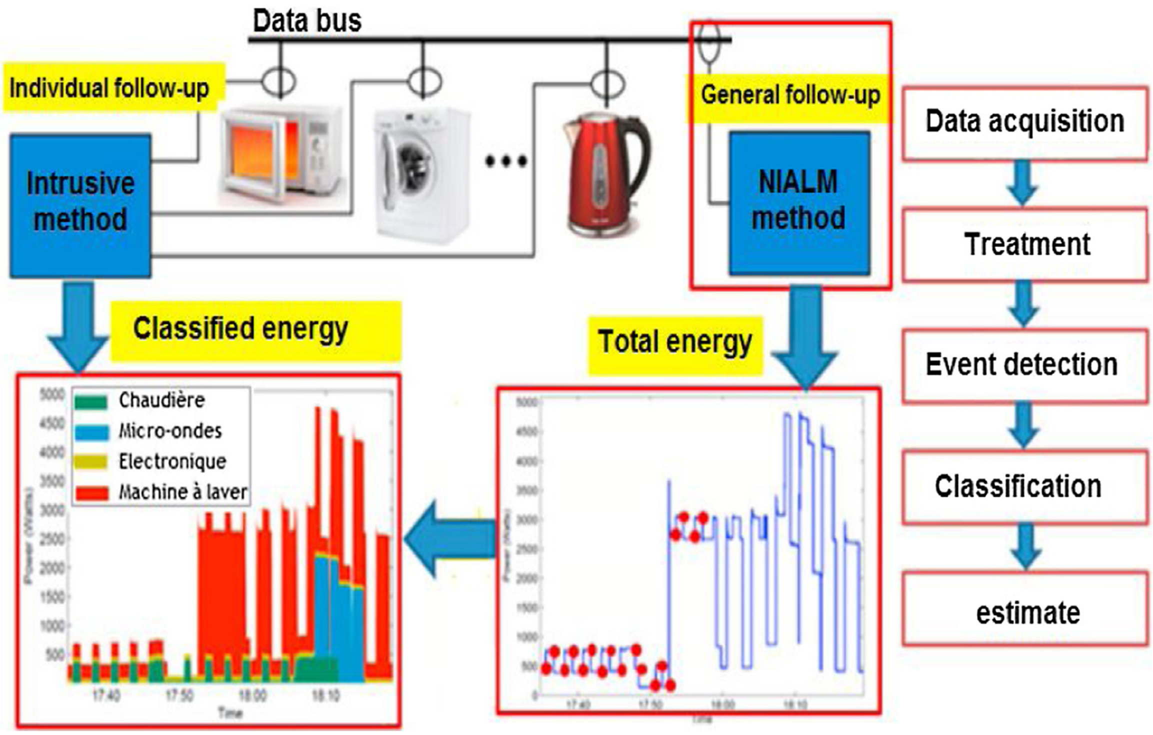

Fig. 2. Electrical power monitoring comparision — conventional and NIALM method.

3.1. Environmental issues

In general, the environment is considered as the second priority for the NIALM algorithm developers after the reduction of energy costs and electrical consumption in commercial and residential buildings.

To be environmentally friendly, users of NIALM technology should choose their appliances according to environmental conditions. In fact, energy management strategies using NIALM systems and renewable energy sources taking into account the seasonal weather and environmental conditions can influence electricity consumption and reduce the use of fossil energy sources.

The NIALM system should take into account the weather data and the location of the building to define the preferred devices of each client. As an example, in Canada with its cold winters, the heating systems consume around 80% of households' total energy consumption [26]. In the other hand, increasing energy demands can be due to environmental issues such as the absence of thermal insulation in the building. In fact, The NIALM process captures current and voltage signatures from real data considering thermal gain and loss due to outside temperature variations in order to simulate the load consumption of the space heating systems.

This case can bring out concerns about the reliability of the NIALM system. In that manner of fact, a NIALM system should be examined under several environmental items in order to achieve a practical method.

3.2. Public data availability and treatment issues

In general, the IALM (intrusive appliance load monitoring) method based classification process requires several types of information about every performing appliance in each building. This variety of information might be pre-registered in a database during an anterior learning phase.

In fact, the system inputs measurement technique in the appliance identification field depends on signal processing tools such as sampling period. This criterion defines the energy acquisition method. For low frequency, current and voltage signatures are collected with sampling intervals that can last for a few minutes to several hours or days. This measurement technique is considered as the closest to the real data acquisition technologies. For high-frequency analysis, these cycles are reduced to seconds in order to allow a precise harmonic analysis. The targeted appliances in the building determine the desired sampling frequency.

Another challenging concern is the system inputs acquisition time. In fact, the computing time must be inferior to the data acquisition time in order to allow real-time identification.

3.3. Technical issues

To develop an effective and well-defined NIALM algorithm in the building there is a need to avoid some technical concerns such as issues about the learning phase. Collecting information about each operational appliance in that building should be without the intrusion of qualified personnel to install sensors on it.

To do this, the construction of the database must be non-intrusive in order to ensure the client's private life without disturbing him with the installation of sensors on each electrical appliance in his home. The data collection required for the NIALM application is done from the main electricity meter of the building under study. Indeed, the period of the learning phase should be reduced to its minimum by taking into account the occupant habits in energy consumption.

In general, there is always a cycle of using the electrical and thermal devices, this cycle is like a unique fingerprint characterizing the building energy consumption and it helps the NIALM developers to reduce the period of construction of the database in the learning phase.

4. Event detection, feature extraction and shape matching

The data acquisition process consists in acquiring the necessary input data for the electrical equipment identification algorithm proposed in this study. These data will be acquired and processed in real time. The utility of real-time processing is to give customers a detailed and instantaneous electrical consumption report of its building (housing, hotel, doctor's cabin). The input data represents the total current consumed by all devices used daily for a specific building, as well as the voltage (single-phase ∼ = 220 V) that may drop when using a specific device. The data acquisition system will be detailed in Section 5. The recording of these data is done at the same time as their acquisition in two separate Excel files. Data recording is automatic thanks to a Matlab program and a dSpace acquisition card. The intervention of qualified personnel in this step is not required.

Generally, the acquired signals (current and power) will pass through a filtering process after the acquisition data process. The resulted signal will be compared to a threshold to find the switching time intervals called windows. These windows will replace the original power signal in the classification algorithm in order to reduce the computing time.

In fact, taking only the valid windows is the objective of the feature extraction process by comparing the distance between the different features and the mean power of the same event.

The resulted windows are the signals to compare with the appliance signatures pre-registered in a database during a learning phase.

The choice of the appliance template signature to compare with the resulted windows is given by the Matrix-Pencil method which classifies the signal if it is for a resistance, capacity or inductance.

In fact, as shown in Fig. 3 a NIALM system is based on event detection, feature extraction and appliance energy estimation.

Their correspondent algorithms are described in the following subsections.

4.1. Event detection

In the case of event detection, the overall power signal observation y (t) is pre-processed using a high-pass filter to obtain a more fluid and noiseless signal where t denotes the measurement time. The N loads corresponding to individual appliances are denoted by x_i (t) and the number of uses load is k ≤ N. An event is defined as a transition between two stable electrical states of duration Δt each. It is considered as "ON" ("OFF") when the transition in the signal is positive (negative) and it is defined by the instant "t_v". The amplitude variation of the signal is defined by "A_v" for a duration Δt. The event detection threshold, A_{min}, is selected according to the mean power presented in each event. b(t) is Gaussian white noise.

Hence, the observation of the general power signal y(t) is noted as follow:

$$y(t) = \sum_{i=1}^{N} x_i(t) + b(t) \tag{1}$$

$$|y(t + \Delta t)| \geq A_{\min} \tag{2}$$

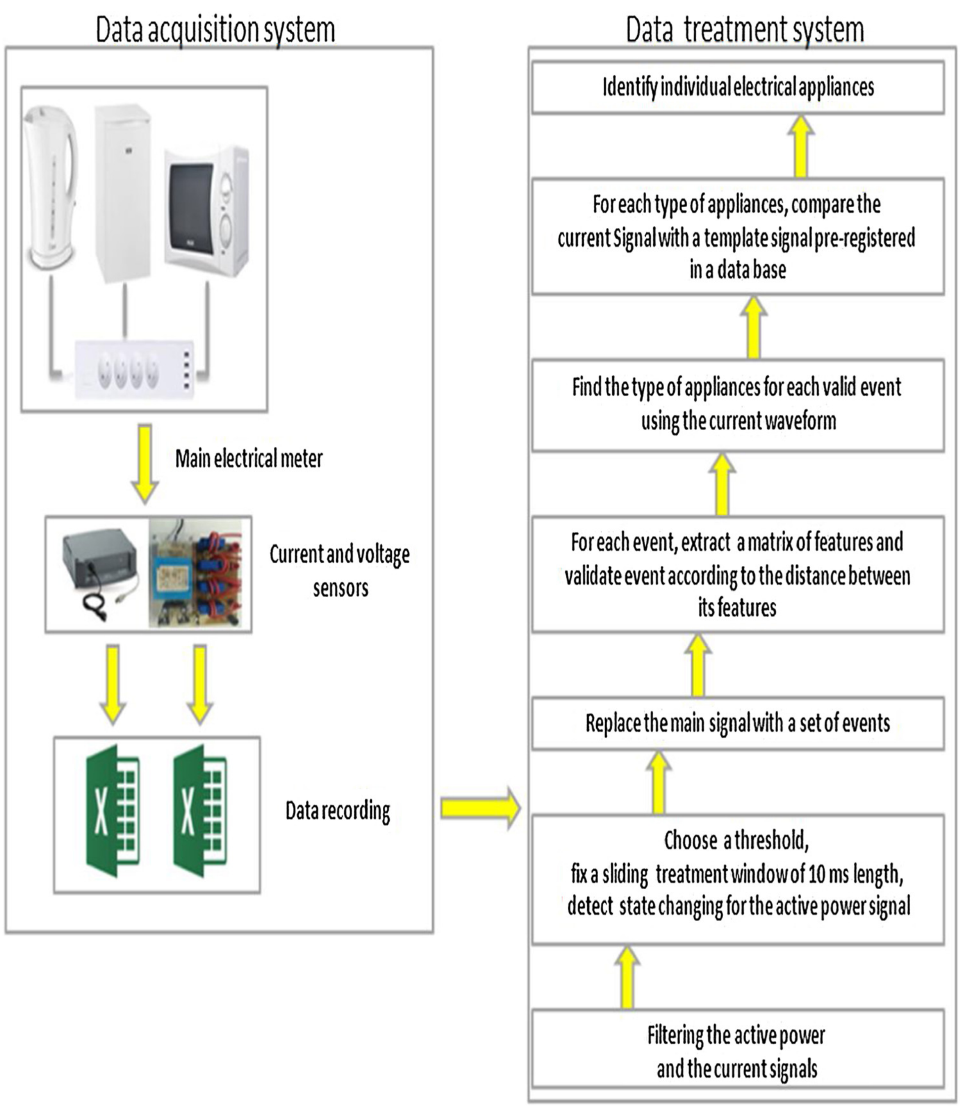

Fig. 3. Electrical appliance identification with the NIALM method.

$$y(t + \Delta t) = A_v \quad (3)$$

To do this, it is necessary to specify the instants of change of state denoted t_{min} and t_{max} to design respectively the beginning and the end of a transient state on N samples of the filtered power signal x_i (t).

In fact, the main objective of this part is to detect each variation of the input signal (current or power signal) according to a defined threshold denoted T_r using the edge technique.

We consider that y (t) is the active power at time t. If $y(t) > T_r$, the proposed algorithm start to consider this variation as an event and continues to calculate y(t + 1), y(t + 2)…, until $y(t + d) < T_r$. The start time of the detected event is the instant t in seconds and the event process end time is t + d measured in seconds where d represents the event total duration [27].

Several types of researche such as in Ref. [12] used a fixed threshold to define an event occurrence. This approach makes a large high power consumption to be seen as a single event. To overcome this problem and to improve electrical signature extraction, we used adaptive threshold values taking into account the steady period of the detected event and the next input value in order to compare it with the adaptive threshold.

The adaptive threshold and the basic event detection algorithm are presented as below:

Adaptive threshold

$ATr_{min} = min_p + T_r$
$ATr_{max} = max_p - T_r$
$ATr_{min} <= ATr <= ATr_{max}$

Where $\min_p$ (max_p) is the min (max) value of the input signal, T_r is the pre-defined threshold in order to avoid classification of very low electrical consumption appliance. *ATr* is the adaptive threshold defined between its min and max values.

Event detection algorithm

Input : Adaptive threshhold *ATr*, input signal *y*
Output : *wJ1*, *wJ2*

For (0 <= *k* <= (length(*y*) − 1)) **THEN**
    tJ1 = find (*y* > *ATr*);
    zJ1 = diff (*y* > *ATr*);
    wJ1 = find (*zJ1* > 0);
    wJ1 = *wJ1* + (*k* − 1);
    kJ1 = find (*zJ1* < 0);
    kJ1 = *kJ1* + (k − 1);
END For

The parameter *WJ1* (*WJ2*) determines the positive (negative) transient detection for each *k* event.

In this approach, we used a steady-state identification algorithm that is very simple, powerful and useful. Its main advantages are:

The reduction of computing time, the targeted selection of events according to peak hours where there are the most electricity consumption and the concentration on devices big consumers of electrical energy in the building.

The event detection diagram, shown in Fig. 4, is applied to data extracted from the ECO open-source dataset [11]. These data represent the overall power consumption of a building acquired and recorded over 24 h representing the result of the simultaneous operation of several appliances.

The first part of the proposed main algorithm enables the obtaining of a reduced form of the overall signal in order to reduce the computing time and to guarantee a non-intrusive real-time identification of individual energy consumption in an optimized manner.

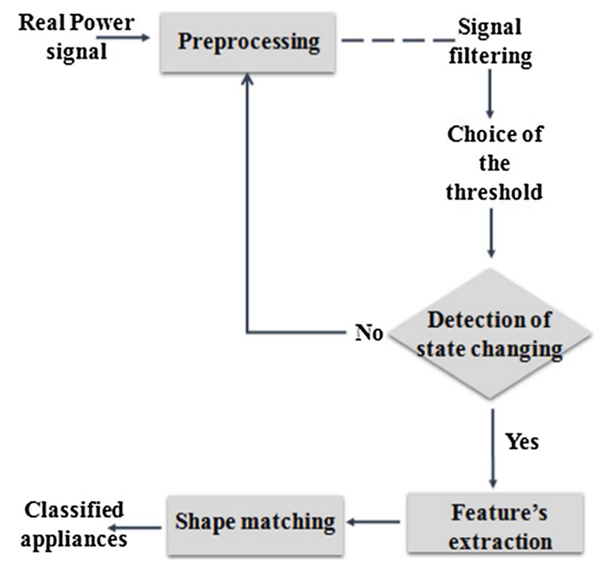

Fig. 4. Algorithm of event detection process.

4.2. Feature extraction

Each window selected in the previous section will be processed to extract several characteristics defining the overall power signal [29]. The relevant characteristics are the maximum value (m_pic) and its location (m_loc), the mean value (moy), the final value (v_f), the area under the curve (AUC) and the class of the devices. The class of a device is chosen according to the average power consumed in a defined window. In fact, if we have an analysis window with mean power equal to 200 W than the class is 2. The feature extraction diagram is shown in Fig. 5.

Indeed, at this point, there are other steps that can help NIALM users focus only on peak hour intervals and reduce computing time. These steps concern the validity of a window which can be decided either according to a length threshold that guarantees the stability of a change of state or according to the total distance d_k between the extracted features and the mean power of the same event.

The feature extraction and event validation algorithms are presented below:

Feature extraction and event validation algorithm

Input : the *k* event E_k
Output : the feature matrix Fm_k, the distance d_k, valid event VE_k

For (0 <= *k* <= Number (E_k)) **THEN**
    [*pks*,*locs*] = findpeaks (E_k);
    locs = *locs* + *k*;
    $F_{m\ k}$ = matrix_function (E_k, *pks*, *locs*);
    size_matrix = size (Fm_k);
    If (size_matrix > 2) and (d_k < Fm_k (2,*k*))

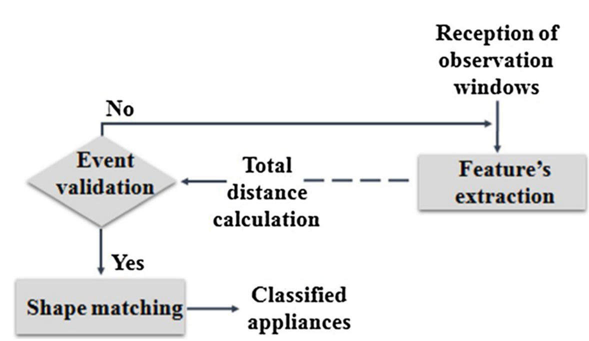

Fig. 5. Algorithm of feature extraction process.

Feature extraction and event validation algorithm

$VE_k \longleftarrow$ True
Else
$VE_k \longleftarrow$ False
End if
END For

The matrix_function algorithm

Input : the k event E_k, the pics *pks* and their locations *locs*
Output : the feature matrix Fm_k

AUC = 0;
som = 0;
For (r = 1 : length (E_k)) **THEN**
Som = som + E_k (r);
End For
moy = som / length (E_k);
v_f = y(length (E_k));
AUC = [AUC trapz (E_k)];
AUC = AUC (1,2 : end);
class = 0;
If ((moy > 0) & (moy < 100))
class = [class 0];
Else
class = [class floor (moy/100)];
End if
class = class (1,2);
m_loc = *locs*;
m_pic = *pks*;
Fm_k = [m_loc ; moy ; m_pic ; V_f ; AUC ; class];

In this case, the given signal is then replaced by all the chosen analysis windows considered as a valid portion of the main power signal. This approach is capable of increasing the accuracy of event search by focusing on periods where there is a maximum of overlapping of ON–OFF. This overlapping might be caused either by the simultaneous operation of several devices or by the operation of a single multi-state device. At this stage, the NIALM proposed algorithm is based on batch processing and does not assume which devices exist in the selected window.

4.3. Shape matching and self-learning

In general, the matching process is based on measuring the similarity between any two waveforms as a function of a time difference applied to one of them. The shape matching algorithm is shown in Fig. 6.

The cross-correlation method, which is similar in nature to the convolution of two functions, is used at this stage in order to find the best match between the chosen analysis windows and signals pre-registered in a database in an earlier learning phase.

In fact, cross-correlation is known as a sliding scalar product. It is commonly used for searching a long-signal for a shorter, known feature.

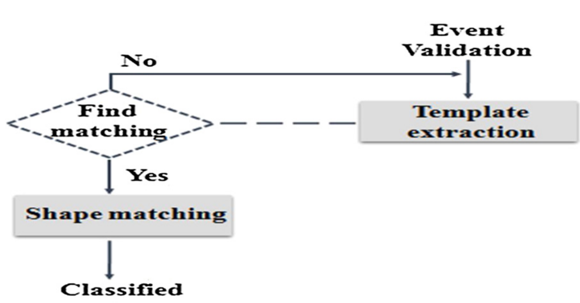

Fig. 6. Algorithm of shape matching process.

It also has applications in shape matching, for discrete functions f and g, where f^* denotes the complex conjugate of f, and m is the displacement, also known as lag, the cross-correlation is defined as:

$$\left(f^*g[n] = \sum_{m=-\infty}^{\infty} f^*[m]g[n+m]\right) \qquad (4)$$

The degree of intrusion of this method is 0.27% (1 day per year).

In fact, if the shape matching process was used directly without being combined with any other classification method, it will give limited results because some signals seem identical when they are changed a little [30]. Therefore, this processing is executed on each identified analysis window in order to increase the identification rate of the proposed algorithm.

This method makes it possible to characterize a long signal with a shorter and known set of descriptors. It supports self-learning, a phenomenon that results from a calculation that takes into account the operating times of classified devices and the usual behavior of residents, to create a set of possible states for a specific device and create a database that can be updated.

The characteristics extracted from the transition events may be slightly different due to voltage fluctuation or noise.

5. Real-time NIALM development

The NIALM system has to handle with intense data processing and real-time appliance detection using Matlab, which is a tool to analyze and illustrate results. It can also process hardware-software co-simulation. The architecture of the NIALM system development is shown in Fig. 7. It includes data acquisition with a Real-Time Interface (RTI) connected with Simulink blocks for graphical I/O configuration and controlled by a DS1104 controller board. The architecture represents also the preprocessing and the disaggregation algorithm working with a Matlab program on a computer.

5.1. Data acquisition system

A chosen sampling rate of 10 kHz for the NIALM system might pose a challenge in data transfer and storage. In fact, appliance classification must be treated in a steady state and transient. To do this, data files might reach a huge size in only one second sampling period. To overcome this problem, the experimental test bench presented in Fig.6. was proposed. As described above, it consists of a data acquisition board linked to a real-time interface for input signal representation and finally, a software that runs on a computer.

With regards to the data acquisition system, it consists of the DS1104 controller board implemented in the computer with its license as a USB key and the CP1104 connection panel. It is an extremely powerful device with 16bit resolution, 8 ADC, 8 DAC, digital input–inputs and a slave DSP to generate the PWM signals.

5.2. Current and voltage sensors

For the voltage displaying, we dispose of the MTX 1032B differential probe that allows safely oscilloscope observation of high voltages for signals not referenced to the ground. This tool offers the possibility of dividing the observed signal by a factor of 10, 20, 50, 100, 200 …

For the current sensor, we dispose of 30 A current range sensor, it helps to avoid over current and ensure perfect sensitivity at low currents.

5.3. dSpace signal interface

It includes a power supply for the current sensor and a standard power outlet for connecting electrical devices to it.

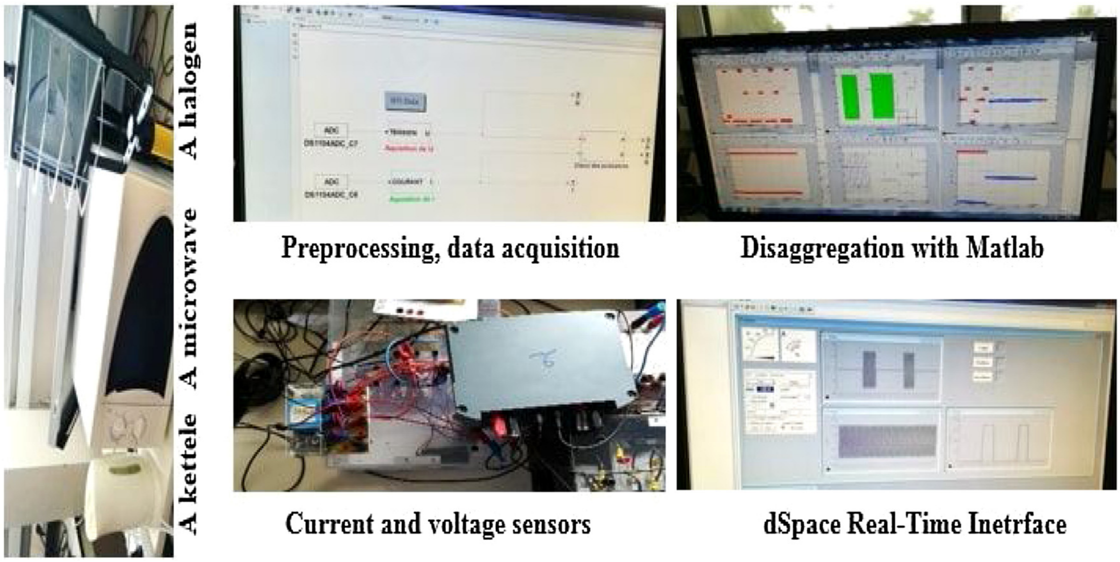

Fig. 7. NIALM system with data acquisition, preprocessing and disaggregation algorithm using DS1104 and MATLAB.

5.4. Algorithm

Real-time execution by the Matlab code is ensured by the choice of a very small width of observation windows (10 ms). Indeed, during each observation window the algorithm focuses simultaneously on two tasks:

- Saving the data to be analyzed during the following window.
- Processing the recorded data during this window.

In order to guarantee that the algorithm operates in real time, it must be ensured that the execution of these two steps does not exceed the maximum period of the observation window (10 ms) as represented in Fig. 8.

For each detected event, the algorithm running in the computer will give results for each processing step. In fact, between the feature extraction and the shape matching processes, the Matrix-Pencil method is used in order to have a more precise classification [31]. The template extraction for the shape matching technique depends on the type of operating devices given by the Matrix-Pencil method as shown in Fig. 9.

The basic Matrix-Pencil algorithm is presented below:

Matrix Pencil algorithm

Input : the k event E_k
Output : Vector fo eigenvalues S

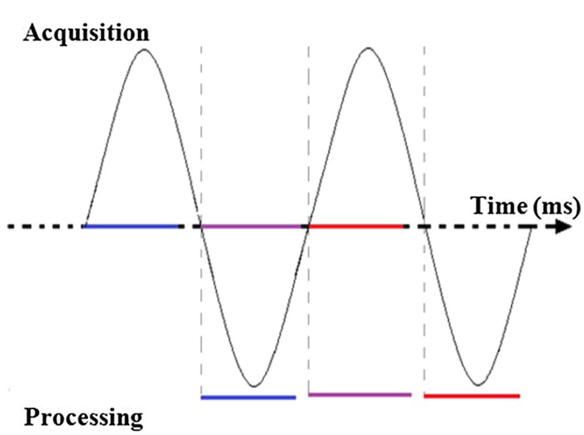

Fig. 8. Acquisition time and data processing time.

Matrix Pencil algorithm

For (0 < = k < = (Number (E_k)) **THEN**
N = size (E_k);
for Q = 1:1:($N - N/2$)
Y(Q,:) = E_k(1,Q:(Q + N / 2));
END For
$Y1$ = Y(:,1:N / 2)
$Y2$ = Y(:,2:((N / 2) + 1));
[U, S, V] = svds (Y);
END For

From the eigenvalues vector S we can extract the Pole–Residue couples. The time tracking of these features proves the distinction between the two appliances (the kettle and the halogen) using the imaginary part of the residue as shown in Fig. 9. For the halogen, the Residue is equal to "$R_h = 0 \pm 2{,}2$ j", and for the kettle, the Residue is equal to "$R_k = 0 \pm 8{,}2$ j".

Moreover, simulation results of the proposed algorithm applied on the ECO dataset are very promising because it proves the reliability of the proposed methodology in developing a practical NIALM system as shown in Figs. 10–12 [11].

5.5. Comparative study of the NIALM method

In order to highlight the sufficiency and the reliability of our proposition in terms of precision, a comparative study of the proposed algorithm has been with the HAND method proposed in the work of Meziane et al. [28]. The HAND approach is based on a new event detection technique for the non-intrusive appliance load monitoring (NILM). The results summarized in Table 1 refer to both approaches and are obtained under a similar experimental framework (The same electrical appliances, the same period of analysis).

We denote with TP: True Positive, FN: False Negative and FP: False Positive.

The precision and recall are noted as follow:

$$precision = \frac{TP}{(TP + FP)} \tag{5}$$

$$recall = \frac{TP}{(TP + FN)} \tag{6}$$

These results indicate that the proposed NIALM approach presents w respectful recall percentage (98.56%) compared to the HAND approach. Both approaches give perfect precision (100%). Hence, the

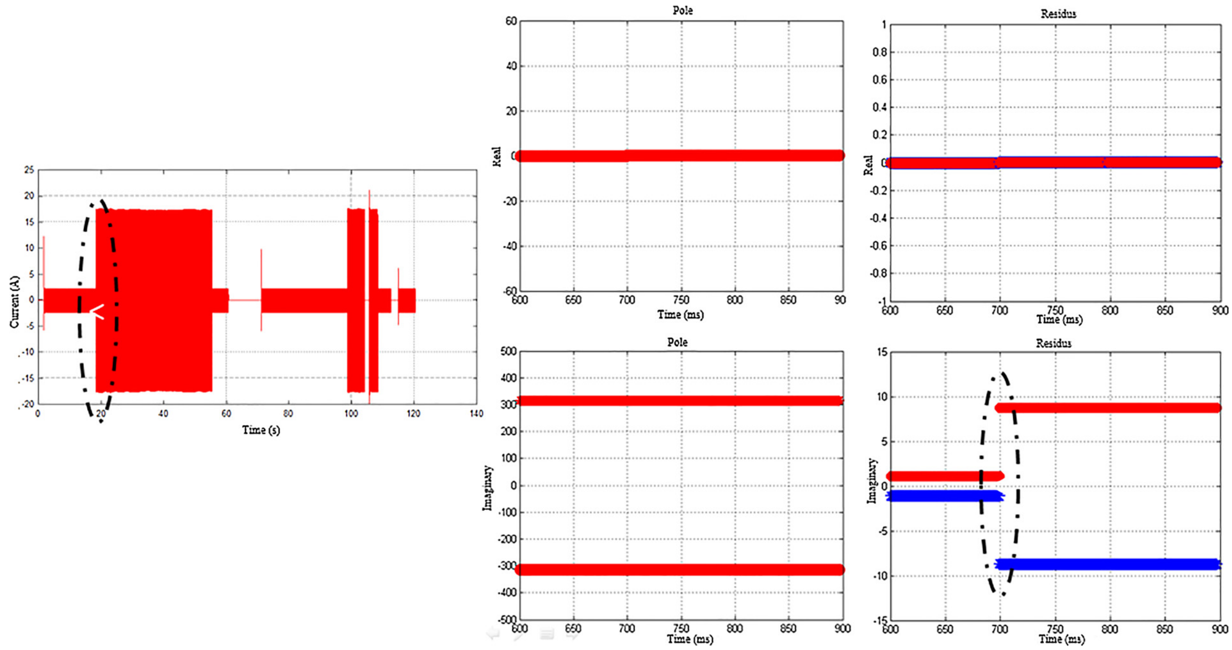

Fig. 9. Results of the Matrix-Pencil technique — state changing detection between the halogen and the kettle.

proposed algorithm gives a remarkable accuracy rate for the electrical appliances' identification.

6. Discussion of the simulation results

The simulation analyses are performed on data from the ECO dataset based on actual houses, which include active and reactive power as well as voltage and current values on each one of the three phases. The power measurements considered in this paper were carried out from a single house over 24 h with one sampling per second at a frequency of 1 Hz.

The proposed non-intrusive appliance load monitoring algorithm is based on the combination of three different and complementary techniques which are: Event detection, Feature extraction, and shape matching. In this section, we will discuss the simulation results of this algorithm using Matlab software. In fact, the idea of combining these three techniques for signals classification in residential and commercial buildings came from the fact that they are limited when used alone.

Following the logic proposed by the algorithm NILM already presented, the overall power signal was processed for filtering in order to obtain a noiseless signal. The filtered signal is then replaced by a set of analysis windows in order to reduce the computing time.

These windows were obtained after comparing the filtered signal to a set of thresholds. Each analysis window was processed by the event detection technique based on rising and falling edges. This method helps to find each variation of the power signature according to a pre-calculated threshold. Its limits are related to the fact of the complexity of the treated signals which may contain several active devices at the same time.

This makes impossible to know which appliance is actually working at the detected variation. To overcome this problem, two methods were combined which are the Matrix-Pencil technique and the feature extraction Matrix. Matrix-Pencil is a method used for appliances classification in order to know if they are resistive, capacitive or inductive. Knowing the exact type of the devices in operating mode is not allowed by Matrix-Pencil technique so the algorithm used the Matrix of extracted features for more precise classification.

For each detected event, the algorithm tries to find the best match based upon the features that are extracted from the general power signal. Fig. 11 presents the extracted characteristics, from each detected event, described in Section 4.2 which are the signal maximum value localization (m_loc), the signal mean value (moy), the signal maximum value (m_pic), the signal final value (V_f), the area under the curve (AUC) and the appliance mean power (class). The main purpose of using this technique is to send only the valid events to the next analyzing step of the algorithm. The validation of an event reflects the

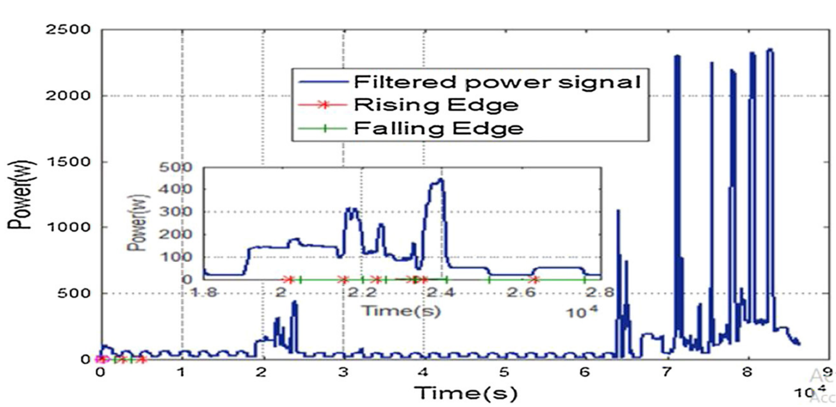

Fig. 10. Simulation results — event detection.

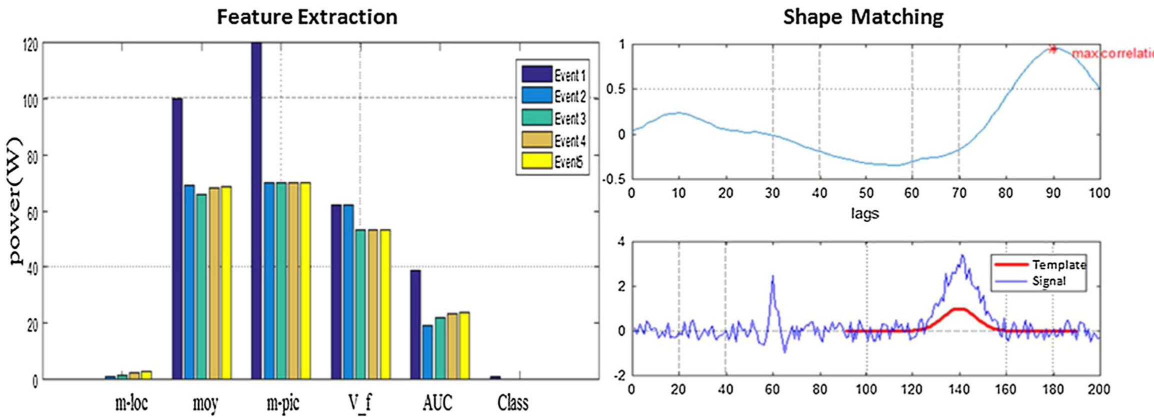

Fig. 11. Simulation results — feature extraction and Shape matching.

analysis of only the periods where there is a high rate of energy consumption in the building.

The method uses a simple subtraction between elements of the feature vectors and then adds all the distances together to find the total distance. An event is considered acceptable to be taken into account in the next treatment if the calculated total distance is less than its mean value (moy) feature.

These two methods were able to identify the device's usage type in a pre-defined time interval and to classify the overall power signal into a set of probable choices of devices. In order to recognize the working devices, the shape matching technique was developed using the cross-correlation method.

Fig. 12 presents the simulation results of appliance classification using the active power and current signals of the ECO open source database. Indeed, using the Matrix Pencil technique, each type of electrical use (resistive, capacitive, inductive) has been classified and recorded in a separate Excel file. The pattern matching technique, the last step of the proposed algorithm, compares each list with a database containing individual prerecorded signals during a learning phase with an intrusion rate of 0.27% (one day/year).

In Fig. 12 the classification period is 9 h and 31 min between 1:38 a.m. and 11:11 a.m. (between 5000 and 40000 s). This period includes a high electrical energy consumption (which attend 400 W) in comparison with the rest of the energy consumed during the same event.

Table 1
TP, FN, FP, precision, and recall of the proposed approach vs. the HAND method.

Method	TP	FN	FP	Precision (%)	Recall (%)
Proposed	3415	50	0	100.00	98.56
HAND	7399	219	0	100.00	97.13

Classified appliances are an average 60 W refrigerator, an average 120 W washing machine, an average 18 W laptop, and an average 32 W freezer.

7. Conclusion

This research presents a new development for NIALM system based on event detection, feature extraction, device classification, and energy estimation. According to the proposed algorithm, a matrix of extracted characteristics for device identification and a matching technique based on an active window to monitor and control household appliances have been presented in this paper. The obtained results clearly show that the identification algorithm has proven their reliability and their capacity in real-time appliance classification. This research work on the NIALM classification method is still ongoing. In our future work, we will further develop the proposed methods to improve the overall accuracy of

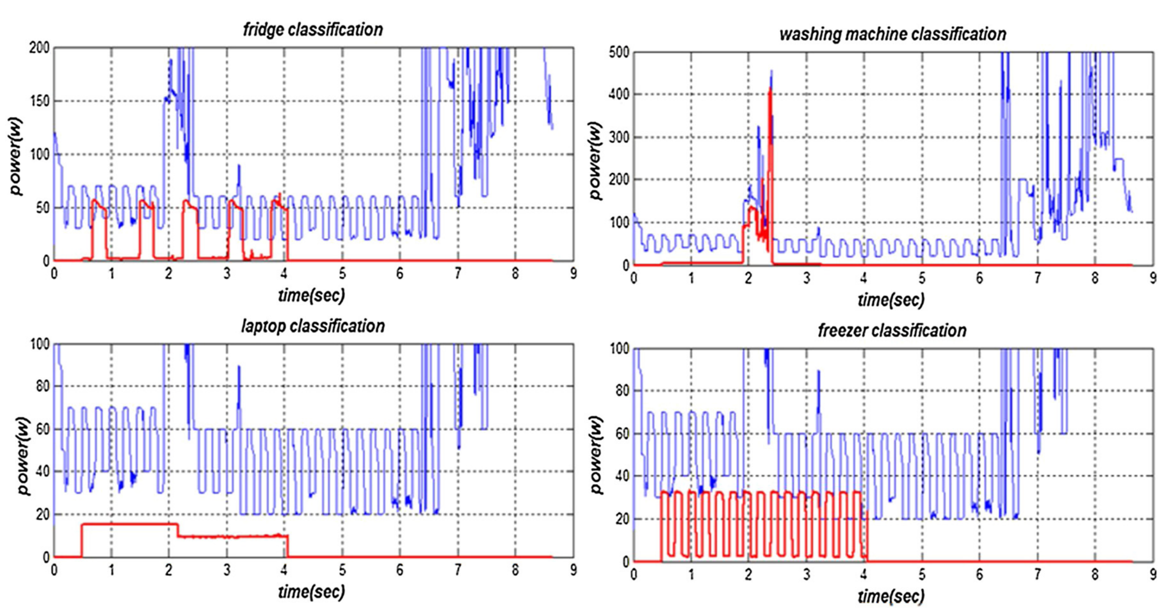

Fig. 12. Simulation results — appliance classification.

our approach. Simulations were done on an open source dataset although the testing has been applied on real data. We plan to combine energy management strategies with our main algorithm in order to extend NIALM system's application in residential buildings.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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