A New Measurement System for High Frequency NILM with Controlled Aggregation Scenarios

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***Abstract*—The Non-Intrusive Load Monitoring (NILM) received a rapidly growing interest these past few years due to the increased energy efficiency requirements and the advent of smart grids. Different techniques have been proposed to solve the NILM problem but most of them are based on the use of low sampling frequency signals (1 Hz or less). The lack of a suitable dataset for high sampling frequency NILM, that is adapted for both training and test of high frequency disaggregation algorithms, hindered a lot the development of related techniques. In this paper, we present a new measurement system that is adapted to the construction of high sampling frequency NILM datasets. The main features of the proposed measurement system are: the high sampling frequency measurements (kHz), the control of the turn-on and turn-off time instants with respect to the voltage time-cycle, and the ability to create aggregate measurement scenarios with up to six appliances working simultaneously. The system should allow the construction of a high sampling frequency dataset that should help the high sampling frequency NILM community moving forward in their effort of solving the NILM problem.**

***Keywords*—Electrical measurement system, energy disaggregation, event detection, high sampling frequency NILM, turn-on transient**

I. Introduction

With the growing need for energy efficiency nowadays, people tried to propose different approaches to help satisfy this need. Non-Intrusive Load Monitoring (NILM) is one of them. The aim of NILM techniques is to disaggregate (or break down) the global energy consumption (of a whole-house for example) to extract the end-use (for example appliance-level) consumption information. The interest in NILM has grown a lot of interest these past few years and different techniques have been proposed. A state-of-the-art for the NILM techniques can be found in [1], [2], [3] and a table that summarizes some of the works done up to 2012 can be found in [4].

Even though, the NILM-related works multiplied these recent years, most of them are based on the use of low frequency (few seconds to few minutes sampling period) electrical signals data. Furthermore, what helped a lot is the release of different low frequency datasets starting from 2011 with the release of the REDD dataset [5]. On the other hand, the lack of *suitable* datasets for high frequency-based techniques (hundreds of Hz to MHz) hindered a lot their development.

To the best of our knowledge, the only openly available (to this date) datasets with high frequency data are:

- REDD [5] (2011): 15 kHz sampling frequency and only whole-house data (aggregate measurement).
- BLUED [6] (2012): 12 kHz sampling frequency. Whole-house data with labels for individual appliance activity.
- UK-DALE [7] (2014): 16 kHz sampling frequency and only whole-house data.
- PLAID [8] (2014): 30 kHz sampling frequency and only individual appliance data (measuring a single appliance at a time).
- HFED [9]: measurements over a range of 10 kHz to 5 MHz. The dataset contains ElectroMagnetic Interference (EMI) traces collected from lab and home settings.

High frequency datasets with only individual appliances data (like the PLAID dataset) can be used for the training of some machine learning techniques in order to identify the individual appliances' types in the single-appliance scenario case [10]. For a scenario with aggregate appliances, we can imagine simulating aggregate signals by randomly mixing the individual appliances' signatures (or traces) and use these aggregates for training. Nevertheless, this kind of datasets is not adapted for the test since we will need real-life aggregate scenarios to check the effectiveness of high frequency disaggregation algorithms in real-life situations. In contrast to this, datasets containing only whole-house data will be adapted for the test but less adapted for the training since the individual appliance signature is not directly available from the whole-house data.

A *suitable* high frequency dataset has to be *informative* [11]. The more control we have over the measurement setup, the more information we get! We propose in this paper a new measurement system that has the ability to build such a dataset that is suitable for the training and the test of high frequency disaggregation algorithms. The main features of our system will be discussed in detail in the next sections and are:

- The high sampling frequency capability (section II).
- The control over the turn-on and -off time instants (section III).

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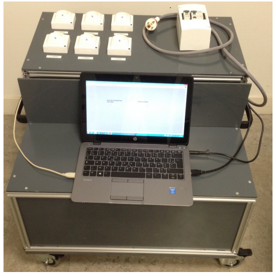


Fig. 1. Photo of the measurement system

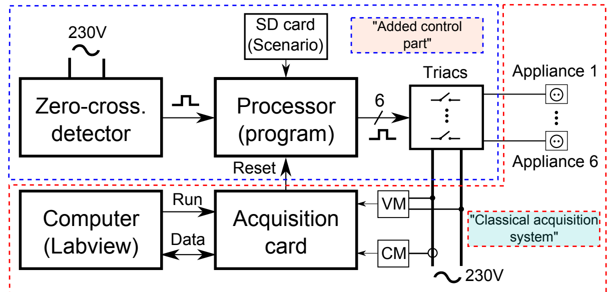


Fig. 2. Block diagram of the measurement system

- The possibility of doing aggregate measurements for up to 6 appliances (section IV).

II. Measurement system description

In this section we will present our measurement system and give details about some of its characteristics such as: the measurement duration and the sampling frequency.

Fig. 1 shows the measurement system. A simple classical measurement system is composed of a computer, an acquisition card and current and voltage sensors (see the block diagram of Fig. 2). The computer controls the running of the measurements and saves the data. The acquisition card works as an interface between the computer and the sensors which measure the signals. For our system, we have added to this classical configuration a *control part* (see Fig. 2). The "Processor" is the main building block of this control part, and the whole system, since it contains the program that specifies how should the system work and according to this gives orders to the "Triacs" block (a set of six electronic switches) that controls the turn-on and turn-off of the six outlets to which the electrical appliances to be measured are connected. The "Zero-cross. detector" is an electronic circuit that detects, permanently, the zero-crossing points (positive to negative crossings) of the power line voltage signal. In France the power line standard voltage has a root-mean-square value of 230 V and a 50 Hz frequency. Also, the mono-phase power line that supplies residential buildings is a single line in contrast to other power line configurations that might be found in other countries. After detection, this detector block sends a cyclic square signal, corresponding to the zero-crossing points, to the processor that uses it as a reference to control the turn-on/off of the appliances.

During a typical measurement instance, we start by giving the *Run* order on the Labview software (see the "Computer" block in Fig. 2). This order, then, allows the "Acquisition card" to send a *Reset* signal to the "Processor" and starts the measurement. After that, the "Processor" reads a "SD card" that contains the pre-loaded measurement scenario and using the output of the "Zero-cross. detector" sends commands to turn-on/off the appliances. Meanwhile, "VM" and "CM" blocks (voltage and current measurement blocks) are measuring the consumed electrical current and voltage at a main point that groups together all the measured appliances. Finally, these measurements are sent to the "Computer" via the "Acquisition card".

The voltage measurement is done using a Metrix MX 9030-Z differential probe with a 30 MHz bandwidth and the current measurement using a Metrix HX0102 current clamp with a 60 kHz bandwidth.

The measurements can be done for either short (few seconds to few minutes) or long time periods (few hours to few days). The only limitation is the memory space. For the sampling frequency, we are limited by the bandwidth of the current clamp (i.e. 60 kHz). Depending on the desired output, we have the flexibility to sample at different rates as long as we respect Shannon's sampling theorem and the bandwidth of our current clamp.

III. Controlled turn-on and turn-off

One of the main features of our system is the ability to control the turn-on and turn-off of the appliances. This control is done with respect to the voltage time-cycle (the duration of this time-cycle is 20 ms). The form of the turn-on transient depend on the turn-on instant. More precisely, the turn-on transient amplitude is not the same depending on the time instant the appliance was turned-on w.r.t. the voltage time-cycle. An appliance can be viewed as a *black box* system with the voltage signal as its input and as output the consumed current. The current is, then, the response of that system to this specific input (sinusoidal signal). If we take one time-cycle (as a convention for all of our measurements, we suppose that the time-cycles start at the positive-to-negative zero-crossings), then, after 5 ms from the beginning of the time-cycle, the voltage signal will reach its negative maximum. After, 10 ms it reaches the negative-to-positive zero-crossing and after 15 ms it reaches its positive maximum and finally it reaches the positive-to-negative zero-crossing again after 20 ms. Whether the *black box* system sees (at the beginning) zero, a positive maximum or a negative maximum will affect its response.

Note that for the remaining of this section we will only consider measurements of a single appliance (the appliance type may differ according to the measurement). Multiple appliances measurements will be discussed in the next section.

A. Measurements reproducibility

As said before, our measurement system (see section II) allows us to control the turn-on instant of the appliance. Since

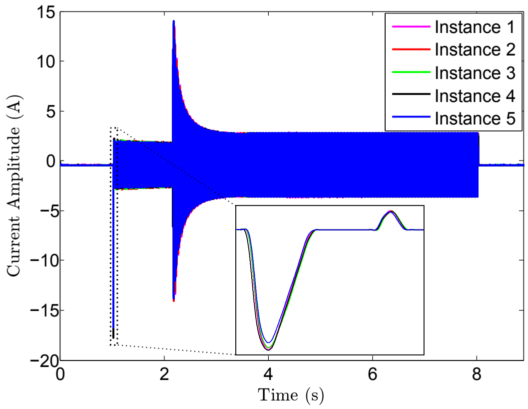


Fig. 3. Current signal of a vacuum cleaner. 5 instances of the same measurement are shown with 0 ms time-delay (w.r.t. the starting of the time-cycle)

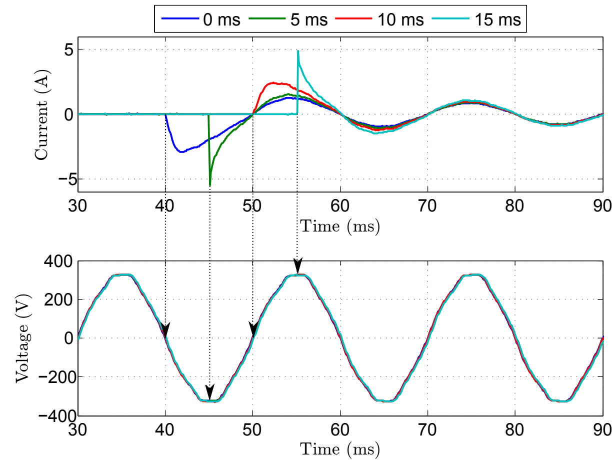


Fig. 4. Current (top) and voltage (bottom) signals of a halogen lamp. 4 instances of the same measurement are shown with a variable time-delay (0 ms, 5 ms, 10 ms and 15 ms)

we have this control, it is interesting to see whether we get reproducible results if we do the same measurement with the same configuration. To test this, we did 5 instances of the same measurement on a vacuum cleaner and we chose to turn-on at the beginning of the voltage time-cycle (i.e. 0 ms time delay w.r.t the start). Fig. 3 shows the result of this measurement. For this measurement, we configured a pre-trigger (pre-turn-on) duration of 1 s and a post-turn-off duration of 1 s. We can clearly see (zoom on Fig. 3) that the measurements are reproducible since all the waveforms are superimposed on one another.

The fact that we see at the beginning a waveform that peaks to negative values is due to our choice of the turn-on time instant. Since the voltage signal at the beginning of the time-cycle starts at a positive-to-negative zero crossing (see the chosen convention in the beginning of section III) and its amplitude continues to decrease until reaching the negative maximum, the current signal tries to follow this trend and we get on the resulting turn-on transient this kind of peaking to negative values.

B. Controlling turn-on/off instants

In this sub-section, we give a measurement example that illustrates how the turn-on transient electrical waveforms vary depending on the turn-on time instant. In real life situations, we do not have control over the turn-on instants. As soon as the switch (mechanical or electronic) is actuated, we directly get the current surge. The main idea of having control over the turn-on instants is to be able to reproduce, in a controllable manner, the current response for different turn-on instants. This allows to understand the appliances behavior and the noticed variability of the turn-on transient which is a step towards a better identification of electrical appliances using transient signals (high sampling frequency signals).

Fig. 4 gives the results of four measurement instances taken with a halogen lamp. Each instance starts at a different time instant. These instants correspond to delays w.r.t. the beginning of the voltage time-cycles and they are, respectively, 0 ms, 5 ms, 10 ms and 15 ms. The delays for each obtained current signal (top of Fig. 4) are indicated using dotted lines on the corresponding voltage signals (bottom of Fig. 4). From this figure we can distinguish two main things. The first one is how the shape and amplitude of the transient current signals change when changing the turn-on instants. Notice, particularly, how the turn-on surge maximum amplitude doubled between the 10 ms (red) and 15 ms (cyan) curves. The highest current values are obtained when the voltage is at its maximum peaks (either positive or negative). The second thing is the way the transient current signals follow the voltage signals (i.e. the current signal is positive-valued when the voltage is positive-valued and vice-versa). Of course, this was expected since our load is resistive and this is what Ohm's law is about! Nevertheless, we expect that the current will still try to follow the voltage even for other types of loads since as we said before, the current signal is the response of the appliance to the input voltage signal.

In Fig. 5, the turn-on active power of a drill is computed and shown. Four instances were considered with different turn-on time instants. This power is computed by averaging the instantaneous power over overlapping sliding windows (with an overlapping of 5 samples at 100 kHz) of 2000 samples duration (1 time-cycle). The resulting powers give another example that illustrates the turn-on transient variability. Note how the transients' shape for 0 and 10 ms are different from the transients for 5 and 15 ms: the amplitude of the first ones increases faster than the others. Also, the maximum amplitudes are different (by around 300 W).

This variability in the turn-on transient signals suggest that when identifying the electrical appliances using such signals, the effect of the turn-on time instant is not to be neglected.

Finally, our measurement system controls the turn-off instants too, also, w.r.t. the time-cycle of the voltage signal. When an appliance turns off, the current signal goes to zero and no particular thing seems to happen on the current signal.

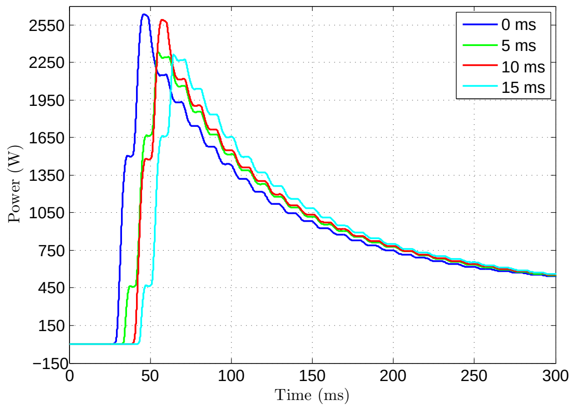


Fig. 5. Turn-on transient power of a drill. 4 instances of the same measurement are shown with a variable time-delay (0 ms, 5 ms, 10 ms and 15 ms)

However, on the voltage signal, a voltage drop is noticed when an appliance is turned-on, especially, for high power consumption appliances. This voltage drop disappears and the voltage finds its initial amplitude as the appliance is turned-off. Controlling the turn-off instants may be a way towards a better understanding of this phenomenon.

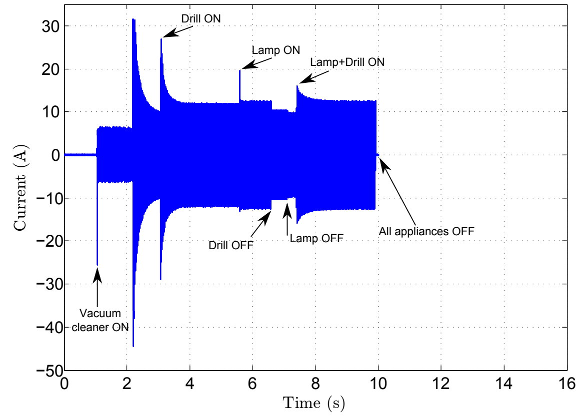
IV. Aggregation Scenarios

Along with the control of the turn-on/off time instants, our measurement system is able to measure an aggregate of up to 6 electrical appliances simultaneously. Since we can play around with the turn-on/off instants, with the working periods and with the number and the type of the appliances, we can imagine creating a whole bunch of scenarios. Nevertheless, the total power consumption of all 6 appliances must not exceed 4600 Watts limited by our 20 Amps circuit breaker.

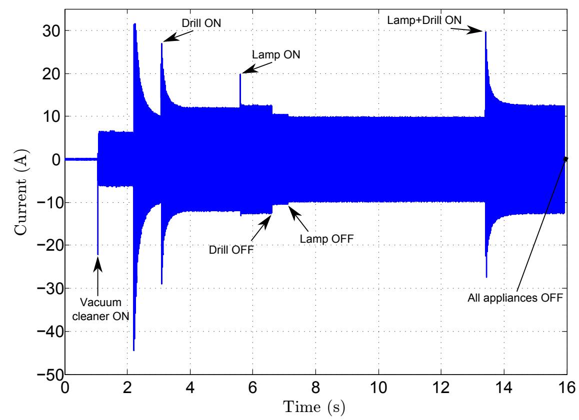
As an example of aggregation, we chose to measure three appliances: a vacuum cleaner, a drill and a halogen lamp (the same ones that were used for the previous measurements which results are shown in Fig. 3, 4 and 5). we chose two aggregate scenarios (read as: Appliance, Event, (time until next event)):

- Scenario I: Vacuum cleaner, ON, (2 s) $\rightarrow$ Drill, ON, (2.5 s) $\rightarrow$ Lamp, ON, (1 s) $\rightarrow$ Drill, OFF, (0.5 s) $\rightarrow$ Lamp, OFF, (**0.25** s) $\rightarrow$ Lamp+Drill simultaneously, ON, (2.5 s) $\rightarrow$ All appliances, OFF.
- Scenario II: Vacuum cleaner, ON, (2 s) $\rightarrow$ Drill, ON, (2.5 s) $\rightarrow$ Lamp, ON, (1 s) $\rightarrow$ Drill, OFF, (0.5 s) $\rightarrow$ Lamp, OFF, (**6.25** s) $\rightarrow$ Lamp+Drill simultaneously, ON, (2.5 s) $\rightarrow$ All appliances, OFF.

The only difference between these two scenarios is that the lamp is off for 0.25 s in the first scenario whereas it is off for 6.25 s in the second one. Fig. 6 shows the current signals of the aggregate scenarios. The vacuum cleaner has a particularly interesting transient waveform containing two working phases with distinct transients. These two phases would have been, most likely, easily confused as two separate appliances if we were in a blind configuration. Hence, a system that is able to create controllable scenarios should help detecting such



(a) Scenario I



(b) Scenario II

Fig. 6. Examples of aggregation scenarios (current signals). Lamp+Drill means that the two appliances were turned-on at the same time

ambiguous cases. Another interesting observation is that the transient for the (Lamp+Drill) is different between the two scenarios. This is due to the fact that for scenario I, the drill motor, after turning-off, keeps rotating for a certain time due to inertia. If we turn it on again, then, it will draw less current than if it were still at a stopping position and we get a different turn-on transient.

V. Conclusion

We have presented a new measurement system that should allow the establishment of a dataset that can push forward the high sampling frequency NILM. The acquired signals should also allow a better analysis and understanding of the turn-on transient and why not the turn-off part too.

Also, having the flexibility to control the turn-on and turn-off instants and creating different measurement scenarios should allow the testing of the robustness of high sampling frequency disaggregation algorithms under different controllable real-life scenarios.

The measurement system is also adapted to low sampling frequency measurements. We have tested it for 24 hours but more tests have to be done to confirm its low sampling frequency measurement capabilities.

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