Unsupervised Learning Algorithm using multiple Electrical Low and High Frequency Features for the task of Load Disaggregation

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***Abstract*—Device specific power consumption information leads to a high potential for energy savings. Smart meters are currently deployed in several countries, but they are only able to track the overall consumption in domestic and commercial buildings. One promising option to gain device specific information is called Nonintrusive Load Monitoring (NILM), which can be of great use in combination with smart metering. In NILM, device specific information is achieved by disaggregating the overall load profile from a single-point measurement using device fingerprints and machine learning techniques. In this paper we focus on unsupervised learning methods to minimize the learning phase of device fingerprints. To increase the algorithm accuracy a range of several electrical features are taken into account. This research is part of a public funded project, which aims to increase the energy efficiency in industrial applications.**

Keywords—Nonintrusive Load Monitoring (NILM); load disaggregation; unsupervised learning; machine learning; electrical disaggregation features; smart metering; energy efficiency; energy management systems

I. Introduction

With increasing energy prices the incentive to save energy is becoming constantly larger. Furthermore, several countries committed to save CO_2 over the next couple of decades to prevent climate change. The rollout of smart meters is trying to address these issues. Nevertheless, field tests show that the main energy savings are either not enduring or not highly significant [1][2]. Even with smart meters, the individual electricity consumer just receives the overall power consumption information over a period of time (e.g. yearly, monthly, weekly), but no appliance-specific information is presented.

Power consumption on an appliance level reaches higher energy savings [1]. Ehrhardt-Martinez *et al.* found that daily or weekly overall consumption feedback can reach up to 8.4 % savings, while real-time device specific feedback increases the energy savings up to 12.0 %. This study was carried out for the domestic sector. In the commercial sector even higher savings can be estimated, as more adjustments to the environmental appliance settings can be made.

A widespread technology to receive appliance specific consumption feedback is submetering, where one sensor per appliance has to be installed. Another method to gain appliance specific consumption feedback is called Nonintrusive (Appliance) Load Monitoring (NILM, NIALM or NALM). The main advantage of NILM is that device specific consumption can be achieved by a single-point measurement for several appliances. This metering point measures several electrical parameters (see section VI) and a suitable NILM algorithm is disaggregating the overall electrical power consumption (see section V). With the smart meter rollout in several countries this approach receives recently more and more popularity [3].

II. Related Work

The NILM approach was firstly proposed by G. W. Hart [4]. Since then, several research groups have worked on this topic. More detailed references to specific working groups will be presented in section V and VI, when discussing a NILM algorithm and different electrical features. Review publications conclude that “no complete NI(A)LM solution suitable for all types of household appliances is available” and that “the available solutions are either unsuitable for some appliances or still at an early developmental stage” [5][6][7]. Zeifman and Roth summarize further “that no complete set of robust, widely accepted appliance features has been identified” [5].

There are four different appliance categories, which are mentioned in [4][5]. Each category comprises individual challenges for recognizing an appliance within an overall load profile:

i) Permanent consumption appliances

ii) On-off appliances

iii) Finite state machine (FSM) appliances

iv) Continuously variable load appliances

Much research has been carried out on ii) and iii). i) is similar to ii), but without any information of a switching event. Category iv) is most likely the most challenging in load disaggregation, as the appliance arbitrarily and continuously changes its power consumption [8].

III. Challenges

Despite the fact that each appliance category is differently complex for recognition, there are even more technical challenges to overcome in load disaggregation:

- Simultaneously switching appliances
- Detecting appliances which are connected to multiple electrical phases
- Large building environments and therefore a large appliance pool leads to more overlapping events and load profiles
- Fluctuations within the electrical power network introduce arbitrary noise into the system
- Cable attenuation changing the appliance signature
- Detecting appliances with subject to wear and therefore changing the appliance signature
- A short and simple training phase of a system.

In addition, also ethical questions like privacy have to be taken into account [9]. Furthermore the difficulty of load disaggregation varies heavily on the application, e.g. applying NILM in commercial buildings has special challenges [10].

We feel that combining a complete set of robust electrical appliance features with an unsupervised learning approach could help to move this research area further forward.

IV. Project Description

The described research is part of a public funded project. It started at the end of 2015 and four private companies (including Discovergy GmbH, GreenPocket GmbH, EasyMeter GmbH and RWE GBS GmbH) plus one research facility (Fraunhofer IMS) are participating. One major goal is to gain more experience in the area of energy efficiency in industrial applications. For this an unsupervised NILM algorithm is developed trying to minimize the training phase as much as possible. To increase the algorithm reliability several electrical features are considered (low and high frequency – see section VI). To lower the algorithm complexity the development focuses on three different areas: franchise stores, municipal buildings and production halls.

The project outcome are 15 NILM-prototypes, which will be evaluated later on in an industrial field test. Each NILM-prototype consists of an enhanced smart meter, a gateway for transmission of measurement data, a server where the NILM-algorithm is executed and an energy management system, to visualize and analyze the algorithm results.

Further information on the project can be found at www.nilm.info

V. Unsupervised Learning Algorithm

NILM algorithms can be classified in eventless and event-based approaches. The latter also take the information into account, which power consumption level was reached before the switching event occurred. For the load disaggregation task machine learning algorithms are applied. They strongly vary on how comprehensive the training phase has to be. Machine learning can be divided into supervised and unsupervised approaches, but also semi-supervised learning methods can be useful in NILM [11].

For practical NILM applications, the training phase should be as short and simple as possible. Some training could happen before shipment of a product, but one main challenge of NILM is that the product should be easy to setup for the final user. Our goal was to develop a NILM-system with a small training phase. Therefore we focused on unsupervised methods with the ability to perform the labeling of the devices with the aid of an appliance database. For data acquisition we used an off-the-shelf hardware with the possibility to continuously digitalize current and voltage with a maximum sampling rate of 500 kS/sec and a 16-bit vertical resolution. This raw data is streamed to a MATLAB program where the NILM disaggregation is performed in near real-time.

Our algorithm can be described with following steps and consists of a typical event-based approach:

1. The data acquisition system measures voltage and current signals. Device features like real power, reactive power or transients are calculated.
2. An event detector checks constantly for a switching event.
3. Once a switching event has occurred, the algorithm analyzes the calculated device features prior a switching event and post a switching event. This analysis is achieved by using an unsupervised clustering method.
4. The device features are compared against a device feature database. From all the possible items the algorithm chooses the best fit within the feature space. If no entry is found, a new device is added to the database and the algorithm starts to search for the next event.

In this version, the following electrical features are used for disaggregation: the overall active power, the overall power transient, the apparent power, the reactive power and the phase angle of the first harmonic. One main property of our algorithm is that it is able to handle completely unknown appliances. It even can start off with an empty appliance database, which means it can be used as a plug-and-play NILM system. The algorithm detects appliance clusters and assigns a unique ID to them. The labeling of the appliance name can be done post disaggregation. A labeling database with known common appliances can assist in this task. In the future, the above mentioned relatively high sampling rate also gives us the opportunity to integrate more electrical features, like harmonics or EMI signatures into the algorithm (see section VI).

Fig. 1 shows an excerpt of the disaggregation algorithm using up to 15 concurrent running appliances. The continuous red line shows the overall measured real power, which would usually be measured with a typical smart meter.

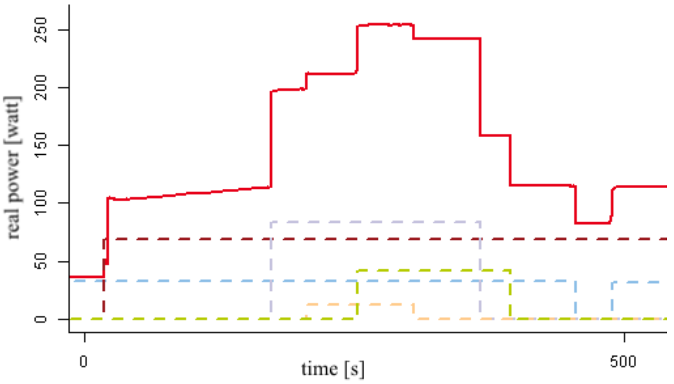

Fig. 1. Excerpt of the unsupervised learning algorithm. The continuous red line shows the overall real power. The dashed lines highlight the results of the disaggregation algorithm, which consist of single power consumers.

The dashed lines in other colors show the recognized appliances: pc monitor 1 (light blue), fluorescent lamp (dark red), ventilation low (grey), ventilation Δ(medium-low) (light orange) and pc monitor 2 (green). Each appliance is detected by the clustering algorithm automatically and labeled afterwards manually. Note that adding up all the dashed lines will result in the measured real power.

VI. Available Electrical Features

As mentioned in section V the presented algorithm uses mainly low frequency features so far. These are highlighted in chapter A. To increase the algorithm reliability and to be able to disaggregate very similar devices, it is planned to incorporate higher frequency features like harmonics and EMI signals in the future. We pre-investigated these (see chapter B, C & D) for feature transformation. A very good classification of different sampling ranges is described in [6].

Usually higher sampling rates lead to higher measuring costs, but provide the opportunity to detect a larger number of appliances. Furthermore, the features can be divided into time-based analytics like real power and frequency based analytics like harmonics.

A. *Real and reactive power (frequency range: 1 h – 50 Hz)*

The most common way to distinguish appliances from each other is to take the real and reactive power consumption into account [4]. This approach is sufficient if all monitored appliances have a distinct power consumption. If not, they can not be solely separated by this feature. Furthermore continuously variable load appliances can not be tracked, as the power consumption changes arbitrarily and continuously.

B. *Harmonics (frequency range: 50 Hz – 10 kHz)*

In addition to the power consumption the harmonics of the mains frequency (50 or 60 Hz) can be used as a NILM feature. Harmonics exist for higher harmonic orders (>1), if the current draw of an appliance exhibits a non-sinusoidal waveform. Previous work from Umeh *et al.* revealed the possibility to identify single devices by observing the generated harmonics [12].

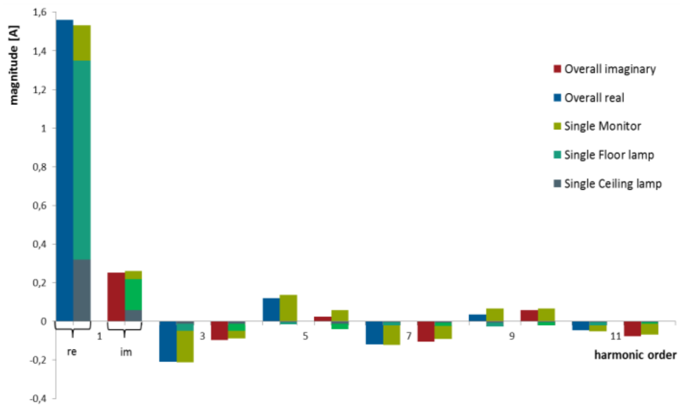

Fig. 2. Measured harmonics for the overall power circuit compared to individual device harmonics. Monitor, floor and ceiling lamp as examples.

We took a power circuit with several attached appliances into account and analyzed the harmonic pattern behavior for each appliance and for the overall load. For examination we looked at the imaginary and real value of each harmonic by analyzing the present nonsinusoidal current waveform using the discrete Fourier transform (DFT). The summed up independent device measurements correspond with little fluctuations to the measured value for the overall power circuit, where all the appliances are switched on concurrently (see Fig. 2). In this example the internal components of the appliances produce a current waveform which is symmetrical to the time axis and therefore only odd harmonics are shown in this figure (even harmonics are zero).

C. *Electromagnetic interference (EMI) (frequency range: 10 kHz – 200 kHz)*

Nowadays more and more consumer electronic appliances are using switch mode power supplies (SMPS). They emit high frequency noise within a power network. This EMI can be detected by monitoring the overall voltage signal and carrying out a FFT analysis of the noise.

To accomplish this, we used an off-the-shelf data acquisition hardware with a 16-bit vertical resolution. To be able to track the noise, it was necessary to filter out the main 50 Hz wave, which was done with a high-pass filter. With this setup, we were able to record EMI signals from different devices and record their switching patterns (see Fig. 3). This method is similar to Patels and Guptas approach [13]. For the first time, they were able to show that the EMI signals of appliances with SMPS are stable and can be used across different buildings.

In a real building scenario the overall power network acts as an antenna. Our measurements showed different radio signals, including the European DCF77 transmitter. Even appliances which are the same brand and model, but exhibit manufacturing deviations, can theoretically be disaggregated by this method. But more work has to be done in overlapping signature frequencies.

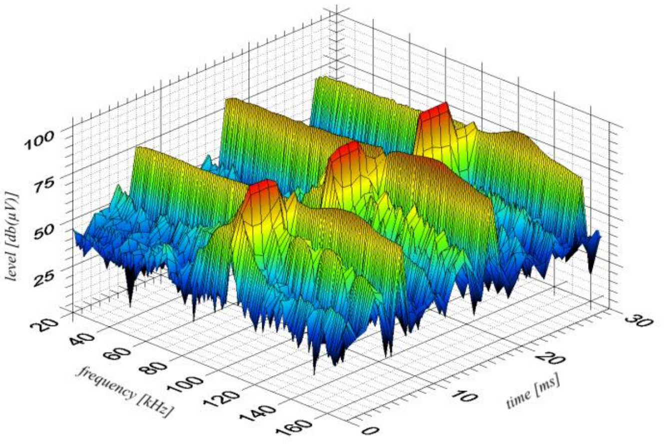

Fig. 3. EMI 3D-spectrum of a 19" LCD Monitor.

D. *Transient and Steady-State examinations*

All the above features can be either examined in a transient or steady-state [14]. Transients require a higher sampling rate than steady-state approaches, as switching peaks have to be detected in detail. These peaks vary in addition from the current state the appliance is in, e.g. if the appliance is hot or cold and therefore transients are not as much of a reliable feature as compared to steady-state approaches. Still they can be beneficial if the steady-state features are too similar, e.g. having the same power consumption level.

E. *Macroscopic patterns*

In addition to the above electrical features it can be beneficial to look at macroscopic patterns. This is especially useful if the appliance to detect is always switched on at a specific time of day or weekday. Also correlations, like which appliances are commonly switched on together, can be examined (e.g. a PC and a monitor). The advantage of this approach is that comparably low sampling rates can be used.

VII. Evaluation

The algorithm evaluation was performed on different scenarios. The evaluation was based on the test protocol of Butner et al. [15]. We combined the low-wattage and the mid-wattage protocol, as our system was able to handle both ranges equally.

We used 5, 10 and 15 appliances as an appliance pool, which can be commonly found either in a domestic or in a commercial environment: 8x distinct lamps, 2x PC monitors, 1x DVD player, 1x network switch, 1x fan heater, 1x hair dryer and 1x air conditioner. These appliances are part of the NILM categories i), ii) and iii). Appliances in category iv) are not considered yet (see section II). The number of test cycles was increased with a growing number of appliances, considering the increasing number of possible switching variations. For 15 appliances 60 randomized switching events were realized in every measurement. Table 1 shows the results with 15 appliances for 5 different measurements. It shows the detection accuracy (DeA), disaggregation accuracy (DiA) and the overall accuracy (OA) corresponding to [15]. Note that a different appliance setup, e.g. more devices, could lead to far lower results in this current algorithm version. Values smaller than 100% are either due to wrongly classified devices or missed events.

Table 1 Results of the evaluation using 15 appliances

#	DeA	DiA	OA
1	100%	100%	100%
2	100%	100%	100%
3	96.7%	96.7%	96.7%
4	100%	100%	95.0%
5	100%	100%	98.3%

VIII. Conclusion & Future Work

Intensive research has been carried out in the NILM field, but no wide spread reliable solution is available so far, which would work in different environments. There are numerous electrical NILM features available for disaggregation, but practical applications just use a small subset of these.

To improve reliability, we evaluated several electrical NILM features and our current results show that they are promising for improving NILM accuracy. Based on this, we developed one version of an unsupervised learning algorithm, which exploits and combines various features. Furthermore, this system avoids a comprehensive learning phase using a plug-and-play appliance signature database. We plan to extend this work in multiple ways. Firstly, our goal is to integrate as many distinct electrical features into the algorithm as possible. We believe this step will enhance the algorithm accuracy further. Secondly, we would like to investigate continuous variable loads further by using harmonics and EMI signatures. This is because we feel that variable loads can not be neglected in realistic environments. Thirdly, we would like to adjust our approach to different building scenarios. Lastly, we plan to integrate our research results into enhanced smart meters.

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