# Autonomous Load Disaggregation Approach based on Active Power Measurements

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***Abstract*—With the help of smart metering valuable information of the appliance usage can be retrieved. In detail, non-intrusive load monitoring (NILM), also called load disaggregation, tries to identify appliances in the power draw of an household. In this paper an unsupervised load disaggregation approach is proposed that works without a priori knowledge about appliances. The proposed algorithm works autonomously in real time. The number of used appliances and the corresponding appliance models are learned in operation and are progressively updated. The proposed algorithm is considering each useful and suitable detected power state. The algorithm tries to detect power states corresponding to on/off appliances as well as to multi-state appliances based on active power measurements in $1s$ resolution. We evaluated the novel introduced load disaggregation approach on real world data by testing the possibility to disaggregate energy demand on appliance level.**

***Keywords*-Non-intrusive load monitoring, load disaggregation, unsupervised classification and learning, factorial hidden Markov models,**

## I. Introduction

The power draw of a household can potentially reveal a lot of information regarding the used devices, their individual power draw and behavioral patterns of the user(s). While this can constitute a severe privacy problem [1], this information can also be used locally to analyze the usage and power consumption of devices in order to provide information for energy counseling, energy management applications, and increasing energy awareness of users by providing detailed device-level feedback [2]. While we expect a raising number of smart appliances [3] in the future, a considerable number of household appliances will be legacy devices which are not able to directly report their operational data regarding time and consumption. Using a high number of dedicated meters to monitor these devices will be neither cost nor energy-effective. Non-intrusive load monitoring overcomes this problem by applying a single meter approach to acquire a time series of power measurements which are then processed in order to infer about the used appliances. However, many of such load disaggregation algorithms require previous knowledge about the devices employed in the system.

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In this paper we present an unsupervised load disaggregation approach that is able to identify device operations based on the characteristic power changes when devices are switched on/off or switched to a different power state. Given, that power states of devices are distinguishable, the proposed algorithm does not need *a priori* information about the system and autonomously adapts to new or removed devices. The algorithm can be used online and is suitable for operation on low-cost embedded system hardware, for example as part of an energy management system.

The presented approach constitutes an important step towards an automatic disaggregation of electrical loads. The approach is especially suitable for household appliances, since these environments feature typically different power draws out of device pool that is also subject to change over a larger timescale by acquisition of new devices. By presenting a working approach for automatizing the detection of devices without supervision, i.e., without the need for querying the user every time the device pool has changed, this paper lays the ground for a broad application of load disaggregation.

The following section gives an overview on related work on load disaggregation, depicts the problem statement and describes our approach. The particular steps of the algorithm are explained in Section III in detail. The approach has been evaluated in a case study based on available household consumption datasets. Limitations and future work are discussed in Section V before the paper is concluded in Section VI.

## II. Background and Approach

### A. Related Work

The first approach of NILM was introduced by G. Hart [4]. He used active and reactive power readings to establish appliance models based on finite state machine (FSM) which he used to infer an appliance to be on or off. Current approaches solving the load disaggregation problem can be distinguished between supervised and unsupervised approaches. A good overview on supervised approaches are described in [5] and [6]. In the following we are focusing on unsupervised load disaggregation approaches. Unsupervised classification approaches do not need any *a priori* information of the system. In particular, no labelled data is needed to learn models and to perform classification. Recent approaches are based on hidden Markov models (HMMs) [7], on factorial hidden Markov models (FHMMs) [8], on different variations of HMMs [9], [10] and on temporal motif mining [11]. For these approaches the distinction between appliances is unsupervised whereas the labelling which model corresponds to which appliance is done not automatic. Approaches performing automatic labelling are based on Bayesian inference [12] and on semi-supervised classification [13]. The most related approach to the presented work is presented in [14], which provides an unsupervised magnitude-based disaggregation approach based on HMMs. Our work is different to this work in several aspects as the proposed algorithm performs online, is autonomous and self-learning, considers all possible appliance states and needs no learning of appliance transitions which often is subject to erroneous observations. Furthermore, we tested our approach on aggregated data from known appliances which makes the comparison on appliance level power states with the detected power states and inferred power states possible. More information about the evaluation process is presented in IV.

### *B. Problem Statement*

The problem to disaggregate appliance readings from the aggregated power draw is composed by overlapping appliance power draws, where each appliance has a power draw $p_i(t)$ and the aggregated power $P(t)$ can be formulated as the sum of each appliance's power consumption:

$$P(t) = \sum_{i=1}^{N} p_i(t) \tag{1}$$

The variable $N$ represents the number of used appliances. Current research approaches as presented in Section II-A are focusing on unsupervised load disaggregation approaches. The amount of *a priori* information should be minimized without a reduction of the information gain produced by load disaggregation. Without any *a priori* information several problems arise for a load disaggregator and have to be considered:

- The number of used appliances has to be identified. Current clustering approaches need to know the number of used appliances
- The appliance model has to be learned without any *a priori* information and in operation. New appliances should be added to the load disaggregation approach and rarely used appliances should be deleted from the set of appliances used by the load disaggregator.
- Suitable appliance features should be extracted from noisy and low frequency active power readings. The detected features are used to generated meaningful appliance models. The load disaggregator should work based on power magnitudes.

Furthermore, the algorithm should work online. This means on the one hand supporting model learning in operation and on the other hand being capable of making appliance state estimations based on the learned models in real time. Therefore, the computational effort of the approach should be bound (for a reasonable set of appliance models) and match the performance of state-of-the-art embedded hardware.

### *C. Basic Approach*

The proposed load disaggregation approach considers the presented problems of Section II-B and is performing autonomously and in an unsupervised way. No *a priori* information as the number of appliances or appliances informations is needed. The load disaggregation approach is usable with a minimal amount of power reading informations. Our proposed approach can be divided into four processing stages which are visualized in Figure 1.

- **Feature Detection**: Aims to detect significant power edges which can be assigned to appliance switching events. Data preprocessing as signal smoothing and denoising takes place at this processing stage.
- **State Clustering and Appliance Creation**: Power edges are formed to state clusters to identify the most important states or switching events. These states are used to create appliance models used by the load disaggregator.
- **Classification**: With the appliance models generated, appliance states should be estimated by an online load disaggregation approach using low frequency active power readings.
- **Appliance Database Update**: To add, to maintain and to update appliance models in an autonomous way, this stages is responsible to find new power states, to improve the power states of existing appliance models and to delete appliance models which appeared only once or very rarely.

## III. Autonomous Load Disaggregation

The presented load disaggregator is autonomous and unsupervised. No *a priori* knowledge about the number and power value of appliances in the system is needed. The used appliance models are created and updated in operation and are used by the load disaggregator to make estimates which detected appliance was used at which point in time. A system overview of all processing stages is presented in Figure 1 including *feature detection*, *state clustering and appliance creation*, *classification*, and *appliance database update*. In the following each processing stage is described in detail.

### *A. Feature Detection*

One of the major tasks of the proposed load disaggregation approach is to detect and to identify useful appliance features. According to our assumption we focus on smart metering readings of active power ratings with a measurements resolution of $1Hz$ due to low costs of a sensing platform and lower computation and storage costs compared to high frequency measurements. With the aggregated power readings we aim to extract appliance features based on appliance switching events. In detail, we concentrate on switching ON and switching OFF events where all power states of an appliance are taken under consideration. The task is to produce abrupt edges with a significant change without losing important appliance related information in which power transients can last several seconds in real. Due to the fact that measurement readings are affected by noise, the readings have to be preprocessed to get

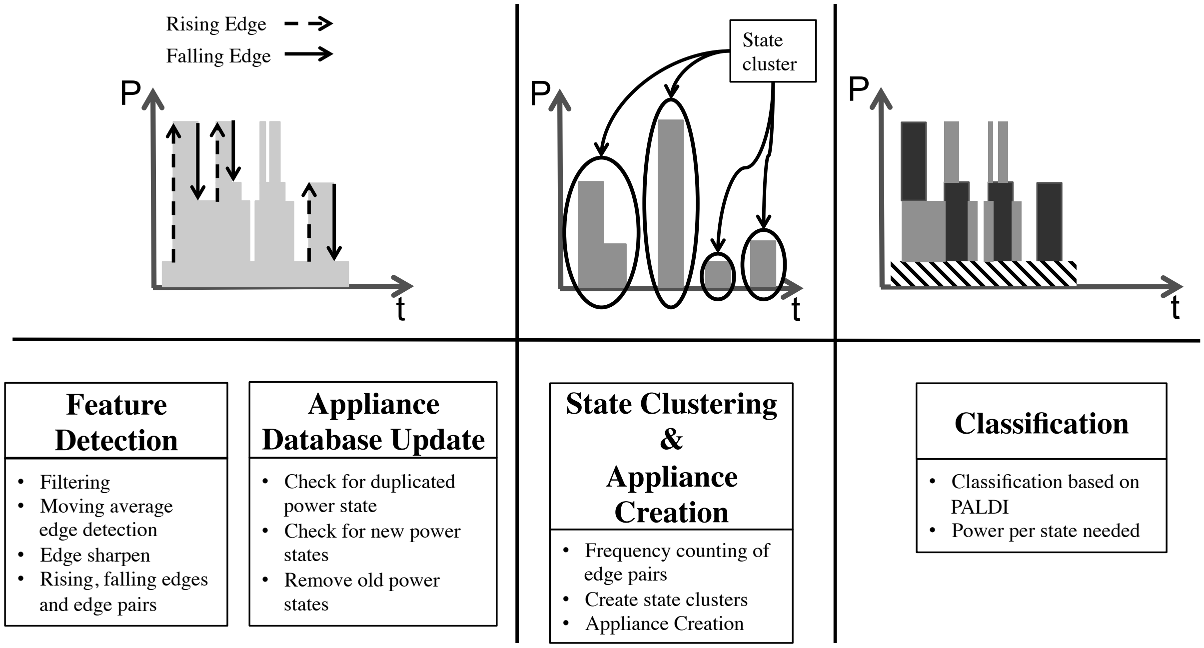


Fig. 1: General computation sequence of the unsupervised disaggregation approach. At the first stage the power draw is preprocessing by filtering and smoothing the signal to perform edge detection. Detected rising and falling edges are paired together trying to find searched appliance power states. Power states are used to model appliances, which are finally used to disaggregated the appliance power draws from the total demand.

sufficient and satisfying data. Thus, we de-noise the power readings by median filtering with an appropriate window size 30 samples which was empirically identified in which the common operation duration of the used appliances was considered to be larger than 30 seconds. The window size has to be chosen carefully since a window chosen too wide could lead to information loss by wiping out important edges. Edge detection based on moving average and thresholding is applied on the filtered power readings to detect rising as well as falling edges. All rising and falling edges are checked for matching pairs to create a pool of possible appliance power states. This processing stage is performed on a sliding time window of predefined size. We empirically identified one day as a suitable time window balancing a fair amount of switching events needed by processing stages. We claim that it is a sufficient assumption that an appliance is on at least one time a day.

### *B. State Clustering and Appliance Creation*

The pool of occurred power edges is the basis for the following analysing process which aims to create appliance models used by the final classifier. To create appliance models, the first task is to create a histogram of all edge pairs detected by the feature detectors. The created histogram counts the occurred power edges from 0 to $3000W$ each $5W$. Thus, the maximum allowed power consumption as well as the power granularity are chosen empirically and can be changed according to used appliances. Next, clustering combines similar occurred edges to one edge pair representing a possible appliance power state. The set of possible power states is used to create appliance models including their nominal power consumption in operation. The appliance models are saved in a simple database which is updated in use. In detail, new appliances according to newly occurred power states are included and appliance models and power states which occur rarely are removed from the appliance model database. We model each appliance as an HMM described by an initial state, by its transition matrix, and by its observations matrix. The detected power states are assigned to the observation matrix of a HMM representing the appliance power demand in operation. The off state $(0W)$ is assigned to each appliance HMM as second observation and as the initial state. The total power demand is modelled by an FHMM where the set of appliance HMMs aggregate their power observations over time.

### *C. Classification*

Our appliance classifier is based on Baysian inference. We use the online load disaggregator presented in [15]. The approach is based on particle filtering (PF) aiming to approximate the posterior density of the FHMM. The approach disaggregates each appliance power demand and appliance state from the household demand, according to the current observed consumption and the given appliance models. The PF output estimates the household consumption and inputs this information and the appliance models to a simple decision maker based on thresholding. The use of a PF as load disaggregator is beneficial for three reasons. First, PF can handle non-linear problems presented by non-linear behaving loads such as a driller or a dimmer. Second, it can handle non-Gaussian noise influences resulting from uncertainty in power trends and consumption data. Third, PF and its performance can be adjusted by the number of used particles. The more particles the PF considers, the better is the estimated posterior density. The number of particles is limited by the computational effort of the approximation process. We empirically identified $1000$ particles as an appropriate number balancing the trade-off between the context of computational effort and detection performance. Exact knowledge of the transition matrix is not necessary since the PF is independently estimating the appliance states by an appropriate number of used particles. In case of a two-state appliance represented by a two-state transition matrix, a clear trend should be visible which state is more probable than the other. This simplifies the appliance modelling stage and makes the approach of [15] usable for the appliance models employed in this work. The disaggregation process is performed on each measurement sample (each second) and considers only the current power sample for the estimation process.

### D. Appliance Database Update

In each time window power edges and appliances are generated. It is obvious that one time window is not representative for an set of appliances. Appliances are used in different times and days as wells as repetitions. Thus, the process to generate appliances has to be performed on each time window which rises the need to update saved appliance models. We implemented an updating process which is checking for new appliances and power states, for appliances or power states which are similar to existing appliances and for appliances which are only rarely used. We are tracking appliance usage meta data including power state, appearance per day, power estimates and operational time for each day. The parameters are used to update the saved appliance model database. Moreover, we use a threshold of $50W$ to distinguish between two appliances which we claim to be a sufficient assumption due to number of different appliances and their significant power consumption differences. Thus, each detected power state with a difference higher than $50W$ are modelled as an appliance which lead to a set of on/off appliances.

## IV. Evaluation

### A. Implementation & Evaluation Settings

We implemented the presented unsupervised approach in Matlab. As input of the approach we used an aggregated consumption dataset based on measurements from real households. No further input is forwarded to the approach. The presented tests and evaluations are based on simulations and were run on a MacBook Pro, 2,8GHz with 8GB RAM. To test the approach we evaluated error between the energy allocated per appliance against the estimated energy per appliance. Due to the fact that the unsupervised approach is based on unlabelled data, the labelling of the power states and appliances was made empirically by the human. Each detected appliance is mapped to the known power state of the ground truth and to the "*unknown*" appliance state container. The "*unknown*" appliance state container presents appliance states which were not previously identified by the human but were detected by the algorithm. Appliance are grouped to virtual appliances, if appliances have similar power states as for example an appliance has a power state $200W$ and another appliance has a power state $220W$. The creation of virtual appliances for the evaluation is needed due to the fact that the algorithm is modelling each appliance has an on/off appliance but is considering all possible states from on/off and multi-state appliances.

### B. Dataset

There exists several publicly available datasets which can be employed to the test our proposed approach such as the REDD dataset [16], the GREEND dataset [17] and the ECO-dataset [18]. We chose the REDD dataset as reference because of the recording parameters and due to its wide application as a standard test set. This dataset offers active power readings on appliance level at approximately 1Hz resolution for 6 different houses. We took house $1$ of the dataset for evaluation using six appliances (oven, fridge, dishwasher, kitchen outlet, microwave, washing dryer) to generate the aggregated power load. The appliances were chosen based on to their contribution to the household power demand [19]. As time period we took 30 consecutive days.

### C. Case Study

*1) Number of Detected Power States per Day:* The presented approch has no *a priori* information about the number of appliances and the number of power states. Thus, one big task is to detect power states and map these power states to states empirically identified as reference power states. To evaluate the performance we took for each day the reference power state and the estimated power states. Firstly, the power draw is de-noised and smoothed as presented in Figure 2. High frequency fluctuations are removed and a steady state of the power draw is reached by sharpening the edges. This stage is helpful and necessary for the edge detection. After removing

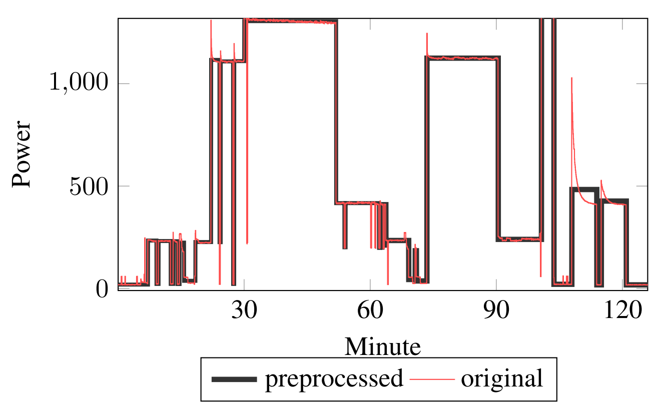


Fig. 2: Measured power signal vs. pre-processed power signal. The de-noising and smoothing filter remove high frequency fluctuations

these power fluctuations, the power states are detected by edge detection and state clustering. We tried to map the detected power states to the real ones by a simple distance measure. As reference value we took a difference of $50W$. The result are two numbers representing the number of appliance states able to be mapped to reference power states and the number of power states which can not be mapped to reference power states. The reference power states are empirically identified and therefore, we claim that appliance power states in group of not assignable power states are not necessarily false detected, but means that they belong to appliance states that are rarely occurring and were not detected by the human as reference. In total, the following 9 appliance states are possible: $100, 200, 390, 800, 1100, 1500, 1650, 2600$ and $2720$ Watts.

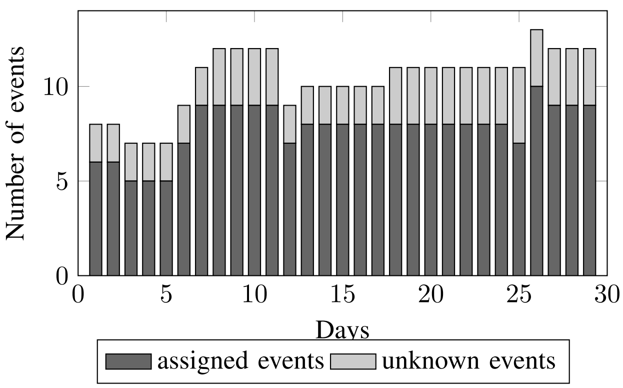


Fig. 3: Number of power events detected and assignable to real power events. The number of real power events is 9.

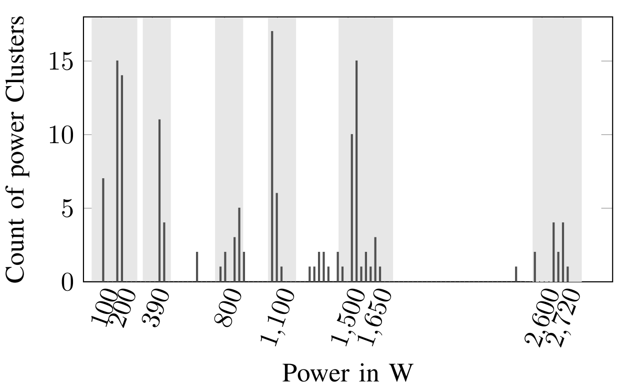


Fig. 4: Histogram of all detected power events over the observation window. The light-gray areas indicate the real power states identified empirically

Figure 3 presents the results of detected and assignable/not assignable power states per day for 30 consecutive days of 6 different household appliances. The graph shows that the number of detected power states is getting better (best result are 9 appliance states) and nearly stable over days in operation. State variations are according to new detected power states from new appliances and their power states The number of not assignable appliances stagnate since power states which are occurring frequently are not eliminated by

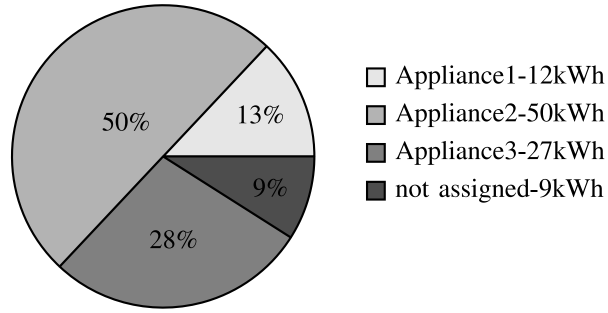


Fig. 5: Pie chart of the estimated energy for the virtual appliances and power states which can be assigned to power states

the database update process. Figure 4 illustrates the known appliance power states (gray area) against the detected power states (black bars) for a time duration of 30 days. Most of the detected power states are in the regions of the appliance states detected by the human. The power region between $1200W$ and $1500W$ indicates that the algorithm detects appliance state which were not identified empirically by hand.

*2) Load Disaggregation error on appliance level and for the total power draw:* The previous case study was evaluating how well the unsupervised state detection and appliance modelling process is working. In the second case study the generated appliance models are used by the presented load disaggregation classification approach. In detail, appliances are modelled as HMMs where the transition matrix is set a-priori. To make the ground-truth appliance data comparable with the results of the load disaggregator we treat appliances with sufficiently similar power states as the same virtual appliances. Therefore, if an appliance A has a power demand of $200W$ and appliance B has a demand of $220W$, these appliances are combined to one virtual appliance. This results in 3 virtual appliances for the used dataset and appliances. Finally, we tried to assign the detected appliance states by the proposed approach to the 3 virtual appliances. Power states not assignable are marked as *unKnown*. In Figure 5 the power shares of the estimated energy per virtual appliance and not assignable power share are presented. As comparison the ground truth pie chart of the power shares is illustrated in Figure 6. The results show that the estimation error is satisfying in which the error between the estimated ($100kWh$) and the real consumed energy ($98kWh$) is around$2\%$. Most of the estimated appliance models and their power estimates can be assigned to virtual appliances. Around $9\%$ of the estimated energy can not be assigned to an virtual appliance which is on the one hand due to erroneous appliance classification and on the other hand due to number of not detected power events as in Figure 4.

## V. Limitations & Future Work

The presented approach has limitations which has to be improved by future research. For example, the approach is

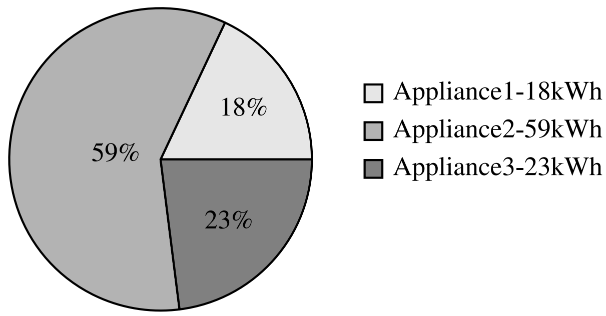


Fig. 6: Pie chart of the ground truth energy for virtual appliance power states

considering two-state appliance models in which the state detection stage is already detecting all possible power states. These power states can be part of an multi-state device. Thus, we aiming to define rules and algorithms how to combine power events to multi-state appliance models. Further, we want also to improve the state detection process concerning long lasting power transients of appliances. Some appliances and appliance types have transients which last for several seconds. This should be improved by advanced detection algorithms. Finally, the problem of automatic appliance labelling to the correct appliance type is not considered yet. Future work has to consider how to label detected appliances according to the detection history and general appliance type information as general operation duration or occurrence frequency per day.

## VI. Conclusion

In this paper an unsupervised approach to solve the problem to disaggregate appliance power draws from the aggregated power load was presented. The approach autonomously detects the power states of the used appliances. It improves the saved appliance models in operation and updates the appliance database by adding new appliance models and maintaining saved appliance models. The detected appliance models can be used by the load disaggregator to estimate the appliance states. The estimation results are promising in particular because of the low amount on not assignable energies and the good overall estimation result. The models for each appliance are learned at run-time. The algorithm contains a preprocessing stage to de-noise and smooth the aggregated power draw in a way to be able to detect sharp and significant power edges. Appliance models are established as on/off appliances only with the knowledge of detected power edges and are finally used by the load disaggregator based on particle filtering. The approach is evaluated on real measurement data where our results emphasizes the proposed NILM approach as a very promising approach. The number of detected appliance states and the corresponding disaggregation result is sufficient and satisfying and had been achieved without appliance information from the user. Future work will aim at multiple appliance modelling and automatic appliance labelling.

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