

# Processing Smart Plug Signals Using Machine Learning

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**Abstract**—The automatic identification of appliances through the analysis of their electricity consumption has several purposes in Smart Buildings including better understanding of the energy consumption, appliance maintenance and indirect observation of human activities. Electric signatures are typically acquired with IoT smart plugs integrated or added to wall sockets. We observe an increasing number of research teams working on this topic under the umbrella *Intrusive Load Monitoring*. This term is used as opposition to *Non-Intrusive Load Monitoring* that refers to the use of global smart meters. We first present the latest evolutions of the *ACS-F* database, a collections of signatures that we made available for the scientific community. The database contains different brands and/or models of appliances with up to 450 signatures. Two evaluation protocols are provided with the database to benchmark systems able to recognise appliances from their electric signature. We present in this paper two additional evaluation protocols intended to measure the impact of the analysis window length. Finally, we present our current best results using machine learning approaches on the 4 evaluation protocols.

**Keywords**—*Intrusive Load Monitoring (ILM); Appliance Identification; Signal length impact*

## I. INTRODUCTION

The general context of this paper is the analysis and modelling of electricity consumption signals using machine learning approaches. A focus is given here on systems able to acquire and process so called *electric signatures* of appliances. The electricity consumption of appliances represents an increasing part of the total energy consumption in residential buildings. From 1993 to 2009, appliances and lighting raised from 24% to 35% of the total energy consumption [1].

Electric signatures can be acquired using two approaches: *Non-Intrusive Load Monitoring (NILM)* and *Intrusive Load Monitoring (ILM)*. With *NILM*, a single smart meter measures the electricity consumption of the whole house. *NILM*'s advantages are ease of installation, low cost and good privacy. However, signal analysis is more difficult as multiple equipments can be used simultaneously. Information on single sources of consumption can be partially retrieved through the application of *disaggregation* algorithms whose performance depends to the type and number of appliances used simultaneously. *NILM* approaches have also more difficulties on less consuming appliances. With *ILM*, several smart meters are placed inside the monitored environment. There are three categories of *ILM* systems [2]: *ILM I* – the meters are placed at circuit-breaker

level with several appliances aggregated, *ILM II* – the meters are located at plug level with few appliances aggregated and *ILM III* – smart meters are dedicated to single appliances (i.e. no aggregated signatures). *ILM III* refers to the finest level of monitoring. *ILM* approaches are per nature more precise in terms of signature analysis but also more intrusive and costlier.

*ILM* is used for several applications, including local / global energy consumption understanding, appliance recognition, appliance monitoring for maintenance purpose, human activity recognition and appliance localisation [2]. In the last years *ILM* has become more and more popular because of sensor cost reduction and availability of technological resources in the sensor communication field. The Internet of Things (IoT) paradigm has improved the sensor communication, granting in this way simple infrastructure for Smart Homes. IoT is particularly useful for *ILM*, especially in Smart Plug integration in the system architecture.

Developing a sensor infrastructure and acquiring electric signatures for scientific analysis and modelling purposes is an expensive and time consuming task. Also, most research done on *ILM* systems has been mainly carried on private, non uniform or limited sets of signatures. To overcome these problems we created the *ACS-F* database, which is publicly available for the scientific community. This database is suitable to carry on experiments on appliance identification systems using a *ILM III* setting. To allow teams comparing their results, two evaluation protocols are also distributed with the database.

The two first protocols were intended to evaluate somehow ideal conditions of training and testing using the full length of the signatures, i.e. one hour length signatures. For some real-time applications this length is probably excessive. We therefore propose in this paper two new evaluation protocols, that we called *Signal length impact*, and intended to evaluate the impact of using shorter portions of the signature.

In Section 2 we provide details about related works dealing with publicly available databases for appliance recognition. In Section 3 we present and provide details about the two versions of the *ACS-F* database. In Section 4 we explain the existing protocols and we present the new *Signal length impact* protocol category. Section 5 is divided in three parts. We first present some pre-processing operations that we usually perform on data, then we summarise the results when using the existing protocols and finally we present and discuss the results when using the new protocols. We conclude the paper in Section 6.

## II. RELATED WORKS

We observe an increasing interest of the scientific community for ILM applications. In spite of the growing interest, we also note that publicly available data impairs fair comparison of systems. Reinhardt et al. [3] report on the *Tracebase* database containing more than one thousand electric signatures spread into 31 categories. The signatures are acquired with a sampling frequency between 1 and 10 Hz. The authors evaluate the accuracy of the appliance recognition task and achieve their best result in terms of accuracy rate using a Random Committee classifier (95.5 %) when. Gao et al. [4] introduce the Plug-Level Appliance Identification Data-set (PLAID) that contains short term measurements of several appliances. The dataset contains more than one thousand measurements from 235 appliances spread into 11 appliance classes. The voltage and current consumed by the appliances are measured with a sampling frequency of 30 kHz. The data-set is public and crowd-sourced.

The number of NILM databases that are publicly available is larger. Kolter et Johnson [5] present the Reference Energy Disaggregation Data-Set (REDD). This data-set contains several types of measurement: the whole home electricity signal acquired at sampling frequency of 15 kHz, 24 individual circuits in the house with information about the appliances (measured at 0.5 Hz) and finally 20 plug-level monitors in the house recorded at 1 Hz. They present an initial benchmark using Factorial Hidden Markov Models. Makonin et al. [6] describe the Almanac of Minutely Power dataset (AMPds) which contains the measurement of 11 features by using 21 sub-meters, positioned at breaker level on the power panel. The sensors acquire a sample every minute for one year. Kyle et al. [7] propose the Building-Level fully-labeled dataset for Electricity Disaggregation (BLUED) which includes the measurements of a whole-house consumption in terms of voltage and current by using a sampling frequency of 12 kHz. They provide the ground truth for every state transition of the appliances. Moreover, they present an initial benchmark using a modified generalised likelihood ratio detector. Monacchi et al. [8] create an energy consumption data-set of 9 households in Italy and Austria, called GREEND, that provides the consumption data of selected devices. They also provide different scenarios to use the data-set, like disaggregation, occupancy detection and appliance usage modelling. Kelly et Knottenbelt [9] present the UK Domestic Appliance-Level Electricity (UK-DALE) dataset. It contains the electricity consumption of the whole house at a sampling frequency of 16 kHz and of 1/6 Hz for individual appliances. They recorded four houses for several days.

Other data-sets contain information coming from highly equipped houses having different kind of sensors. Such data can be used for appliance recognition, cost optimisation, prediction and more. Barker et al. [10] created the Smart\* Home Data-Set that contains data from three houses. They provide the electricity at the main panel, electricity at outlets, renewable generation, wall switch events, thermostat events, motion events, door events and weather station data. Batra et al. [11] released their collection of data, called Indian data for Ambient and Electricity Sensing (iAWE), which consists in the acquisition of as much data as possible from a smart environment. Electricity, water, ambient and other

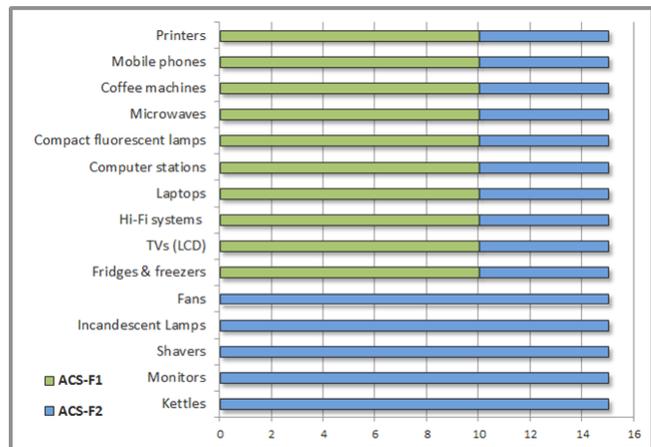


Fig. 1. Current versions of the ACS-F database: ACS-F1 (light green) and ACS-F2 (blue).

parameters are constantly monitored. Regarding electricity, the consumption is monitored at the meter level, circuit level and appliance level. Voltage, current, frequency, power (active and apparent), energy and phase are monitored for 10 appliances with a sampling rate of 1 Hz.

## III. ACS-F DATABASE

In previous works we presented two versions of the *Appliance Consumption signature - Fribourg* (ACS-F) database: ACS-F1 and the ACS-F2 [12][13]. Compared to other databases publicly available, the ACS-F has two peculiarities:

- Electric signatures are acquired from appliances of different brands and/or models, without repetition of identical appliances in the database. Data is varied and heterogeneous: models of the appliance classes can be created without being biased by signature repetitions.
- We propose two protocols for the appliance identification task to let researchers compare their performance on common settings. The protocols are detailed in the next Section.

The electric signatures are time series of vectors including real power (W), reactive power (var), RMS current (A), RMS voltage, frequency of the network (Hz) and phase of voltage relative to current ( $\phi$ ). The signatures are acquired at a sampling frequency of  $10^{-1}$  Hz. There are two acquisitions of 1 hour for each appliance, so, two signatures per appliance.

### A. First version - ACS-F1

ACS-F1 is the first version of the ACS-F database [12]. The database contains 200 electric signatures acquired from 100 appliances. The signatures are uniformly spread in 10 categories: mobile phone chargers, coffee machine, computer workstation (including monitor), fridge and freezer, Hi-Fi system (CD players), lamp (CFL), laptop (via chargers), microwave oven, printer, and television (LCD or LED). More information about the acquisition procedure is available in [12].

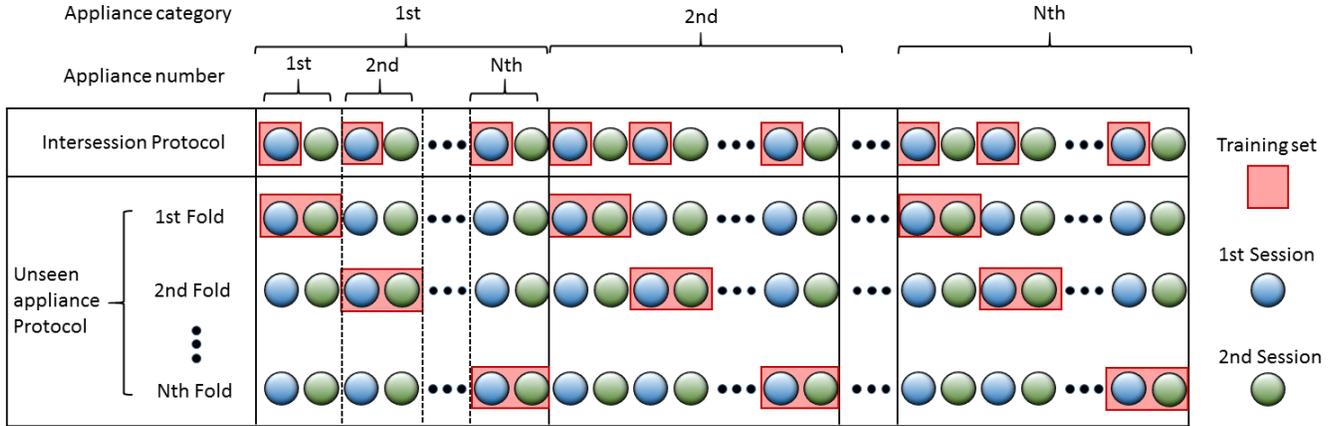


Fig. 2. Difference between the *Intersession* and *Unseen Appliance* protocols. First session signatures are shown in blue, second session signatures are in green. The red squares underline the signatures included in the training set.

### B. Second version - ACS-F2

ACS-F2 is the second version of the *ACS-F* database [13]. It can be considered as an extension of the ACS-F1. Figure 1 illustrates the difference between both versions. The ACS-F2 version contains 450 signatures acquired from 225 appliances uniformly spread into 15 categories: mobile phone, coffee machine, computer station (including monitor), laptop, fridge and freezer, Hi-Fi system (CD players), lamp CFL, incandescent lamp, microwave oven, printer, television (LCD or LED), monitor, kettle, fan and shaver. More information about the acquisition procedure is available in [13].

## IV. EVALUATION PROTOCOLS

### A. Fixed signal length

Two protocols are provided with the ACS-F1 and ACS-F2: *Intersession* and *Unseen Appliance*. These protocols use a fixed time length for the analysis window covering the whole 1 hour duration of the acquisition. Figure 2 illustrates the concept of these two protocols: first session signatures are shown in blue, second session signatures in green and the red squares indicate the signatures included in the training set.

- **Intersession protocol**

In this protocol all the signatures contained in the first session are included in the training set, while the remaining signatures compose the test set. The training and the test sets have the same size, i.e. 100 instances for ACS-F1 and 225 for ACS-F2. According to the protocol requirements, results have to be presented in the form of confusion matrices and total accuracy rates.

- **Unseen Appliance protocol**

In this protocol all instances of both sessions are taken to perform a  $k$ -fold cross-validation. For the ACS-F1,  $k$  is set to 10 and for the ACS-F2,  $k$  is 15. The signatures are separated in order to have in every fold both instances of one (and only one) appliance per category. Similarly to the previous protocol, results have to be presented in the form of confusion matrices and total accuracy rates averaged over the  $N$  folds.

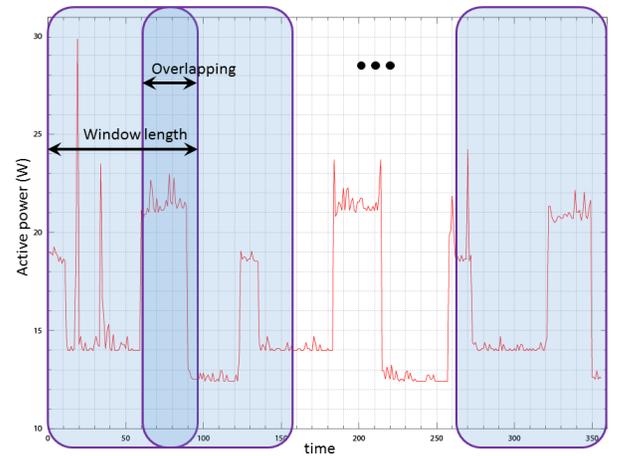


Fig. 3. Illustration of the windowing process: portions of the signature are extracted for the identification task.

According to the terminology used in [14], the protocols mentioned above correspond to real situations having opposite intrusiveness level, called Manual-Setup and Automatic-Setup approaches. The Manual-Setup requires a period of human-driven setup to label one time each appliance signatures. This approach, corresponding to our *Intersession* protocol, requires a rather high involvement of the user who needs to manually intervene in the training of the system. The Automatic-Setup corresponds to our *Unseen Appliance* protocol where signatures of the test set are acquired from unseen appliances. The system has to, in this case, identify the category of appliances never seen in the training set, just relying on common characteristics of the categories, making the assumptions that, for example, a fridge from brand A will behave in a somehow similar manner than a fridge from brand B.

### B. Signal length impact

The *Intersession* and *Unseen Appliance* protocols presented above are allowing to use the whole duration of the signals, namely 1 hour in our case. For some application scenarios such as building management systems, this period of time is probably too long. Shorter signature portions are more realistic

and should be investigated. For this reason we propose a new protocol category, called *Signal length impact*, which aims at evaluating the impact of the analysis window length. The goal is to measure the performance of the appliance identification task as a function of the window lengths. As illustrated in Figure 3, such signals are obtained through a simple windowing operation moving a fixed length window on the signal and extracting the corresponding “sub-signatures” for further identification. The protocol proposes window lengths of 1 up to 60 minutes by 1 minute increments. The window length constraint is applied at testing time while, in the training phase, the length of the training is free, up to the hour available in the training set.

We use the same structure and naming as for the *Fixed time length* protocols but this time using the term “dynamic”.

- **Dynamic Intersession protocol**

The train and test sets are split in the same way as for the *Intersession* protocol. The signatures in the first session belong to the training set and those in the second session to the test set. For the training phase the whole duration of the signature (i.e. 1 hour) can be used. In the test phase the window length is increased from 1 minute up to 1 hour with a step of 1 minute. A total of 60 accuracy rates are then computed. The trend of the accuracy rate with increasing window length can be reported in a graph. The overlap between consecutive analysis windows is not specified in the current definition of the protocol.

- **Dynamic Unseen Appliance protocol**

The train and test sets are split in the same way as the *Unseen Appliance* protocol: a  $k$ -fold cross validation is performed and every fold includes both instances of one (and only one) appliance per category. As for the *Dynamic Intersession* protocol, the whole duration of the signature can be used at training time. In the test phase, the window length is increased from 1 minute up to 1 hour with a step of 1 minute. A total of 60 accuracy rates are then computed. As for the previous protocol, the trend of the accuracy rate with increasing window length can then be reported. The overlap between consecutive windows can be chosen at discretion.

The window size should of course show an impact on the accuracy rate. A smaller window should reflect a more difficult identification task and therefore reports lower accuracy rates. Table 1 shows a summary of the existing and proposed protocols.

## V. RESULTS AND DISCUSSION

### A. Features

A signature is a time sequence  $O = \{o_1, \dots, o_N\}$  of observation vectors  $o_n$  sampled at  $10^{-1} Hz$ . An observation  $o_n$  is a vector of 6 coefficients with the real power (W), the reactive power (var), the RMS current (A), the RMS voltage, the frequency of the network (Hz) and the phase of voltage relative to the current ( $\phi$ ). For all protocols, we performed some basic feature extraction and normalisation on the raw

TABLE I. SUMMARY OF THE EXISTING AND PROPOSED PROTOCOLS.

Type	Fixed time length		Signal length impact	
	Intersession	Unseen appliance	Dynamic Intersession	Dynamic Unseen appliance
Train set	Instances Session 1	k-folds on all session instances <sup>a</sup>	Instances Session 1	k-folds on all session instances <sup>a</sup>
Test set	Instances Session 2		Instances Session 2	
Train time	1 hour max. (whole instance)		1 hour max. (whole instance)	
Test time	1 hour max. (whole instance)		1 minute to 1 hour with an increment of 1 minute	
Result form	Confusion matrix, accuracy		Trend of accuracy rate when varying the window length	

<sup>a</sup> k=10 for the ACS-F1 and k=15 for the ACS-F2.

data. We first append to the feature vector the *velocity* and *acceleration* coefficients computed with

$$\Delta o_n = \sum_{w=-W}^W w \times o_{n-w} \quad (1)$$

$$\Delta\Delta o_n = \Delta o_{n+1} - \Delta o_{n-1} \quad (2)$$

where  $W$  is the length of the analysis window (in our settings 50 seconds).

We then normalise the features using a z-norm approach leading to zero-mean and one-variance values with

$$x_{kn} = \frac{o_{kn} - \mu_k}{\sigma_k} \quad (3)$$

where  $\mu_k$  and  $\sigma_k$  are respectively the mean and variance vectors computed on all signatures in the training set.

We finally perform feature selection as the six raw features contains redundant information [15]. For the *Intersession* protocol we reduced the feature space by a half, removing the RMS voltage, frequency of the network and the phase of voltage relative to current and their dynamic coefficients; for the *Unseen Appliance* protocol no meaningful conclusions could be established because of the large variability of the features that is intrinsic in this protocol so we decided not to perform feature selection for this protocol.

The signatures are then transformed into a time sequence  $X = \{x_1, \dots, x_N\}$  of feature vectors  $x_n$  composed of normalised raw observations and normalised velocity and acceleration coefficients.

### B. Fixed signal length

In our past works we performed several tests for the appliance identification on both versions of the ACS-F database. We applied three machine learning algorithms: k-Nearest Neighbours (k-NN), Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM). In [16] we applied the *Intersession* protocol to the ACS-F1 database. As machine learning algorithm we used k-NN and GMM, tuning respectively the number of Neighbours and the number of Gaussians. We obtained respectively accuracy rates of 90% and 93.6%. Later we applied the *Unseen Appliance* protocol to the ACS-F1 database using the same machine learning techniques [17]. We obtained respectively accuracy rates of 58.5% and 66%. Given

TABLE II. SUMMARY OF THE RESULTS USING THE ACS-F DATABASE.

Version	Protocol	k-NN <sup>a</sup> (%)	GMM (%)	HMM (%)
ACS-F1	Intersession	90	91 <sup>b</sup> - 93.6 <sup>c</sup>	93 <sup>b,d</sup>
	Unseen Appliance	58.5	66 <sup>b</sup> - 74 <sup>c</sup>	74 <sup>b,d</sup>
ACS-F2	Intersession	83.1	89.8 <sup>c</sup>	93.9 <sup>c,e,f</sup>
	Unseen Appliance	53.6	73.3 <sup>c</sup>	74.2 <sup>c,e</sup>

<sup>a</sup> Number of Neighbours tuned.

<sup>b</sup> Using a total of 12 Gaussians among all the states.

<sup>c</sup> Number of Gaussians tuned.

<sup>d</sup> Heuristic HMM without data label.

<sup>e</sup> HMM with data label.

<sup>f</sup> Feature selection.

the poor results, linked to the difficulty of the protocol, we tried to increase the accuracy rate by including and tuning a weight in the dynamic coefficient. For both *Intersession* and *Unseen Appliance* protocol we evaluated the benefits of injecting dynamic information in the feature extraction step. Our last work on the ACS-F1 database consisted in the application of the HMM algorithm to both protocols [18]. For every appliance classes we compared different models having from 1 up to 4 hidden states while maintaining constant the model complexity. We imposed a fixed number of Gaussians, equal to 12, even if this choice could lead to a suboptimal solution. We compared GMM with HMM obtaining respectively 91% and 93% for the *Intersession* protocol and respectively 66% and 74% for the *Unseen Appliance* protocol.

In a second step we released the second version of the database and we presented our initial benchmark using k-NN and GMM for both protocols [13]. We obtained respectively 83.1% and 89.8% for the *Intersession* protocol and respectively 53.6% and 73.3% for the *Unseen Appliance* protocol. In our last work we applied HMMs on the ACS-F2 database using a quite different approach [15]. We labeled the data by recovering the state sequences and we associated the states of the models with real (physical) states of the appliances. Doing this we shown that the information about the device state can be recovered (for example to detect indirectly presence or absence in the house). We obtained an accuracy rate of 93.9% and 74.2% when using respectively the *Intersession* and *Unseen Appliance* protocols. Table II summarises all results in terms of accuracy rate using both versions of the ACS-F database.

### C. Signal length impact

We report here on the trend of the accuracy rates for the *Dynamic Intersession* and the *Dynamic Unseen Appliance* protocols. As stated above, we use the whole duration of the signature (i.e. 1 hour) for the training phase. For the test phase we use windows of different lengths: we start with windows of 1 minute length and we iteratively increment the length up to 60 minutes by steps of 1 minute. A total of 60 accuracy rates are computed. We apply the feature selection for both the protocols as explained in [15].

Figures 4A and 4B show the trend of the accuracy rates for the *Dynamic Intersession* and the *Dynamic Unseen appliance* protocol. In red we report the trend with no overlapping in the windowing operation, in green with an overlapping of 50% and finally in black with an overlapping of 90%. As expected, we observe that larger overlapping leads to smother performance curves. For both protocols the accuracy rate increases as a

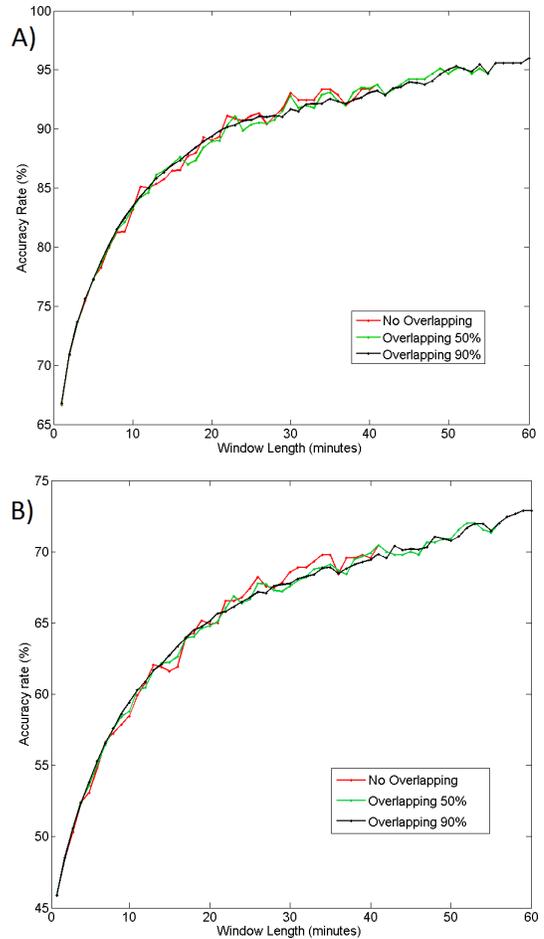


Fig. 4. Trend of the accuracy rates for the *Dynamic Intersession* (A) and *Dynamic Unseen Appliance* (B) protocols, no overlapping in the windowing operation (red), overlapping of 50% (green) and overlapping of 90% (black).

function of the window length, with a saturation appearing with lengths of 30 to 60 minutes.

## VI. CONCLUSION

In this paper we report on machine learning approaches for the identification of appliances through their electric signatures. This work is divided in two parts. In the first one we present the ACS-F database, a collection of electric signatures made available for the scientific community. The database contains signatures of appliances of different brands and/or models acquired at low frequency ( $10^{-1}Hz$ ). The following electrical features are available in the database: real power (W), reactive power (var), RMS current (A), RMS voltage, frequency of the network (Hz) and phase of voltage relative to current ( $\phi$ ). The database is available in two versions: ACS-F1 and ACS-F2. The main differences between both versions is the size with a number of signatures going from 200 to 450, and the number of categories from 10 to 15. Two evaluation protocols are provided with the database: the *Intersession* and the *Unseen Appliance*.

In the second part we propose two new protocols to evaluate the impact of using shorter portions of the signatures to identify the appliance. The protocols are implemented using a

simple windowing process and are called *Dynamic Intersession* and *Dynamic Unseen Appliance*. Baseline results using our machine learning systems are reported according to these two protocols, showing that most performance accuracy can be gained using up to 30 minutes of analysis window. Longer lengths are showing increasing but damped performances.

## VII. ACKNOWLEDGMENT

This work is supported by the grant Smart Living under the project Green-Mod from the Hasler Foundation in Switzerland and by the HES-SO.

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