# APPLIANCE CONSUMPTION SIGNATURE DATABASE AND RECOGNITION TEST PROTOCOLS

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## ABSTRACT

We report on the creation of a database of appliance consumption signatures and two test protocols to be used for appliance recognition tasks. By means of plug-based low-end sensors measuring the electrical consumption at low frequency, typically every 10 seconds, we made two acquisition sessions of one hour on about 100 home appliances divided into 10 categories: mobile phones (via chargers), coffee machines, computer stations (including monitor), fridges and freezers, Hi-Fi systems (CD players), lamp (CFL), laptops (via chargers), microwave oven, printers, and televisions (LCD or LED). We measured their consumption in terms of real power (W), reactive power (var), RMS current (A) and phase of voltage relative to current ($\varphi$). We now give free access to this ACS-F1 database. The proposed test protocols will help the scientific community to objectively compare new algorithms.

## 1. INTRODUCTION

Nowadays, growing prices of energy, political objectives of governments or simply personal convictions encourage people to look for solutions reducing their environmental impacts. From this perspective, a substantial progress can be made in the optimisation and control of the electrical consumption of appliances in habitations. Everyday, new smart meters are installed in houses, and the market is opening to plug-based energy monitoring devices. Recent publications in the domain report on several mobile and web-based energy monitoring systems aiming at providing pertinent information to the user [1, 2]. Studies have shown that a continuous information feedback and fine-tuned automated management of home equipments would allow an energy bill reduction from 15% up to 30% [3, 4]. However, such solutions are still expensive and complicated to configure. One needs to install monitors on the plugs and manually label the associated appliances which can be moved in the house. To help those systems become more adaptive, efficient and easier to use, an important task to be done is the automatic recognition of the appliances running in a house based on their electric consumption profiles or signatures.

Within the framework of our projects, we have built a considerable database containing the consumption signatures of many home appliances. We used low-end smart outlets called PLOGGs [5] for measuring electric consumption signals at low frequency, typically every 10 seconds. Such devices periodically measure various parameters of the electricity consumption and are able to communicate it to the computer via a ZigBee USB dongle. We made two acquisition sessions of one hour on about 100 home appliances divided into 10 categories: mobile phones (via chargers), coffee machines, computer stations (including monitor), fridges and freezers, Hi-Fi systems (CD players), lamp (CFL), laptops (via chargers), microwave oven, printers, and televisions (LCD or LED). We measured their consumption in terms of real power (W), reactive power (var), RMS current (A) and phase of voltage relative to current ($\varphi$). The so-called ACS-F1 database is freely available on [6]. The whole scientific community will thus able to perform various machine learning tasks, tests and performance comparison on those appliances consumption signatures.

In a previous paper [7], we showed that machine learning techniques can be used to perform appliance recognition. Such techniques are very powerful thanks to their capability to learn models from data and to generalize the recognition on unseen appliances. The performance of those algorithms notably depends on the quality of the train data. Therefore a challenging part of this database project was the settling of a data acquisition protocol that could allow us to elaborate and propose recognition test protocols flexible and precise enough for benchmarking the performances of the biggest variety of algorithms. For example, to obtain representative appliance signatures, we had to deal with all possible running states of the different appliances.

This paper is organized as follows. Section 2 gives an overview of the related work. Section 3 gives details about the appliance consumption signature database in terms of data acquisition protocol, data format and database content. In Section 4, we present and discuss the elaborated recognition test protocols which should be applied in order to perform appliance recognition tasks. Finally, in Section 5, we conclude and speak about future works.

## 2. RELATED WORK

Over the last few years, many researchers have been working on energy consumption analysis in order to improve

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the efficiency of the various appliances installed in buildings. We can mention two main approaches to the problem: multi-sensor metering and single-sensor metering, also called nonintrusive load monitoring (NILM) [8].

Multi-sensor metering requires plug-based devices to be installed between appliance power plugs and electricity sockets. On the contrary, single-sensor metering (NILM) relies on the recent smart meters which monitor the overall load of all running appliances on the electrical network in a house. NILM permits to obtain consumption data at a minimal cost and installation time, thanks to the slight hardware it requires. In the NILM approach, the appliance recognition process is usually divided into three steps: the feature extraction, the event detection and the load appliance disaggregation. In fact, multiple independent devices are recorded, thus the main goals is the determination of the contribution of the single appliances. This last point constitutes the main drawback of the approach. Many machine learning algorithms have been used, such as Artificial Neural Networks (ANN) [9], Hidden Markov Models (HMM) [10], Factorial Hidden Markov Models (FHMM) [11], and others [12, 13].

The multi-sensor metering approach allows to perform a fine-grained analysis, given that the appliance signatures are directly available. After the feature extraction, classifiers can be trained and new unknown data classified into a specific appliance category. Moreover, the various single appliance signatures can be aggregated in order to build more complex signal looking like the one returned by a smart meter in the NILM case. Zufferey *et al.* [7] identified five types of appliances with six different models each. They used a modeling approach based on Gaussian Mixture Models (GMMs), obtaining an accuracy rate of 85%. Adeel Abbas Zaidi and Palensky [14] performed the automated load recognition using the Dynamic Time Warping (DTW) and HMMs. In particular they analyzed the features extracted from the power consumption data coming by six different appliances, acquired with a sampling rate of 10 seconds. Reinhardt A. *et al.* [15] identified sixteen appliances analyzing the current flow at a sampling rate of 1.6 kHz and they achieved the 98% of classification accuracy rate.

In the field of power consumption analysis, the number of works is not as large as in other fields that apply the same machine learning techniques. Main raisons are the lack of public data and the difficulty to obtain a sufficient number of samples for the analysis. This pushed us to provide a public database to make the research progress. Some databases are already available for the scientific community. Zico Kolter J. and Johnson M. J. [16] provided the Reference Energy Disaggregation Dataset (REDD) that contains data from six households, both high-frequency current/voltage waveform data and lower-frequency power data including labeled circuits in the house. The database is aimed to the analysis of the contribution of the single appliances to the aggregated data. Anderson K. *et al.* [17] provided the Building-Level Fully labeled Electricity Disaggregation Dataset (BLUED) containing aggregated data from one household. As ground truth, the database is complemented by an event list indicating when the appliances change state. Barker *et al.* [18] provided aggregated data from three households. Part of the database is completed with appliance data, coming from each circuit, and nearly every plug load, measured every few seconds. Reinhardt *et al.* [19] collected 43 different appliance types for a total of 158 appliance instances recorded 24 hours a day. They proposed an algorithm able to identify most appliances with a high accuracy.

## 3. APPLIANCE CONSUMPTION SIGNATURE DATABASE

In this section, we first present the protocol and the XML data format which were worked out to acquire the consumption signatures of all appliances. Then we give an overview of the overall content of the resulting ACS-F1 (Appliance Consumption Signatures - Fribourg 1) database.

### 3.1. Data Acquisition Protocol

In order to acquire the various electrical signals of the target appliances, we first had to set several acquisition modalities and parameters:

- Acquisition sampling frequency: $10^{-1}$ Hz – Most approaches use high sampling frequency [20, 21] in order to capture the electrical noise generated by the appliance and use this noise to distinguish the different categories of appliances. In our approach, we use a larger time space in order to build what we call an electrical consumption signature of an appliance. Moreover, the minimal sampling frequency of our recording device (PLOGGs actually) is limited to one hertz.
- Acquisition duration: 2 sessions of 1 hour each – According to the sampling frequency, one hour of acquisition is a reasonable value to build an electrical consumption signature for an appliance, so that all possible running states are recorded (cf. next paragraph). These two acquisition sessions are performed for each appliance of each category, at a different time and with a different use profile. It is essential to have a common and varied use of the equipment being acquired.
- Number of categories: 10 – We selected the following categories: fridges & freezers, TVs (LCD), Hi-Fi systems (with CD players), laptops, computer stations (with monitors), compact fluorescent lamps (CFL), microwaves, coffee machines, mobile phones (via battery charger), and printers. Those categories well represent most common appliances in home or office
- Number of appliance instances per category: 10 (at least).
- Number of appliances per acquisition device (i.e. PLOGG): 1– We want to record disaggregated signals.

- Acquisition place: home or office.


**Fig. 1**. A PLOGG acquisition device and the communication ZigBee USB dongle

Then we had to settle on a way to proceed for acquiring data of appliances of all categories in all possible running states:

- Coffee machines must be either in operating mode, in standby mode or turned off. The size of the coffee cup should vary.
- Computer stations (composed of a tower with a monitor) must be either in operating mode, put into sleep mode or turned off. The use profile must vary, i.e. the users must change their activities (e.g. surfing on the web, watching movies, performing high or low CPU tasks).
- Fridges & freezers can never be turned off. Their door must sometimes be opened during a variable time. Foodstuff should be removed or added (at ambient temperature).
- Hi-Fi systems (equipped with CD players) must be either turned on, turned off or put in standby mode. CD tracks must be changed and sound volume increased or decreased.
- Lamps (CFL) must be switched on or off from time to time.
- Laptops must be either in operating mode, put into sleep mode or turned off. Like with computer stations, the use profile must vary, i.e. the users must change their activities (e.g. surfing on the web, watching movies, performing high or low CPU tasks). Their battery can be fully charged or charging.
- Microwaves can be either in operating mode, in standby mode or turned off. The cooking time and power should vary.
- Mobile phones (via chargers) can be fully charged or in charging phase.
- Printers must be either turned on, turned off or put in standby mode or print some documents from time to time.
- TVs (LCD / LED) must be either turned on, turned off or put in standby mode. Channels must be changed and the sound volume increased or decreased.

### 3.2. Data Format

An XML data structure has been designed for storing the raw observations, some meta-data and the ground truth values of the appliance categories. The format consists of two main parts. The header part covers the description of the database, the acquisition campaign, the author who did the acquisition, the acquisition place, the sensor device used, and the electrical parameters recorded. The body part contains the signal values with timestamps for all electrical parameters. This generic and self-described format permits to deal with different types of sensors and signals (even for non-electrical) in the future. We wanted the format to be as flexible as possible. Here is an acquisition example in our XML format:


```xml
<?xml version="1.0" encoding="UTF-8"?>

<signalData>

  <acquisitionContext database="GreenLine"
    databaseSet="Set1" session="1" version="1" />

  <validation status="ok" id="christophe" date="2011-09-01" />

  <acquisitionPlace name="living room" type="room">
    <feature name="buildingName" value="christophe" />
    <feature name="buildingType" value="residential" />
    <feature name="energyClass" value="D" />
    <feature name="constructionYear" value="1975" />
    <feature name="rooms" value="6.5" />
    <feature name="surface" value="200" />
    <feature name="address" value="CH-1700 Fribourg" />
  </acquisitionPlace>

  <targetDevice type="laptop" brand="Apple" model="MacBook Pro"
    energyClass="" comment="Personal laptop" />

  <acquisitionDevice type="electricity_socket" brand="PLOGG" model="PLG-ZGB-CH"
    samplingFrequency="0.1" comment="Sampling frequency is expressed in Hz.">
    <channel name="time" type="date" precision="1" units="s" />
    <channel name="freq" type="float" precision="0.1" units="Hz" />
    <channel name="phAngle" type="integer" precision="1" units="" />
    <channel name="reacPower" type="float" precision="0.001" units="var" />
    <channel name="rmsCur" type="float" precision="0.001" units="A" />
    <channel name="rmsVolt" type="float" precision="0.001" units="V" />
    <channel name="power" type="float" precision="0.001" units="W" />
  </acquisitionDevice>

  <signalCurve>
    <signalPoint time="2011-04-11 15:53:31" freq="50.0" phAngle="0"
      reacPower="-0.31" rmsCur="0.144" rmsVolt="231.481" power="18.944" />
    <signalPoint time="2011-04-11 15:53:41" freq="50.0" phAngle="0"
      reacPower="-0.414" rmsCur="0.142" rmsVolt="231.616" power="18.944" />
    <signalPoint time="2011-04-11 15:53:51" freq="50.0" phAngle="0"
      reacPower="-0.31" rmsCur="0.143" rmsVolt="231.516" power="18.84" />
    <signalPoint time="2011-04-11 15:54:01" freq="50.0" phAngle="0"
      reacPower="-0.414" rmsCur="0.146" rmsVolt="231.686" power="19.254" />
    <!-- ... -->
    <signalPoint time="2011-04-11 16:52:50" freq="50.0" phAngle="0"
      reacPower="-0.621" rmsCur="0.111" rmsVolt="235.247" power="12.525" />
    <signalPoint time="2011-04-11 16:53:00" freq="50.0" phAngle="0"
      reacPower="-0.724" rmsCur="0.11" rmsVolt="235.249" power="12.629" />
    <signalPoint time="2011-04-11 16:53:10" freq="50.0" phAngle="0"
      reacPower="-0.724" rmsCur="0.11" rmsVolt="235.295" power="12.525" />
  </signalCurve>

</signalData>
```


### 3.3. Resulting Database Content

Our ACS-F1 database is getting bigger, but at the time we are writing this paper, its content state is given by Table 1. One of our objectives was the equiprobability of all appliance categories, i.e. each one must be equally distributed by containing the same number of instances.

Figure 2 shows an example of the active power consumption measured on an appliance of category *Laptop*.

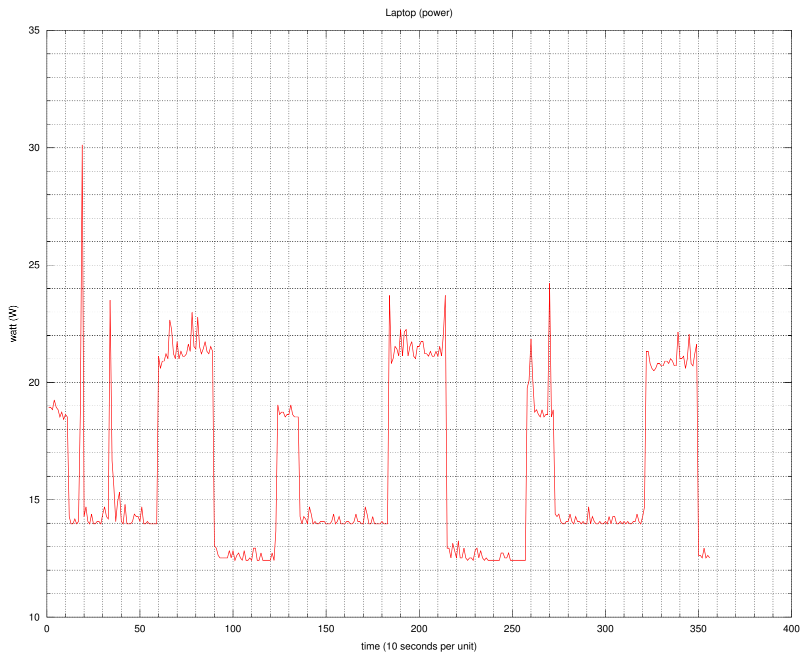


**Fig. 2**. Example of the active power consumption measured on a laptop

## 4. RECOGNITION TEST PROTOCOLS

As said before, the ACS-F1 database is now available for free to the whole scientific community [6]. Hence, everybody will be able to perform various machine learning tasks. In this section, we present the preliminary test protocols that will allow to make different performance comparisons in the task of appliance recognition. As the protocols and the corpora will be publicly available, we speak of an "in-house evaluation with existing benchmark" [22]. Table 2 shows a summary of two proposed protocols. Figure 3 shows a graphical representation of the splitting of the train and test set for both protocols.

### 4.1. Test Protocol 1.0 – Intersession

In the test protocol 1.0 (or *intersession* protocol) for appliance recognition, all instances of acquisition session 1 (resp. 2) must be taken in the train (resp. test) set. In other words, cardinalities of both train and test sets are equal. For a given recording, it is allowed to use the whole duration of the signal, namely 1 hour. Classification results must be presented in the form of a confusion matrix and the overall recognition rate.

### 4.2. Test Protocol 2.0 – Unseen Instances

In the test protocol 2.0 (or *unseen instances* protocol) for appliance recognition, all instances of both sessions are taken to perform a $k$-fold cross-validation [23], where $k = 10$. In other words, we randomly partitioned all instances into $k = 10$ subsets. The cross-validation process consists then in taking successively each of the $k$-folds for testing and the remaining $k - 1$ ones (i.e. 9) for the training. As for test protocol 1.0, for a given recording, it is allowed to use the whole duration of the signal, namely 1 hour. Classification results must be presented in the form of a confusion matrix and the overall recognition rate averaged over the $k$-folds.

| **Categories** | **Instances** | **Sessions** |
|---|---|---|
| 1. Coffee machine | 10 | 2 |
| 2. Computer station (with monitor) | 10 | 2 |
| 3. Fridge / Freezer | 10 | 2 |
| 4. Hi-Fi system (with CD player) | 10 | 2 |
| 5. Lamp (CFL) | 10 | 2 |
| 6. Laptop | 10 | 2 |
| 7. Microwave | 10 | 2 |
| 8. Mobile phone (via charger) | 10 | 2 |
| 9. Printer | 10 | 2 |
| 10. TV (LCD / LED) | 10 | 2 |
| **Total** | **200 recordings** | |

**Table 1**. Content of the consumption signature database

| **Protocol** | 1.0 Intersession | 2.0 Unseen Instances |
|---|---|---|
| **Task** | Appliance Recognition | |
| **Train set** | Session 1 instances | 10-folds on all session instances |
| **Test set** | Session 2 instances | |
| **Train time** | 1 hour max. (whole instance) | |
| **Test time** | 1 hour max. (whole instance) | |
| **Result form** | Confusion matrix, accuracy | |

**Table 2**. Recognition Test Protocols

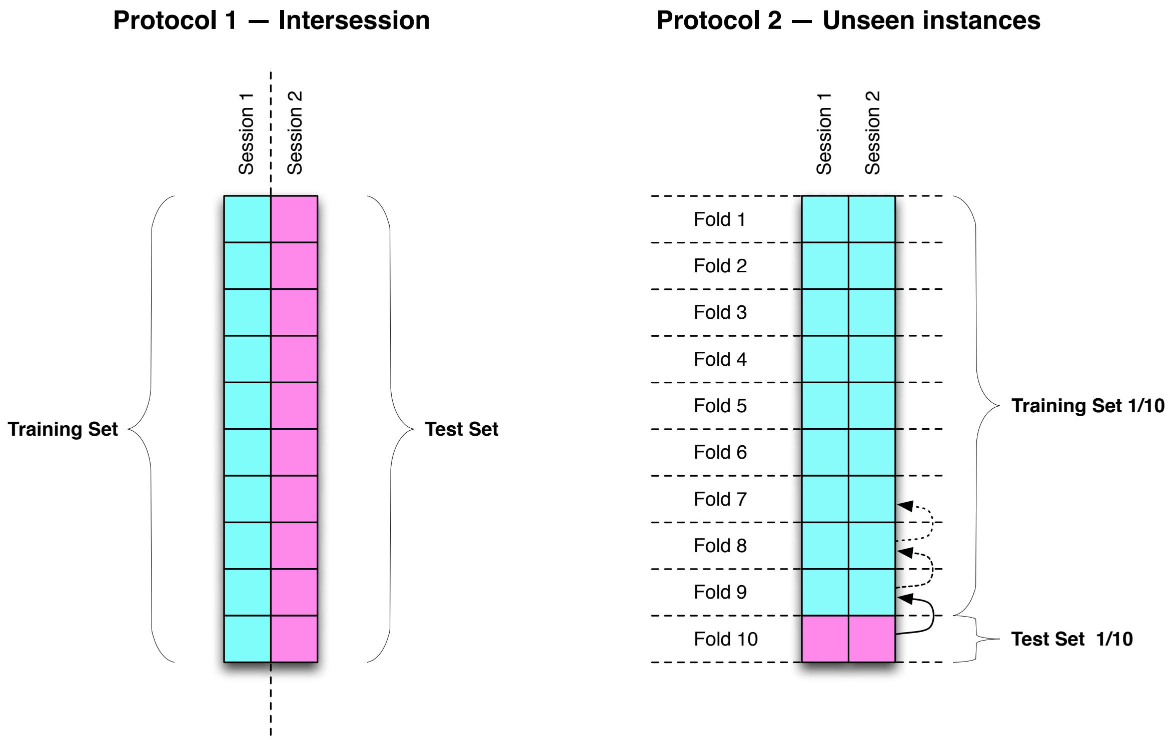


**Fig. 3**. Train and test set splitting for both protocols

## 5. CONCLUSIONS & FUTURE WORKS

In this paper we presented a database of appliance consumption signatures that fills the lack of available public data in the field of power consumption. Works on other available databases usually concern the disaggregation of the power consumption of multiple independent appliances in order to determine the contribution of each single appliance separately. In our approach, we tackle the appliance identification problem on the other side by proposing a database of single appliance signatures that is free for the whole scientific community.

We populate the so-called ACS-F1 database with the power consumption signatures obtained using plug-based low-end sensors placed between appliance power plugs and electricity sockets. We made two acquisition sessions of one hour for 100 different appliances distributed among 10 categories. For each appliance category, we established an acquisition protocol indicating all possible running states (e.g. on, off, standby) to be recorded. This protocol ensures that each appliance category contains signatures coming from different devices. We wanted the database to be ideal for the various machine learning tasks.

We proposed then two test protocols intended to compare the performance of future algorithms in the task of appliance recognition. In this way, we give the researchers the possibility to work on common data. In the first protocol, first session instances are used for the train set and the second session instances for the test set. In the second protocol, all instances of both sessions are successively taken in train and test sets by performing a $k$-fold cross-validation.

As future works, we plan to follow the proposed test protocols for appliance identification by using conventional machine learning algorithms. Hence we will be able to compare the obtained classification results with those provided by other research groups across the world. Finally, we want to propose new test protocols based on more complex identification scenarios, for example involving aggregated appliance signatures or different appliance running states within the consumption signatures.

## 6. ACKNOWLEDGMENT

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## 7. REFERENCES

[1] M. Weiss, T. Staake, D. Guinard, and W. Roediger, “eMeter: An interactive energy monitor,” *Higher Education*, pp. 3–4, 2009.

[2] D. Guinard, M. Weiss, and V. Trifa, “Are you Energy-Efficient: Sense it on the Web!,” Tech. Rep., Institute for Pervasive Computing, ETH Zürich, Zürich, 2009.

[3] B. Neenan, “Residential Electricity Use Feedback: A Research Synthesis and Economic Framework,” Tech. Rep. February, Electric Power Research Institute, 2009.

[4] S. Darby, “The Effectiveness Of Feedback On Energy Consumption - A review for DEFRA of the literature on metering, billing, and direct displays,” *Environmental Change Institute, University Of Oxford*, vol. Technical, no. April, pp. 21, 2006.

[5] Energy Optimizers Limited, “Plogg wireless energy management,” http://www.plogg.co.uk.

[6] University of Applied Sciences of Western Switzerland (HES-SO), “The watt-ict project,” http://www.wattict.com.

[7] D. Zufferey, C. Gisler, O. Abou Khaled, and J. Hennebert, “Machine learning approaches for electric appliance classification,” in *Proceedings of the 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA'12)*, Montreal, Canada, July 2012, pp. 740–745.

[8] G. W. Hart, “Nonintrusive appliance load monitoring,” *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870–1891, 1992.

[9] A. Prudenzi, “A neuron nets based procedure for identifying domestic appliances pattern-of-use from energy recordings at meter panel,” *IEEE Power Engineering Society Winter Meeting*, vol. 2, pp. 941–946, 2002.

[10] T. Zia, D. Bruckner, and A. Zaidi, “A hidden markov model based procedure for identifying household electric loads,” in *Proceedings of the IEEE 37th Annual Conference on IEEE Industrial Electronics Society (IECON 2011)*, Melbourne, Australia, Nov. 2011, pp. 3218–3223.

[11] J. Z. Kolter and T. Jaakkola, “Approximate inference in additive factorial hmms with application to energy disaggregation,” in *Proceedings of the IEEE 15th International Con- ference on Artificial Intelligence and Statistics (AISTATS 2010)*, La Palma, Spain, Apr. 2012.

[12] J. Liang, S. K. K. Ng, G. Kendall, and J. W. M. Cheng, “Load signature studypart ii: Disaggregation framework, simulation, and applications,” *IEEE Transaction on power delivery*, vol. 25, no. 2, pp. 561–569, 2010.

[13] M. Zeifman, “Disaggregation of home energy display data using probabilistic approach,” *IEEE Transaction on Consumer Electronics*, vol. 58, no. 1, pp. 23–31, 2012.

[14] F. K. Adeel Abbas Zaidi and P. Palensky, “Load recognition for automated demand response in microgrids,” in *Proceedings of the IEEE 36th Annual Conference on IEEE Industrial Electronics Society (IECON 2010)*, Glendale, USA, Nov. 2010.

[15] A. Reinhardt, D. Burkhardt, M. Zaheer, and R. Steinmetz, “Electric appliance classification based on distributed high resolution current sensing,” in *Proceedings of the 7th IEEE International Workshop on Practical Issues in Building Sensor Network Applications (SenseApp 2012)*, Clearwater, USA, Oct. 2012.

[16] J. Z. Kolter and M. J. Johnson, “Redd: A public data set for energy disaggregation research,” in *Proceedings of the ACM Workshop on Data Mining Applications in Sustainability (SustKDD 2011)*, San Diego, USA, Aug. 2011.

[17] A. Kyle, A. Filip, D. Bentez, D. Carlson, A. Rowe, and M. Bergs, “Blued: A fully labeled public dataset for event-based non-intrusive load monitoring research,” in *Proceedings of the ACM Workshop on Data Mining Applications in Sustainability (SustKDD 2012)*, Beijing, China, Aug. 2012.

[18] S. Barker, A. Mishra, D. Irwin, E. Cecchet, and P. Shenoy, “Smart*: An open data set and tools for enabling research in sustainable homes,” in *Proceedings of the ACM Workshop on Data Mining Applications in Sustainability (SustKDD 2012)*, Beijing, China, Aug. 2012.

[19] A. Reinhardt, P. Baumann, D. Burgstahler, M. Hollick, H. Chonov, M. Werner, and R. Steinmetz, “On the accuracy of appliance identification based on distributed load metering data,” in *Proceedings of the 2nd IFIP Conference on Sustainable Internet and ICT for Sustainability (SustainIT 2012)*, Pisa, Italy, Oct. 2012.

[20] E.K. Howell, “How switches produce electrical noise,” *Electromagnetic Compatibility, IEEE Transactions on*, , no. 3, pp. 162–170, 2007.

[21] S.N. Patel, T. Robertson, J.A. Kientz, M.S. Reynolds, and G.D. Abowd, “At the flick of a switch: Detecting and classifying unique electrical events on the residential power line,” in *Proceedings of the 9th international conference on Ubiquitous computing*. Springer-Verlag, 2007, pp. 271–288.

[22] A. El Hannani and J. Hennebert, “A Review of the Benefits and Issues of Speaker Verification Evaluation Campaigns,” in *Proceedings of the ELRA Workshop on Evaluation at LREC 08, Marrakech, Morocco*, 2008, pp. 29–34.

[23] David G. Stork Richard O. Duda, Peter E. Hart, *Pattern Classification (2nd Edition)*, Wiley-Interscience, 2000.