Detecting changes in residential electric consumption

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Abstract - This paper proposes methods for detecting electric components being switched on or off in a residential electricity grid. This is a common change detection problem: we have no prior information about the components being switched on or off, and we are searching for changes in a signal with an unknown amplitude, and at an unknown time. We divide the problem into two steps: filtering to enlighten the on/off switchings, and setting up rules to detect them. To date, researchers have focus on variations in active power when searching for changes in the residential electricity consumption. In this work, we propose two new approaches. First, we also consider active power variations but we reorganize the functionalities allocated to the algorithms they use. We devote the usual stochastic method—the Generalized Likelihood Ratio—to the enlightening of the on/off switchings; and we leave the decision related to the detection to a new automatic threshold algorithm. The algorithm takes into account both local and global properties to calculate the optimal threshold. Second, we propose an alternative to the analysis of active power variations: we show that applying a well designed filter to the current waveform leads to better results considering the experimental data. We compare the results we obtained by using existing methods with those we obtained using the methods we suggest in this paper.

Keywords - Change detection, signal segmentation, automatic thresholding, non intrusive analysis, electric consumption

1 Introduction

Detecting transitions in signals has occupied researchers since the mid- 1970s with the work by Willsky and Jones [1], as noted in the survey paper by Basseville [2]. However, because there is neither a unique theory nor a rule of thumb that fits to any application, in order to segment experimental data, existing techniques have to be combined and improved for the creation of the desired output. In this introduction we explain the technical problem we want to solve, why we want to solve it, how we propose to proceed, and how this paper has been structured.

1.1 Problem statement

Our aim is to detect switching on or off of electric components when only the total electric current is known. We therefore need to develop a global filtering function, binary output of which is 1 when a change occurs and 0 when nothing happens. A change is defined as the switching on or off of an electric component in the residential electricity grid.

The detection problem is divided into two steps, as proposed in [2]. The first step is to generate the signal to be monitored by the detection functions. This signal will be called the 'residual'; it should have high amplitudes when changes occur and low amplitudes when not, as illustrated in Figure 1. In this first step, the rough measurements are filtered and the output—the residual—is given to the second step of the global filtering function. The second step is to detect the changes by using decision rules: when receiving the residual, whose amplitude reflects the possibility of component on/off switching, we have to decide whether or not a change has occurred. The binary output is then set to 1 or to 0 accordingly; that output will be called the 'detection signal'.

1.2 Motivation for the work

Tools are being developed in order to provide consumers with energy consumption advice. These tools attempt to identify appliances operating in a house in order to track down energy waste. An appliance can switch on and off several electric components (motors, resistors and electronics) while running. In our non intrusive appliance recognition described in details in [6], we first have to detect electric components being switched on or off in domestic electricity grid. Therefore, the experimental data under study are measurements of the current drawn by domestic appliances. We study fridges, washing machines and clothes dryers as they involve several electric components while running.

1.3 The proposed approach

A new paradigm is proposed to solve the detection problem with stochastic methods applied to the active power. Usually the rough signal—the active power in our case—is filtered to create a residual that reflects changes; and a stochastic algorithm—namely the Generalized Likelihood Ratio (GLR)—decides if changes occur. In the literature, stochastic solutions are distinguished from threshold based ones. However, in the stochastic methods proposed in [1] and [3], a threshold value must still be defined to decide the likelihood of changes, as explained in Section 2.1.3. We propose to consider the value of this likelihood of changes as the residual. This residual is then given to the detection algorithm.

Then, an automatic threshold algorithm detects component on/off switching. Usually, a global threshold is experimentally determined to detect changes in a signal. However, this appears not to be robust for the variety of data to process. We consider as robust a solution where performances do not heavily vary when modifying the processed data with fixed parameter values. Therefore, we propose a method which automatically calculates a threshold value with local and global properties of the signal, as developed in Section 3.

Finally, whereas the available papers dealing with non intrusive electrical load analysis, such as those by [4] or [5], concentrate on active power variations to look for changes in the running appliance set, we propose an alternative method using the variations in the electric current waveform.

1.4 *Organization of the paper*

The paper is organized as follows. Section 2 sets out the filters used to create the residual which is an artificial signal reflecting component switchings. In Section 3, we investigate how the threshold is determined automatically to perform the decision related to the occurrence of on/off switching. Section 4 presents the strategy we followed to fix the optimal values for the parameters involved in the filters and in the threshold algorithm. The results are reported in Section 5 and discussed in Section 6. Finally, Section 7 is devoted to the conclusions and the perspectives for future researches.

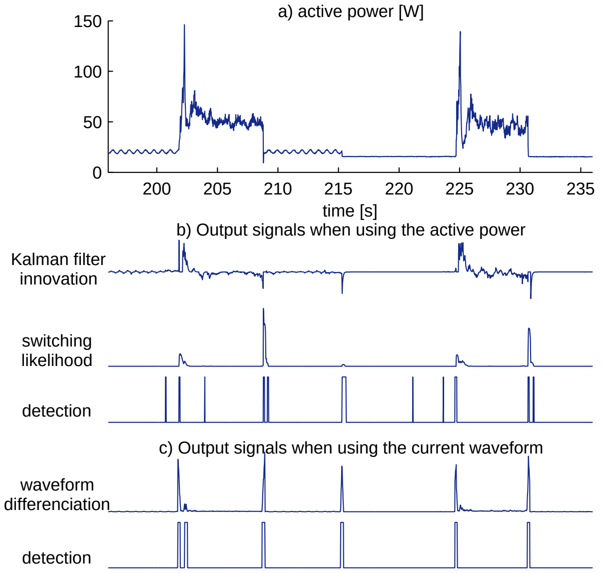

Figure 1: Components are switched on and off while the washing machine is running, as seen in a). The solution illustrated in b) consists successively of the application of a Kalman filter to the median filtered active power, the calculation of the likelihood of change and the detection via automatic thresholding. The solution whose outputs are plot in c) consists in filtering the current waveform and applying the same detection procedure.

2 Enlightening the component on/off switching

The total current measured at the electric panel changes when electric components are switched on or off. This results in sudden changes visible in the active power or, obviously, in the current waveform itself. Up to now, existing methods have been mainly focused on the analysis of active power variations as in [4].

Section 2.1 is devoted to solutions based on the analysis of active power variations. We only give the material required to understand the line of thought we followed when detailed information on the implementation could be found in the cited literature. Then, Section 2.2 proposes a solution based on the observation of the current waveform which seems more appropriate when components draw variable load (e.g. a variable load torque for a motor). In both sections the results shown are based on computation performed off-line.

2.1 *Using the active power*

This section details the different stages required to elaborate a signal that reflects the switching on or off of electric components when the primary data used is the active power (computed once every period, i.e. a $50Hz$ signal). First, we show how the noise can be filtered from the rough signal to keep only the required information for detection purpose. Then, we expose how a Kalman filter can help to amplify the changes generated by the switching on or off of electric components. Finally, we present the Generalized Likelihood Ratio as a tool to evaluate the probability of on/off switching occurrence which is the targeted residual.

2.1.1 *Filtering the noise*

The active power can be very noisy. The variable power drawn by some components is responsible for this noisy behaviour which is not linked to measurement noise. This noise is not useful for detection purpose as it is not related to the on/off switching of electric components. It should then be filtered out.

Two sliding-window filters could be used to get rid of the undesired fluctuations in the active power: the mean filter and the median filter. The mean filter replaces the central value of the window with the mean value of the samples in the window. It is just a weighted sum and requires thus only few calculations. The drawback is its incapability of keeping sharp changes unlike the median filter which filters out the noise without distorting the shape of changes, as illustrated in Figure 2. This second filter consists in replacing the central value of the window with the median value of the samples in the window. Accordingly, the median filter will be further used for filtering purpose.

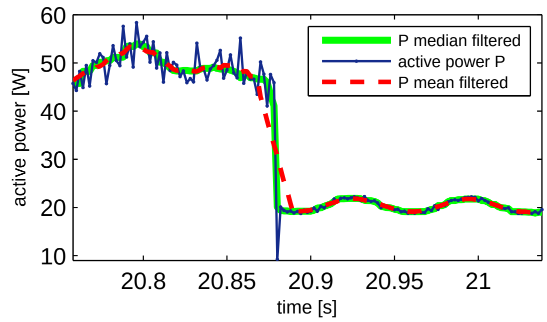

Figure 2: Unlike the mean filter, the median filter allows the filtering of the noise while keeping the saillance of the changes.

2.1.2 *Amplifying the jumps with a Kalman filter*

In order to detect changes, a model of the signal can be used to predict the value of the next samples. The gap between the prediction and the observation is quantified. This gap is an image of the change that occurred. This idea leads to the use of a Kalman filter. This filter allows the calculation of the proposed gap. Additionally, because of the adaptive nature of this filter, the model is updated according to observations.

A model has to be defined and the Kalman filter must be designed. The model used is the one proposed in [3] where it is applied to the detection of abrupt changes in geological data. It consists of a slope Δ on the mean μ of the active power and can be written with the following matrix equations:

$$X_{k+1} = \Phi\, X_k + W_k \quad (1)$$

$$y_k = H\, X_k + e_k \quad (2)$$

with

$$X = \begin{pmatrix} \mu \\ \Delta \end{pmatrix},\ \Phi = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}\ and\ H = \begin{pmatrix} 1 & 0 \end{pmatrix} \quad (3)$$

W_k and e_k are two Gaussian white noise sequences whose variances are parameters to fix. They are usually respectively called state noise and measurement noise. This model does not depend on the time k; it is then time-invariant. As depicted in [1] and [3], the Kalman filter corresponding to this model is:

$$\hat{X}_{k+1|k} = \Phi \hat{X}_{k|k}, \quad (4)$$

$$\hat{X}_{k|k} = \hat{X}_{k|k-1} + K\gamma_k, \quad (5)$$

$$\gamma_k = y_k - H\hat{X}_{k|k-1}. \quad (6)$$

K, the gain of the filter, is designed in such a way that γ_k, the 'innovation', is a Gaussian sequence with minimum variance. The symbol $\hat{}$ refers to variables calculated via the Kalman filter and $\hat{X}_{k|k-1}$ means the estimation of $\hat{X}$ at time k knowing the values of $\hat{X}$ until time $k-1$. At this stage, the innovation γ_k is the signal that reflects the occurrence of on/off switching. The adaptive property of the filter is implemented through update equations developed in [1]. We refer the interested reader to [1] for details about the filter design. The innovation computed for an example trace is plotted in the upper graph of Figure 1-b.

2.1.3 *Evaluation of the probability of transitions occurrence with GLR algorithms*

The two hypotheses of change (H_1) and no change (H_0) must now be evaluated on the basis of the sequence of the innovation γ_k. The likelihood of the no change hypothesis is written $\mathcal{L}\left(\gamma_1, ..., \gamma_k | H_0\right)$. The likelihood of having a change is written $\mathcal{L}\left(\gamma_1, ..., \gamma_k | H_1, \theta = \hat{\theta}, \nu = \hat{\nu}\right)$, with $\hat{\theta}$ and $\hat{\nu}$ being the maximum likelihood estimates of the time and amplitude of change respectively. The Generalized Likelihood Ratio then computes the ratio

$$\Lambda_k = \frac{\mathcal{L}\left(\gamma_1, ..., \gamma_k | H_1, \theta = \hat{\theta}, \nu = \hat{\nu}\right)}{\mathcal{L}\left(\gamma_1, ..., \gamma_k | H_0\right)} \quad (7)$$

where the likelihood functions $\mathcal{L}\left(\right)$ can be calculated under Gaussian assumption because the innovation of the Kalman filter γ_k is a Gaussian sequence. Again, we refer the interested reader to [1] for further details about the implementation.

The important difference is that, in our work, we keep this likelihood ratio for a later decision about the occurrence of component on/off switching. In the cited works, even if the GLR is a stochastic method, the likelihood ratio is compared to a fixed predefined threshold in order to choose between the two following hypotheses: H_0 for no change and H_1 for a change. As discussed in [3], this threshold is not easy to find. Moreover, it will be shown in Section 5 that it is not really effective. In order to exemplify, the likelihood ratio is illustrated in the middle plot of Figure 1-b for an example trace.

2.1.4 *Using the active power: summary*

Section 2.1 showed how the residual is computed from active power data. First, the noise is filtered with a median filter. Second, a new signal with an amplitude which reflects the component on/off switching is generated with the use of a Kalman filter combined with an appropriate model of the signal. The residual is finally obtained with the likelihood of change output by a GLR algorithm. The choice of the parameter values is presented in Section 4 and the results are shown in Section 5.

An alternative to the analysis of active power variations is proposed in Section 2.2. Then, Section 3 develops how to define decision rules that will be applied to the residual which is output by the filters proposed in Section 2.

2.2 *Using the current waveform*

The active power contains information on the amplitude and the phase of the current that is absorbed by the component. Nevertheless, components such as motors or devices with electronic power supply could draw a variable power when they undergo a variable load. The shape of the current waveform would then be more representative of the running component than its amplitude.

Even for a fixed set of components drawing the power, active power variations can occur. In order to cope with those fluctuations, we propose to look at the waveform of the current drawn by the loads. The idea is that even if the amplitude of the drawn current varies, its waveform should conserve its properties because they are linked to the running components.

The proposed strategy is to compute the normalized difference between successive periods of the current. The waveforms are normalized with respect to their amplitude. Then, the shapes of the two waveforms, whose amplitudes equal 1, are differentiated. Let k be the sample of interest, $2M+1$ the size of the observation window centered on sample k and i_k the value of the current at time k. The residual is then computed with

$$r_k = \sum_{u=k-M}^{k} \left(\frac{i_u}{\max\limits_{v\in[k-M,k]} i_v} - \frac{i_{u+M}}{\max\limits_{v\in[k,k+M]} i_v} \right)^2 \quad (8)$$

The residual of this filter reacting to variations in the current waveform is plot in Figure 3 in order to exemplify the formula given in Equation (8). As already mentioned, this result is based on computation performed off-line. Actually, samples from time $k - M$ to $k + M$ are considered to evaluate the formula at time k.

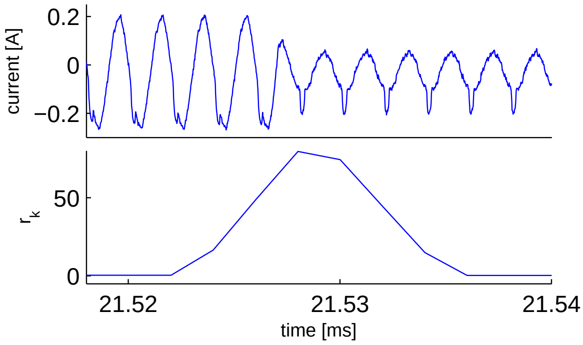

Figure 3: In the analysis of the current waveform, we compute the normalized difference between successive waveforms (plot for $M = 3$). The maximum of the residual is well synchronized with the variation in the current waveform.

3 Detection step

At this stage, the signal to be treated—the residual—has high amplitudes when component on/off switching occur and low amplitudes when nothing happens. Rules must be defined to decide, at each time, whether the detection function outputs 0 or 1. In the literature, two types of method are proposed to perform this decision: stochastic methods and thresholding methods. Stochastic methods consist in evaluating likelihoods of changes, as the one proposed in Equation (7). But in these methods, the likelihood is still compared to a predefined threshold; therefore, we preferred considering the existing stochastic algorithms as a part of the enlightening step. Consequently, the detection step is left to a threshold algorithm. Sections 3.1 to 3.3 develop the arguments that lead to the threshold definition proposed in Section 3.4.

3.1 A threshold based on searching for a stable region in an histogram

The threshold value is automatically determined and based on the signal content. The other method which consists in fixing a threshold value experimentally is not appropriate for a robust solution, as is shown in Section 5. We might expect the number of detections to be constant over a range of threshold values, as proposed by Rosin [9]. That is, when the number of detections does no longer depend on the threshold value, it can be concluded that the noise is no longer responsible for these detections and the threshold value is then considered as optimal. This idea has led us to the automatic threshold method described in Sections 3.2 and 3.3. The methods based on modes of the histogram, as the one proposed by Melgani [10], cannot be used in our case. Actually, the histogram contains no mode; instead, it has the form of an exponential decay. We then look for stable regions in a modified histogram, following the idea proposed in [9], as illustrated in Figure 4 and developed in the following paragraphs.

3.2 A threshold related to the background noise

The threshold must be defined according to the background noise in the vicinity of the spikes to be detected in the signal. Actually, what really matters is the amplitude of the spikes with respect to the amplitude of the neighbouring noise; a low amplitude spike with no noise in the vicinity is as significant as a spike with high amplitude lost in a noisy part of the residual. This can be seen in Figure 5 when comparing the amplitude of the residual between times $150s$ to $200s$ with times $200s$ to $300s$. Thus, a short time observation window centered on the sample is used to estimate the background noise, and the amplitude of the signal is compared to this noise. The threshold is then defined as a function of this background noise. This method is a mix between the global region dependent technique and the local technique both presented by Sahoo [7]. Actually, the properties of the signal in the vicinity of the considered sample are used and the function of these properties is optimized globally with the method proposed in Section 3.1.

3.3 Evaluation of the background noise

The estimation of the background noise should not be biased by the amplitude of the highest spikes, which are not part of the noise. Therefore, the amplitude of the noise in the local window is defined as the mean value of the samples under the p-th percentile of the samples in the window, p being a parameter to define. This allows not to consider the highest spikes in the noise evaluation. If the threshold value was influenced by their amplitude, increasing the threshold in order to avoid excessive over detections would lead to the non-detection of the smallest spikes in the vicinity. This is illustrated in Figure 5 where the noise is evaluated using $p = 40$ and $p = 100$. Note that $p = 100$ corresponds to a sliding mean calculation.

3.4 Definition of a threshold signal

The threshold signal λ is defined as a globally determined multiple of the background noise signal n, which is locally defined. Let x_p represents the samples of x with value under the p-th percentile in the window of size N centered on sample k, the background noise values n_k and the threshold values λ_k are defined as

$$n_k = \frac{1}{\frac{p}{100}N} \sum_{u=1}^{\frac{p}{100}N} x_{p,u} \quad (9)$$

$$\lambda_k = \alpha \, n_k \quad (10)$$

where the scalar α represents the optimal multiple for the threshold. It is globally determined on a five-minutes window. In this window, we search for the multiple of the locally defined background noise that leads to a stable region in the number of detections. Two successive equal values in the modified histogram are considered as stable. The term 'modified' is used because the histogram does not plot the intensity distribution. Instead, the number of detections with respect to the scalar α is considered. This number of detections differs from the number of over threshold values because successive over threshold values are considered as only one detection.

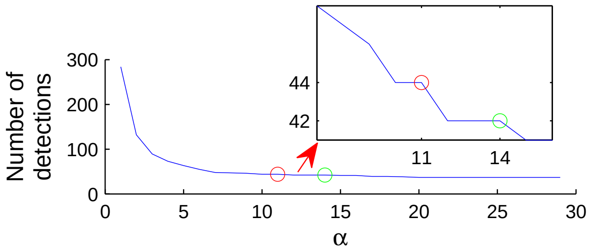

Figure 4: The first value of α that corresponds to a stable value in the histogram is chosen. Because over detections are prefered to under detections, we do not select any longer stable region corresponding to higher α.

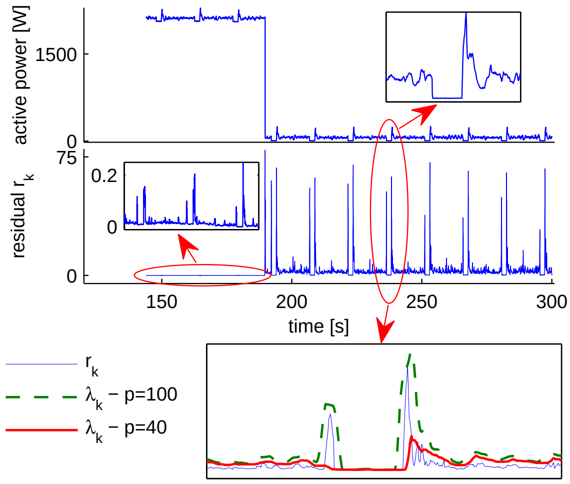

Figure 5: The use of the 40th percentile in the evaluation of the background noise allows not to bias this noise evaluation with the amplitude of the spikes to detect. Also, a fixed global threshold value is not appropriate because although amplitudes of the spikes stay significantly higher than the local noise, their absolute value can be lower than the noise in other parts of the signal. Computed on washing machine data with $M = 6$, $N = 20$ and $\alpha = 3$.

4 Tuning the parameter values

Filters have been proposed to amplify and detect changes in the signal generated by electric component on/off switching. Parameters are involved to design these filters and, consequently, it is necessary to search for the set of parameter values leading to the best output. This output is the residual in the case of the enlightening step and the detection signal in the case of the detection step. The strategy we follow to search for the optimal parameter values is first proposed in Section 4.1. Then, the chosen values are given in Section 4.2.

4.1 Evaluating the quality of the residual

We want to find which parameter values give the best residual. This implies analysing the quality of the filters' output. Therefore, we have defined a signal to noise ratio (SNR) to evaluate the quality of a residual. In this ratio, the signal is the amplitude of the residual when on/off switching occur and the noise is its amplitude when nothing happens. Let O_k represents the sequence of the residual received in output of the enhancement stage which could be Λ_k or r_k defined earlier. Signal and noise are respectively defined by

$$O_{signal} = O_k\,[k \in [1, L] | S_k = 1] \tag{11}$$
$$O_{noise} = O_k\,[k \in [1, L] | S_k = 0] \tag{12}$$

and the ratio is written:

$$SNR = \log \frac{mean\,(O_{signal})}{mean\,(O_{noise})} \tag{13}$$

S is a supervision binary signal manually defined. For each of the 12 traces described in the next section, a supervision trace was manually set to 1 when component on/off switching were visually detected and left to 0 when no on/off switching were visible.

Obviously, the same supervision traces are used to optimize the parameters of the detection algorithm. In this case, rates of over detection and under detection are used. Over detections correspond to values of 1 for the binary detection signal whereas the supervision equals 0; and on the contrary, under detections correspond to values of 1 for the supervision and 0 for the detection signal.

4.2 Choice of parameter values

For the enhancement step, the parameter values are chosen to maximize the above defined SNR. The size of the sliding-window of the median filter is set to 140 periods which corresponds to $1.4\,s$. The variance of the white noise added on the state variables of the model defined in Equation (1) are both chosen to 0.01. The ratio of the variances of the noise added on the output and the state variables appeared to be more significant than the values of the variances themselve. For the noise added on the output, we have chosen a variance of 3, i.e. 300 times the variance of the noise on the state variables. A global threshold must be defined to use the initial method which uses the GLR algorithm as detection function. The value 0.008 led to the best results. The filter to enhance the current based data contains only one parameter, namely the value of M for the local window of size $2M + 1$. The value $M = 6$ periods gave the best SNR.

For the detection step, three parameters must be defined: the sizes of the local and global window and the value p for the percentile. At this time, we fixed the global window to five minutes without any further analysis. 10 periods (i.e. $200ms$) for the local window allong with $p = 40$ led to the best detection rates.

5 Results

The methods are evaluated according to their detection rates. We give the results obtained from the solutions using the filtered active power and the current waveform. They are both combined with the dynamic threshold algorithm for the detection step. We have compared the results with the ones obtained with the method found in the literature. The figures are computed on 12 experimental data traces (4 for each type of appliance) on which 205 changes where manually identified: 20 in the fridge tracks, 138 in the washing machine tracks and 47 in the clothes dryer tracks. The parameter values proposed in the previous section are used. The results are presented in the form: number of $(right - under - over)$ detections.

When the current is filtered with Equation (8), the detections are $(193 - 11 - 12)$. This result is comparable to the one obtained with the method using the active power which gave the detections $(192 - 13 - 15)$. Figure 6 shows the detection signal, the supervision signal and the active power of the trace which gave the worst result when using the current waveform analysis. As we can observe, on/off switching of small electric components are mainly missed when superposed to high power components.

If the initial detection algorithm described in [1] is applied to the median filtered active power, the detections fall to $(178 - 24 - 23)$. According to these figures, leaving the decision to the dynamic threshold algorithm is more effective. Note that in our solution using the active power, a threshold value is still needed to update the equations of the Kalman filter; we used the threshold value that gives the best results with the initial detection algorithm. If the update procedure is skipped, the detections become $(193 - 12 - 29)$. Thus, updating the equations of the Kalman filter mainly affects the number of over detections. Moreover, we verified that the median filter improves the efficiency of detection; without this filter the detections fall to $(178 - 24 - 23)$.

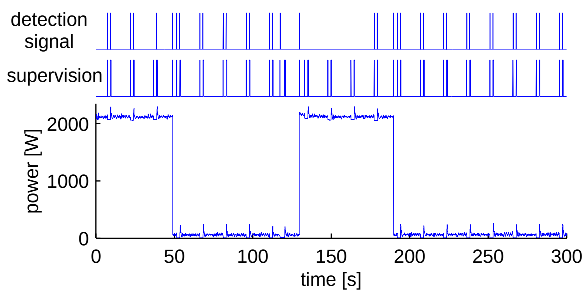

Figure 6: The method which analyzes the current waveform allows the obtention of an output binary signal (the detection signal), that reaches the detections manually performed (the supervision). This figure presents the worst case where 8 out of 48 changes are not detected. Computed on washing machine data.

6 Discussion

In this section, we discuss the limitations, weaknesses and strengths of the exposed work.

6.1 *Comments over the supervision traces*

In order to evaluate the developed solutions, we have to know when changes actually occur. Therefore, a supervision is manually performed but human errors can occur and may affect the results. Actually, we noticed in the results some changes that could have been manually defined but were not. However, we chose not to modify the supervision and the results have been presented accordingly. We are currently working on an infrastructure whose aim is to build an automated supervision while acquiring the data.

6.2 *Limitations of the results*

We achieved pretty good results compared to what has been obtained when using the methods from the literature. However, these results cannot be directly extended to the detection of on/off switching in houses. Actually, the measurements we used contain only one running appliance at a time, involving at most three different superposed components. This number has to be compared to the tens or even hundreds of components that will be switched on and off in a house in usual operations. Moreover, heavily varying electrical loads such as electronics will have to be taken into account in the future.

6.3 *Quality of both proposed solutions*

Even if the results of both proposed methods are comparable, there is a fundamental difference. The analysis of current waveforms misses some changes whereas most under detections of the analysis of active power variations are caused by a lag in the detection. This lag is inherent to the method because we estimate at time k if a change occurs between times $k - (window\ size)$ and k. The detections obtained via the analysis of current waveforms are well centered on the changes, as illustrated in Figure 3. This is a considerable advantage for a detection algorithm.

The non linearity of the current based method is worth being commented. We illustrate this non linearity problem with an example. Let a and b be two components drawing a variable power. As postulated earlier, the normalized current waveforms of a and b are both constant. The problem arises when they are running simultaneously; the waveform resulting of the sum of both waveforms of a and b has no reason to be constant because this system is not linear. Thus, even if the results are conclusive with the considered data, we only used one appliance data with few variable power components. More complex situations should be analyzed in order to validate the method.

6.4 *Influence of the data on parameter values*

For tuning the parameters, the mean of the SNRs computed on the different traces has been considered. However, we studied variations of parameter values which maximize the SNR considering different data. These variations would reflect that optimal parameter values depend on the analyzed data. In that case, the method is considered not robust. The proposed methods have been chosen according to their robustness (unlike other methods under study).

Moreover, whereas the parameters for generating the residual were tuned with the SNR approach, the residual that gives the best detection signal is not the one which produces the highest SNR value. We conclude that other properties of the residual should be defined to quantify the efficiency of the designed filters.

6.5 Detection algorithm not appropriate for real-time applications

With regard to our final aim, the proposed method for automatic thresholding is appropriate for the analysis. Nevertheless, it would probably not be convenient for a real-time application, such as failure detection. Actually, we look at the signal with a five-minutes window and such delays would not be relevant for real-time applications.

6.6 Another use of the GLR algorithm

In [8], an algorithm is proposed to search for changes in the mean of the active power with a modified Generalized Likehood Ratio algorithm without the use of a Kalman filter. This modified version of the GLR allows the detection of multiple changes in the observation window. This solution has not been fully implemented and results were not presented here because a model including a slope in the mean of the active power seemed more appropriate to represent the observed data. The change of mean detector proposed in [8] is equivalent to a fixed mean model which led to excessive over detections when applied to a $50Hz$ sampled active power. The results should be further analyzed with under sampled active power, as done in [8]. However, it can be supposed that under sampling will lead to a less accurate results as far as the lag in the detection is concerned.

7 Conclusions and future works

We faced a detection problem; indeed, we wanted to detect on/off switching of electric components with only the total current they draw. We showed that the results of the change detection method using a Kalman filter and a Generalized Likelihood Ratio algorithm are improved when using an automatic thresholding algorithm.

This automatic threshold algorithm has been developed in this paper. It is based on an evaluation of the background noise in the vicinity of the spikes to be detected. The threshold is defined as the mutliple of this background noise that leads to a stable region in the plot of the number of detections with respect to the threshold value.

An alternative to the use of the active power for change detection in electric consumption is also proposed; it consists of the evaluation of changes in the current waveform regardless of its amplitude. This showed slightly improved but comparable results with respect to the method based on a GLR algorithm applied to the active power treated with the Kalman filter. Moreover, this solution involves the definition of only one parameter which is the size of the local observation window. The best result is achieved with this method. Detection rate of 94% is reached. However, we only took into account a few amount of simultaneously running components compared to normal operations in a house. After having validated our solutions on more complex (realistic) solutions, the next step of our appliance recognition project should evaluate if these results are sufficient to realize component and appliance identification or if further improvements are required.

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