Dynamic Analysis of Electronic Devices' Power Signatures

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***Abstract*—Nowadays we are witnessing the fast spreading of smart grid technology deployments. An increase of smart grid services and applications is also expected. Therefore in our work we aim to propose and develop user applications on top of smart grid power infrastructures that monitor, analyze, classify and characterize different electronic devices connected to this infrastructure. The present paper aims to propose a solution for ideal power signature extraction for consumer devices. Power signature may deeply characterize the electronic devices functioning. This signature can be used to identify energy efficiency usage patterns and provide feedback to users in order to reduce energy consumption and increase the lifetime of the products. Power signature of an electronic device is defined as the power consumption response to certain workload or program executed by the device.**

Keywords-power consumption; smart grid; power signature; execution patterns, washing machine

I. INTRODUCTION

During the last years an increased interest in developing the power grid infrastructure was observed. Many researchers consider that the electric power system is undergoing a profound change toward smart grid power networks [1]. The Smart Grid is the term used to refer to the enhancement of the electric power grid with digital technology, to make it more reliable, secure and efficient [2]. Once the smart grid infrastructure will be widely available, an increased request of user applications and services will also be observed. Furthermore, smart grid acceptance by the consumers will be improved if it comes with a full set of applications and services. In our work we aim to develop user applications on top of smart grid power infrastructures that monitor, analyze, classify and characterize different electronic devices connected to this infrastructure. The proposed solution deeply characterizes the electronic devices to identify energy efficiency usage patterns and provide feedback to users in order to reduce energy consumption and increase the lifetime of the products. Most today power meters are primary used to support energy billing information [3]. They measure and report electrical parameters and compute energy consumption for a specific period of time. However, we aim to use them to extract consumer devices' power signatures for deep characterization of their usage patterns. Power signature of an electronic device is defined as the power consumption response to certain workload executed by the device. The signature is thus specific to a device or to a program executed by the same device.

One important step toward this goal is to find a simple, efficient and general method of power signature extraction and analysis in order to deeply characterize the operation of various consumer devices. The workflow of the power signature and product workload detection software application is shown in Fig. 1. Power metering infrastructure continuously measures the electrical parameters of the consumer device and stores data into the measurements database. Measurements database feeds two software components one that detects device specific events from the power series and the second that detects device specific workload. The database also contains the ideal power signature computed in advance at nominal workload parameters. A power event is defined as a change in power values of a device that identifies a specific functional event of the product. A power workload is a complete set of actions an electrical device executes in order to provide its intended service.

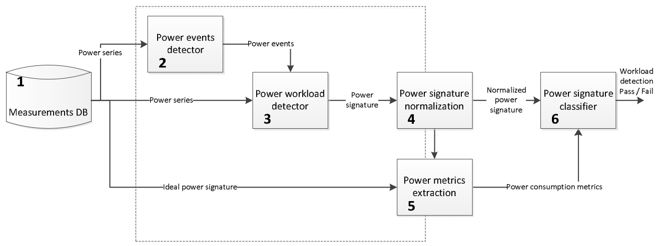

Figure 1 Power workload detection workflow

In this paper we analyze the possible solutions for power ideal and normalized signature construction (3 and 4 in Fig. 1). Furthermore, we intend to discuss the mechanisms available to detect individual power events within the power signature (2 in Fig. 1). The original aspects of our work are the definition and extraction of power signatures and their relation with the usage patterns and the parameters that have influence on energy consumption of the product.

The article is organized as follows. In Section 2, we give a brief overview on power signatures in the literature. Next, in Sections 3 and 4 we describe the process of power signature extraction, exemplified by a washing machine under test. Finally, we conclude our paper in the Section 5.

II. Related Work

The concept of power signature is not new. Current signatures have been widely used for nondestructive testing of integrated circuits and printed circuits boards [4]. For testing purposes the measuring devices (current and power consumption) have to be accurate in order to emphasis the differences between failure and normal execution of the device under test. The opposite are the power meters available on the market. The current way one can measure power consumption of an electric system is to use an on-the-self device like Kill A Watt or Watts Up Pro [5]. Both of these features make it difficult to develop a practical real time system specific picture of energy usage that contains many individual devices because the user must go to each monitor in order to record the data. Furthermore, these devices lack the needed accuracy to build a good power signature.

Most installed energy meters today are primary oriented to support utility's billing features. In [3] the authors propose to obtain and analyze disaggregated energy used data dispatched to individual devices. Their goal, similar with ours, is to provide much richer information extracted from energy consumption patterns of monitored devices. However the authors focused primarily on providing solution for power signature acquisition and interpretation. In our work we have already implemented the intelligent monitoring solution proposed by us in [6].

In [7] a detailed analysis of power signal is presented. The authors discuss spectral and transient components within the power signature of aggregated monitoring. Nonintrusive workload monitoring of a group of devices, can determine the operating schedule of electrical loads. It is important information needed by electric utility service providers to balance their resources. On the other hand the consumers can benefit of workload signatures to schedule the execution of home appliances in order to reduce the electricity costs [8]. One open problem is to predict the energy consumption of consumer devices and the duration of the workloads function of its specific parameters or environment conditions. We plan to address these goals by the means of power signatures analysis, proposing a workload nominal power signature. We further propose to extract the workload specific parameters comparing the current signature with the nominal one.

III. Power Signatures Analysis

In this section we analyze the power signatures of one specific washing machine program. The main goal of this analysis is to identify the ideal signature that characterizes the program execution. Both signal shape and parameters are needed to analyze an electric signal. Several methods have been tried in order to achieve these goals. Each method will be briefly discussed together with its advantages and disadvantages. Finally, we propose a unique method capable of obtaining both a clear shape of energy signature and all its parameters.

A. *Power Signature Definition*

Power signature of an electronic device is defined as the power consumption response to certain workload executed by the device. It is the variation in time of power consumption measurements when certain usage pattern is applied to the device. Power signature is specific to a device or to a program executed by the same device. A power event is defined as a change in power values of a device that identifies a specific functional event of the product (Fig. 2). A power workload is a complete set of actions a product executes in order to provide its service.

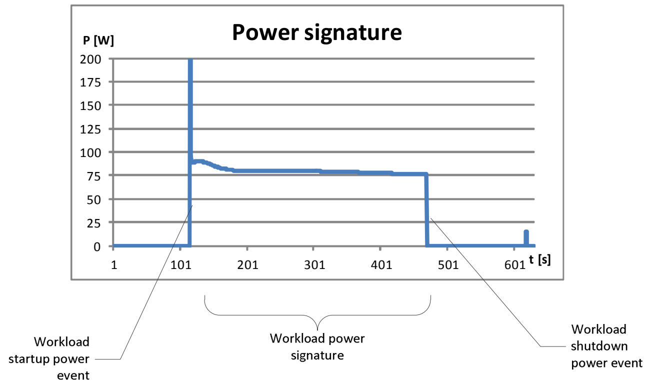

Figure 2 Power events and power workloads

Obtaining the power signature of an electronic device is a simple task to achieve. We need to place a power electricity meter connected to AC lines of the electronic device under test. The intelligent power monitoring solution, we presented in [6], was used for the execution of the power characterization tests. Such a test is needed to emphasize the energy consumption of one specific program or workload of the device under test.

B. *Analysis of Original Power Signatures*

In our power signature analysis tests we targeted a washing machine because it has simpler program tasks to complete, compared to a TV set or computing system. The power measurements of the washing machine when executing the selected program, forms the signal named electronic device signature of that time execution. If we have a complex device, capable to execute multiple programs, each type of program will have its own signature. The power measurements of the selected program executed on the washing machine under test are presented in Fig. 3.

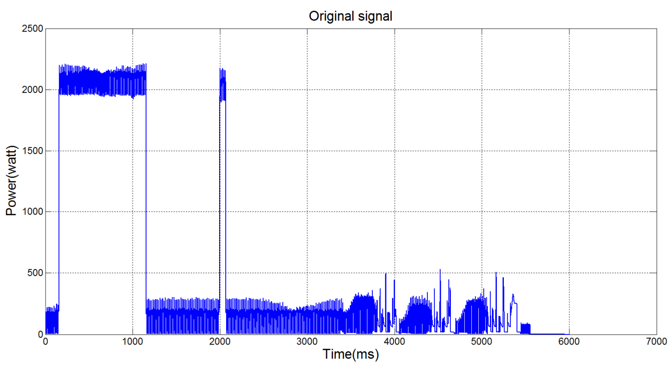

Figure 3 The energy signature of a washing machine running a normal program

A first observation is that the original signal is not a clean signal and has many oscillations. The oscillations are due to the way the engine is on / off in a time interval of few seconds. It is possible that a single frequency signal to control the main engine. The present study aims to find and measure the amplitude of this frequency.

All the engine's stops / starts strongly influence the power consumption signal. Because of these “noises” we can’t have an automatic method to extract the original signal parameters. For any type of signal an intensive and highly customized work must be performed. If we want an analysis of the signal by doing some comparison with other similar signals, the difficulty of work increases. Even more, making an ideal shape for the energy signature is projected as an impossible job. Because of these problems, we want to create a new signature shape, which will be easier to use than the original. We call this signature the ideal power signature of the washing machine program.

The original (measured) signal is of vital importance because it allows a quick view of the intervals in which the electronic device presents a constant behavior. These intervals represent small phases (steps) of the main program. For a washing machine these steps are: the pre-washing phase, the water heating phase, the washing phase, an optional heating phase, the rinsing phase and the ending phase (see Fig. 4).

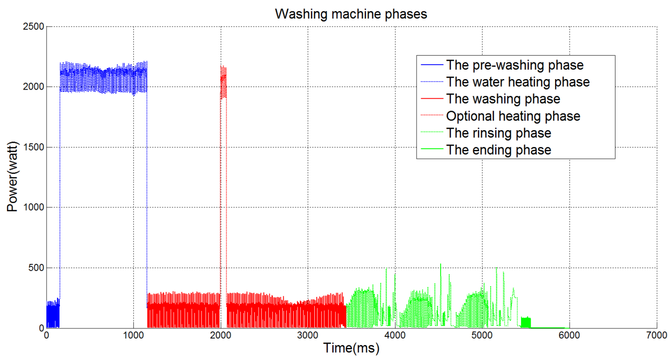

Figure 4 Program phases of a washing machine

C. *Analysis of Filtered Power Signature*

The first signal “cleaning” method consisted of applying a low-pass filter. A low-pass filter cuts all oscillations caused by high frequency (in our case the stop / start engine). For the implementation of the low-pass filter we used the following formulae:

$$y(n) = \sum_{k=0}^{M_n} B(k+1)x(n-k) - \sum_{k=1}^{N_n} A(k+1)y(n-k), n = \overline{1, N_x} \quad (1)$$

,where $N_x \triangleq length(x)$, $N_n \triangleq min\{N, n-1\}$, $M_n \triangleq min\{M, n-1\}$. The first element of the array A is 1, otherwise all A and B elements are divided by A (1). For the original signal presented in Fig. 3 we used the following coefficients: B=0.1, A=[1,-0.9], and the resulted signal is shown in Fig. 5.

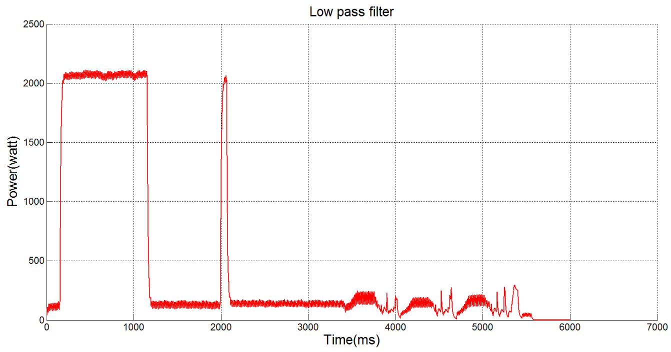

Figure 5 Low-pass filter of power signature

By filtering with a low-pass filter we achieved a first shape of signal that can be used in further processing. The obtained signal has a clear shape and it may be analyzed more easily than the original signal. Unfortunately, after this transformation some distortions of the signal could be observed. The distortions consist in a slightly smaller water heating phase and a different shape for the optional heating phase. In addition, some energy spikes disappeared from the rinsing phase. We should mention that all changes are characteristic to the low-pass filtering and are independent of the signal nature.

D. *Analysis of Power Signature’s Fourier Transform*

The second studied method is based on Fast Fourier Transform (FFT). The Fourier transform is a mathematical operation that expresses a function of time as a function of frequency. After that, a number of frequencies can further be selected, based on the largest amplitudes. In the last step, the original signal is rebuilt using only the selected frequencies.

Selecting the correct number of frequencies is itself a separate study and is not a subject for the present article. We should mention that the variation of the number of selected frequencies can lead to very different results (see Fig. 6).

Thus, if we select the top 50 frequencies (with the highest amplitude), the shape of the reconstructed signal is different than the original shape. As an advantage, a large number of oscillations (present in the original signal) disappear from the reconstructed signal.

In contrast, we have the case when a total of 150 frequencies were selected to reconstruct the original signal. Consequently, we can see that the method succeeded and the reconstructed signal is similar to the original. The disadvantage is that the remaining oscillations could not be removed. For both cases, we analyzed only the shape of the original signal and not the signal parameters. The reconstructed signal does not have the same parameters as the original one. If we analyze the washing machine original signal the differences are: the optional heating phase different (amplitude and duration), the energy consumption during the rinsing phase is smaller and we have another shape for the ending program phase.

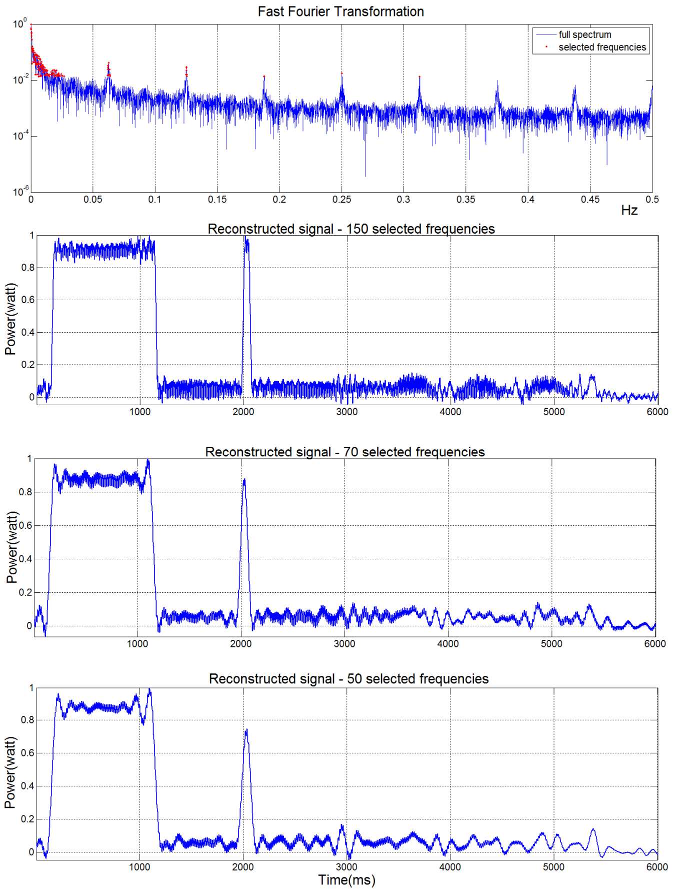

Figure 6 FFT transformation of the power signature. From top to bottom: a) the whole frequencies spectrum and their amplitude (the red dots represent the 150 selected frequencies with the highest amplitude), b) the signal reconstruction using a total of 150 frequencies, c) the signal reconstruction using a total of 70 frequencies d) the signal reconstruction using a total of 50 frequencies

Another selection of frequencies to reconstruct the signal was performed. This involved a hand-picked selection directly on the FFT graphic. Since the original energetic signature presented approximately 2000 frequencies, the method failed and the worst results have been obtained.

The study showed that FFT applied to the original signal did not lead to significant results. Because of this, in the next step we applied FFT to low-pass filtered signal. The result for our washing machine signature is shown in Fig. 7. It can be seen that most of the oscillations disappeared, but also, a lot of the signal parameters lost their original value.

However, the result is the second clear shape of the original signal that can be further used by other processing algorithms.

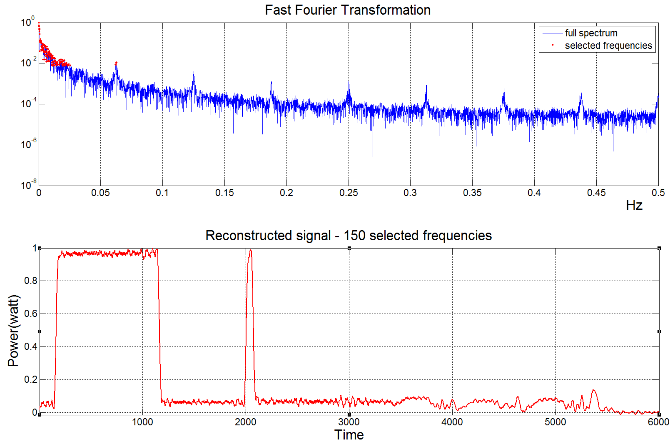

Figure 7 FFT applied to a low-pass filtered signal

E. Analysis of Power Signature's Power Spectral Density

Another method which identifies a signal in a unique way could be the power spectral density of the signal. There are several approaches used when the power spectral density must be estimated. In our study, the chosen method is based on Welch's algorithm. The signal is converted from time domain to frequency domain and, the most powerful frequencies are chosen. Like the previous methods, the Welch's algorithm was applied both to the original and to the filtered signal. The results are displayed in Fig. 8 and the two power densities can be easily seen.

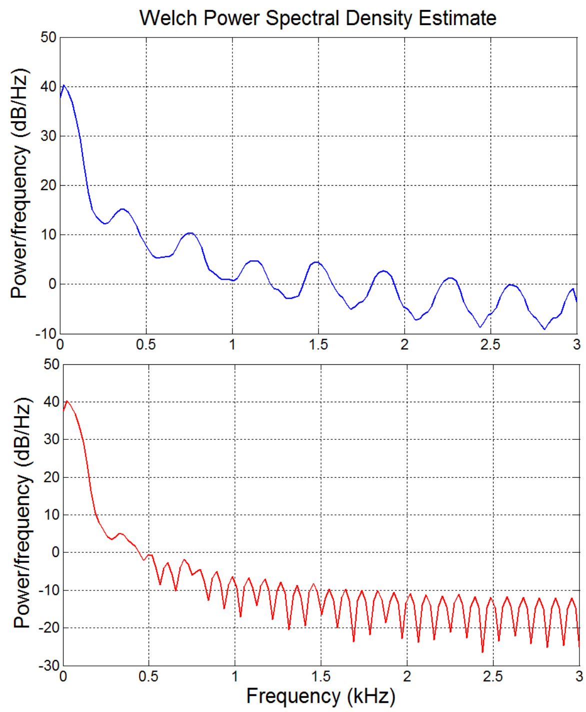

Figure 8 Power spectral density for a) original signal b) low pass filtered signal.

For lower frequencies we have a similar power distribution. It can be seen a peak power for a low frequency in both diagrams. It is the on/off engine frequency and it is an important parameter for the study.

For medium and higher frequencies the power of filtered signal is spread out over a wider interval than the unfiltered signal.

F. Analysis of Smoothing Functions

Since the beginning of the chapter, we have said that our primary goal is to obtain a smooth shape of the signal. To achieve this goal, we further apply a couple of smoothing functions. A smoothing function is based on the fact that any signal tends to have a smooth evolution of the amplitude in relation to the time axis (axis Ox). This behavior allows us to make a distinction between a noise and a signal, because a noise presents a rather rapid evolution and random amplitude.

Smoothing a signal is necessary if we want to compare our signal shape with other shapes. We also believe that a cleared shape is good enough even in retaining most of the signal parameters. This study used a number of 4 smoothing functions [9]:

- Rectangular smooth - it is the simplest smoothing algorithm. Each point is replaced with the average of m adjacent points (usually m it's a positive odd number) For m = 5 we have the following formulae :

$$s(x) = \frac{y(x-2) + y(x-1) + y(x) + y(x+1) + y(x+2)}{5} \qquad (2)$$

- Triangular smooth - it's a rectangular smooth which implements a weighted smoothing function. It preserves the peaks and other features. For m=5 we have the following formulae:

$$s(x) = \frac{y(x-2) + 2 * y(x-1) + 3 * y(x) + 2 * y(x+1) + y(x+2)}{9} \qquad (3)$$

- Pseudo-Gaussian - it's equivalent with 3 passes of rectangular smooth.

- Savitzky-Golay or DISPO (Digital Smoothing Polynomial) - is based on the least-squared fitting of polynomials. This filter type is less capable of reducing noise but it keeps better the shape of the original signal.

The best results were obtained when we used the pseudo-Gaussian smoothing function. For all smoothing functions, a total of 11 adjacent points were used to construct a new point. In Fig. 9 we can see that the obtained results are mainly the same (only minor differences are present).

A third shape for the signal was made possible by applying the smoothing functions. This time, due to its high quality, we did a comparison between two energy signatures to see how well the methods worked. For our washing machine, we recorded two signals for the same program type. A comparison between the two signals is presented in Fig. 10 and it can be seen that the two shapes have a real similarity.

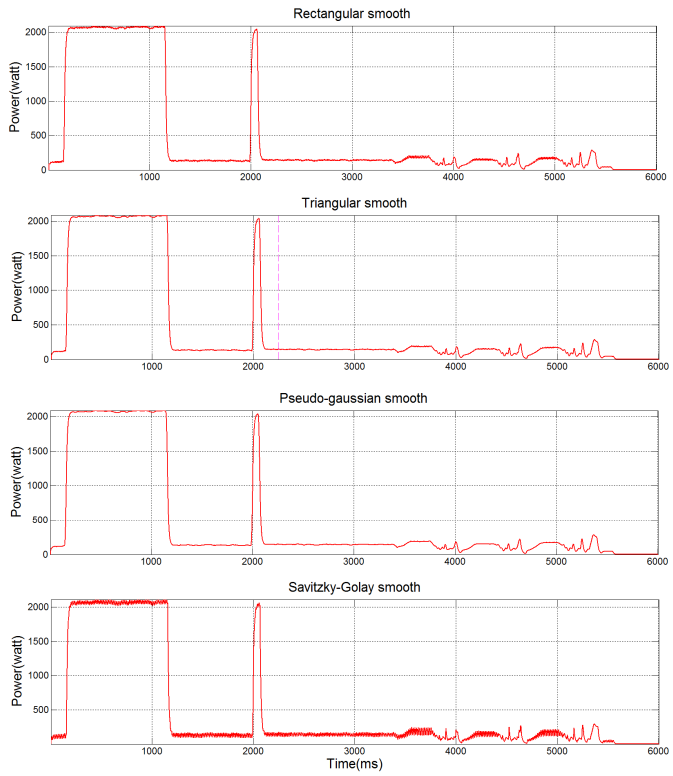

Figure 9 Smoothing functions on a filtered signal. From top to bottom: a) rectangular smooth b) triangular smooth, c) pseudo-gaussian smooth d) Savitzky-Golay smooth

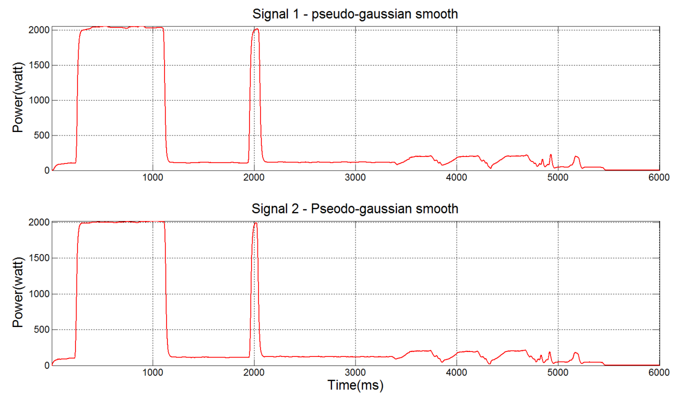

Figure 10 Signature shapes for two signals obtained from the same program.

IV. NORMALIZED IDEAL POWER SIGNATURE

A. Power Signature Averaging

A final technique analyzed in this study is “ensemble average” and we believe it can bring major improvements to signal quality. The technique involves measuring the signal several times and gathering point by point all the measurements. The sum of measurements will be further divided by the number of total signals. The technique is frequently quoted in the literature especially when same several measurements of the signal are known [10].

Unfortunately, in our case a digital signature of a household device is not the same even if we use the same program. The differences are caused by the temperature of the water, the wash load and the time usage of the device.

Figure 11 shows how these differences influence the final outcome. The signal quality increases but finally, many parameters will have a different value.

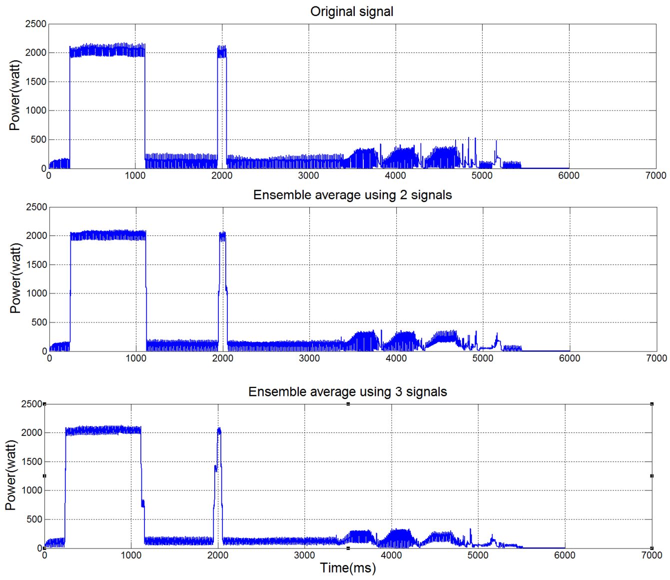

Figure 11 Ensemble average. From top to bottom a) original signal b) ensemble average using 2 signals c) ensemble average using 3 signals

B. *Events Finding*

To find other parameters of the electronic device signature, a “peak finding” algorithm must be used. A peek into the signal is particularly important because it could clearly mark a change in the actual behavior of the electronic device. The change can be the beginning or ending of a program phase, an undesired event, a random event, etc. Peaks finding algorithm successfully manages to find all the changes that occurred in the amplitude of the program (see Fig. 12). These changes may be used for a future analysis.

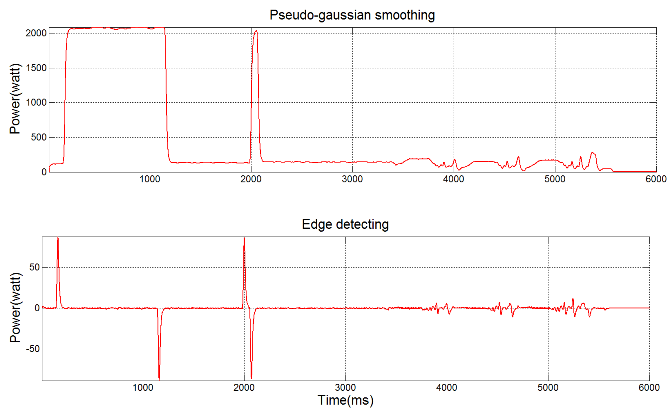

Figure 12 Normalized ideal power signature and events finding algorithm

V. Conclusions

In this paper we presented a complete analysis of power signature detection for a washing machine. We defined the concept of power signatures of different types of devices and we run a number of tests for a washing machine. With this analysis we proposed a normalized ideal power signature detection method using smoothing filters and ensemble averaging. Based on these preliminary results for power signature further specific analysis can be done in order to observe usage flaws and malfunctions of the devices. For these types of devices, power signatures can be used to monitor the usage pattern of that device and further power management assumptions can be made

Acknowledgment

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References

[1] A. Ipakchi and F. Albuyeh, “Grid of the Future”, IEEE Power and Energy Magazine, Mar.-Apr. 2009.

[2] R. Kazman, L. Bass, J. Ivers, and G. A. Moreno, “Architecture Evaluation without an Architecture: Experience with the Smart Grid”, 33rd International Conference of Software Engineering, May 2011.

[3] J. Froehlich, E. Larson, S. Gupta, G. Cohn, M. S. Reynolds, and S. N. Patel, “Disaggregated End-Use Energy Sensing for the Smart Grid”, IEEE Pervasive Computing, Special Issue on Smart Energy Systems, Jan–Mar 2011.

[4] I. C. Miller, “IDDQ testing in deep submicron integrated circuits”, Proceedings of International Test Conference, ITC 1999, Atlantic City, USA, Sep. 1999.

[5] K. Fehrenbacher, “10 Monitoring Tools Bringing Smart Energy Home”, Business Week, Apr. 2009, http://www.businessweek.com/technology/content/apr2009/tc20090414446611.htm.

[6] M. Marcu, C. Stangaciu, A. Topirceanu, D. Volcinschi, and V. Stangaciu, “Wireless Sensors Solution for Energy Monitoring, Analyzing, Controlling and Predicting”, Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, Volume 57, 2011.

[7] C.Laughman, K. Lee, R. Cox, S. Shaw, S. Leeb, L. Norford, and P. Armstrong, “Power Signature Analysis”, IEEE Power & Energy Magazine, Mar.-Apr. 2003.

[8] M. Damm, S. Mahlknecht, C. Grimm, T. Bertenyi, T. Young and C. Wysoudil, “A partially decentralised forecast-based Demand-Side-Management approach”, IEEE-PES ISGT EUROPE, Dec. 2011.

[9] T. Haver, “An Introduction to Signal Processing in Chemical Analysis”, http://terpconnect.umd.edu/~toh/spectrum/TOC.html

[10] B. H. Brumley, K. L. Deines, “Optimal sampling distribution and weighting for ensemble averages”, Proceedings of the IEEE Sixth Working Conference on Current Measurement, 1999.