# PALDi: Online Load Disaggregation via Particle Filtering

Dominik Egarter, *Student Member, IEEE*, Venkata Pathuri Bhuvana, and Wilfried Elmenreich, *Senior Member, IEEE*

***Abstract*— Smart metering and fine-grained energy data are one of the major enablers for future smart grid and improved energy efficiency in smart homes. Using the information provided by smart meter power draw, valuable information can be extracted as disaggregated appliance power draws by non-intrusive load monitoring (NILM). NILM allows to identify appliances according to their power characteristics in the total power consumption of a household, measured by one sensor, the smart meter. In this paper, we present an NILM approach, where the appliance states are estimated by particle filtering (PF). PF is used for nonlinear and non-Gaussian disturbed problems and is suitable to estimate the appliance state. ON/OFF appliances, multistate appliances, or combinations of them are modeled by hidden Markov models, and their combinations result in a factorial hidden Markov model modeling the household power demand. We evaluate the PF-based NILM approach on synthetic and on real data from a well-known dataset to show that our approach achieves an accuracy of 90% on real household power draws.**

***Index Terms*— Factorial hidden Markov model (FHMM), hidden Markov model (HMM), load disaggregation, non-intrusive load monitoring (NILM), particle filter (PF), state estimation.**

## I. Introduction

THE smart grid aims to improve the current grid to be more efficient, reliable, and to support sustainable energy sources. Modern smart meters provide fine-grained demand information of households where not only the consumers get the overall cost of his/her consumption, but also future consumers of energy will get the possibility to see which amount of power is used at which point in time [1]. This will give the consumers the opportunity to establish and to develop an energy-aware behavior, which accordingly can lead to a reduction of the energy demand as well as of the energy costs [2]. Different studies [2], [3] showed that 20–40% of the overall consumption of a country is determined by the domestic household consumption. Improving the energy awareness at household level is one of the major issues in future energy research. Smart meters are a key factor to support and improve the future smart grid.

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D. Egarter and W. Elmenreich are with the Institute of Networked Embedded Systems, Alpen-Adria-University Klagenfurt, Klagenfurt 9020, Austria (e-mail: dominik.egarter@aau.at; wilfried.elmenreich@aau.at).

V. P. Bhuvana is with the Department of Marine Engineering, Electrical, Electronics, and Telecommunications, University of Genova, Genoa 16126, Italy (e-mail: venkata.pathuri@aau.at).

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Smart meters provide the possibility to show the consumers not only when and what quantity of power is consumed, but also which appliance is consuming what amount of power at what time. Therefore, the household energy demand is disaggregated to individual appliances, which, additionally, can lead to energy savings of up to 12% through a real-time energy feedback at appliance level [2]. One possible way to provide energy data at appliance level would be to equip each device at home with a metering and monitoring unit, but this approach comes with high acquisition, installation and communication costs. Another approach was based on a single sensor monitoring the overall energy consumption of a house[1] on the grid connection point was introduced in [4] and was designated first under the name non-intrusive appliance load monitoring. Recently, the terms non-intrusive load monitoring (NILM) and load disaggregation are used in the same context as the term proposed by Hart and are used synonymously in this paper. NILM aims to identify appliances according to the appliance power characteristics. Different appliance types such as refrigerators and water kettles have different power characteristics. Some appliances consume their power in an ON/OFF switching manner whereas others consume the power in a continuous manner according to the load [5]. NILM approaches use this information with smart algorithms and techniques to identify and classify single appliances in the total power load. Until now, a variety of NILM algorithms were proposed, but no approach could solve the disaggregation problem in all its diversity. Zeifman [6] suggested that a NILM approach should fulfill the following requirements to be able to contribute positively for energy-efficient management systems and to solve the problem of aggregated power profiles.

1) The selected feature should be the active power sample at 1 Hz.
2) The minimum acceptable accuracy of the algorithm is 80%–90%.
3) No algorithm training should be necessary.
4) The algorithm should perform in real time.
5) The method should be scalable in the sense of robustness and number of used appliances up to 20–30 devices.
6) The types of used appliances should be diverse. It should work for the following appliance types [5]: ON/OFF appliances, multistate appliances, continuous consuming appliances, and permanent consuming devices.

[1]The household demand is the aggregated power demand of all used appliances in the household.

Accordingly, we claim that a modern and novel load disaggregation algorithm should fulfill the presented requirements due to its applicability with modern smart meters and due to a simplified computational effort. The approach, we propose, is based on the work in [7]. It is unsupervised and contains appliance models based on hidden Markov models (HMMs). We model our household consumption using the factorial HMM (FHMM). The problem of disaggregating aggregated appliances is computationally complex and suffers on nonlinearity if instead of ON/OFF and multistate appliance, nonlinear appliances such as a drill are used. It suffers from non-Gaussian noise according to appliances that have activities not consciously noticed or where the existence of the appliance is not known. To solve the problem, the Viterbi algorithm [8] could be used to compute the inference of the HMM. Nevertheless, in the case of an FHMM, the Viterbi algorithm is no longer usable for computing the inference. Therefore, approximation methods such as Gibbs sampling [9] should be applied. Recent NILM approaches that are stressing on this topic are based on approximating the FHMM interference by Kolter and Jaakkola [10] or making use of structural variational approximation methods by Zoha *et al.* [11]. The work of Zoha uses several appliance features such as active reactive power. Our proposed approach is based on simple active power features in one second granularity. This supports a wide range of state-of-the-art smart meters. However, we propose the well-known estimation approach of sequential Monte Carlo or PF to estimate disaggregated appliance states. PF is a suitable approach for state estimation problems with nonlinear behavior and non-Gaussian noise in different areas of application such as industrial systems [12]. We show that PF is an alternative to current proposed NILM solutions that meet the requirements identified by [6]. We evaluate our approach on synthetic household power draws to show the ability of the algorithm to detect appliance states of up to 18 different appliances, and we test the approach on the well-known REDD data set [13] to make the proposed approach comparable and real-world tested. The remainder of this paper is organized as follows. In Section II, we describe how an appliance and how the total household consumption is modeled by the HMM and the FHMM. In Section III, we provide information about the basic knowledge of particle filtering and how particle filtering can be used to estimate appliance states using measured data, followed by Section IV that explains how the evaluation of the proposed approach is established, which evaluation metric is used, and which test scenarios are evaluated. Moreover, Section VI shows the results of the proposed algorithm based on the evaluation mechanisms defined in Section IV. Finally, the proposed approach and the achieved results are discussed in Section VII, related work is presented in Section VIII, and we concluded this paper in Section IX.

## II. Household and Appliance Model

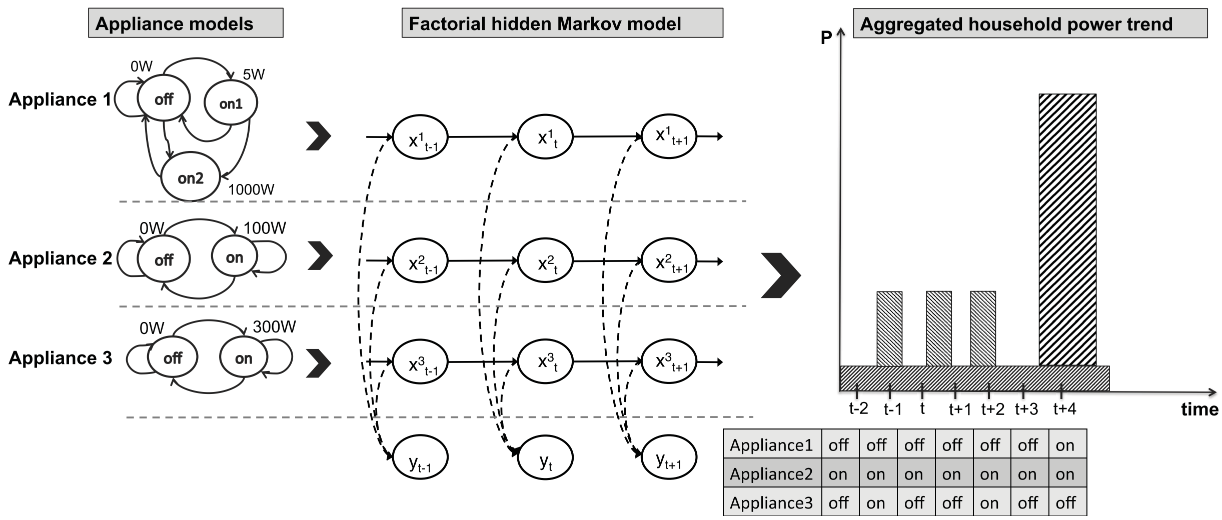
The load of a household is characterized by the power profiles of household appliances. Thus, the total power load is the aggregated sum of power profiles, where each appliance is modeled by a HMM, and the total power consumption is modeled by FHMM. In the following section, we describe in detail how the appliance and household model is generated and established.

To model the time series behavior of an appliance, we describe each appliance as a HMM [14]. The HMM is a probabilistic graphical model describing time series as a Markov model, in which the states are not directly observable. The state of a HMM is characterized by a probability distribution function. States cannot be directly observed but can be estimated from the available measurements. The HMM model has $n$ hidden states $s = \{s_1, \ldots, s_n\}$ as well as a transition matrix $A = \{a_{i,j} \leq i, j \leq n\}$ representing the state transition from $s_i$ to $s_j$. In detail, $a_{ij} = P(x_{t+1} = s_j \mid x_t = s_i))$, where $a_{ij} > 0$ and $\sum_{j=0}^{n} a_{ij} = 1$. The term $x_t$ is the state observable at each time slice $t$, which represents the power consumption of an appliance in a particular state. The HMM of an appliance is a discrete-time model because the observed time $T$ is separated into equally spaced time slices $t$. Furthermore, an emission matrix $B$ must be defined for the HMM, which represents a symbol in an actual state. In the appliance model, the emission matrix shows the possible power values in each state of an appliance. Finally, the initial probability $\pi = P(x_1 = s_i)$ must be defined for the HMM. The vector $\mathbf{z} = \{\mathbf{z_1}, \mathbf{z_2}, \ldots, \mathbf{z_t}\}$ is the result of the hidden states $\mathbf{x} = \{\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_t}\}$, where the next state of the HMM is dependent on the HMM's current state and is independent of past states. This is the Markov property $P(x_{t+1} \mid x_t, x_{t-1}, \ldots, x_1) = P(x_{t+1} \mid x_t)$. In Fig. 1, an example for a general model of an ON/OFF appliance model used to generate the hidden states is shown. In this paper, we consider ON/OFF devices and multistate appliances with several power states. Thus, the appliances are dependent on more than two different states and accordingly, the parameter matrices of the HMM $\{\pi, A, B\}$ grow by the number of states $n$. To establish a desired appliance type such as a standby device, the definition of $A$ and $B$ is the crucial task of the appliance model design. The two matrices $A$ and $B$ have to be learned online or offline with or without knowledge about the HMM. The knowledge of the HMM includes, for example, information of the appliance structure (such as an ON/OFF appliance) or information about a generic appliance structure that is refined during operation time [15]. In this paper, $A$ and $B$ have been selected either randomly in a predefined range or based on learned models from measured appliance power profiles.

The household power profile can be observed as the aggregate power profile of $N$ different appliances such as $Y = \{y_1, y_2, \ldots, y_t\}$ and is generated by the state sequence of $x = \{x^{(1)}, x^{(2)}, \ldots, x^N\}$, which is the superposition of the appliance states at each time slice $x^{(n)} = \{x_1^{(n)}, x_2^{(n)}, \ldots, x_t^{(n)}\}$. The household model is based on an FHMM. An FHMM is commonly used to model multiple independent hidden states and to decrease the number of parameters in contrast to using a standard HMM with a large set of operational states. The general structure of an FHMM is represented in Fig. 1.

## III. State Estimation

In the following sections, we discuss background information on particle filtering and on how to apply particle filtering to the problem of appliance state estimation.




| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Appliance1 | off | off | off | off | off | off | on |
| Appliance2 | on | on | on | on | on | on | on |
| Appliance3 | off | on | off | off | on | off | off |

Fig. 1. Appliance models for ON/OFF or multistate appliances, a sketch of the FHMM model, and the power draw of the aggregated power trends for three appliances.

We start with Bayesian estimation, explain the shortcomings of using Bayesian estimation with nonlinear problems and non-Gaussian noise and present the particle filter as a solution for this problem.

### A. Sequential Bayesian Estimation

According to the Bayesian approach, the state of a physical system $x_t$ at time $t$ can be inferred from the probability density function (PDF) of a state given all the measurement $y_{1:t}$ until time $t$. The sequential Bayesian estimation has two primary steps at every time instance $t$.

1) State prediction predicting the state as the expectation of the prediction PDF is as follows:

$$p(\mathbf{x}_t \mid \mathbf{y}_{t-1}) = \int p(\mathbf{x}_{t-1} \mid \mathbf{y}_{t-1}) p(\mathbf{x}_t \mid \mathbf{x}_{t-1}) d\mathbf{x}_{t-1} \quad (1)$$

where $p(\mathbf{x}_{t-1} \mid \mathbf{y}_{t-1})$ is the posterior PDF available from time $t-1$ and $p(\mathbf{x}_t \mid \mathbf{x}_{t-1})$ is the state transition probability given by the system process model.

2) Measurement update, where upon receiving the measurement, the predicted state is computed as expectation of the posterior PDF

$$p(\mathbf{x}_t \mid \mathbf{y}_t) = \frac{p(\mathbf{x}_t \mid \mathbf{y}_{t-1}) p(\mathbf{y}_t \mid \mathbf{x}_t)}{\int p(\mathbf{x}_t \mid \mathbf{y}_{t-1}) p(\mathbf{y}_t \mid \mathbf{x}_t) d\mathbf{x}_t} \quad (2)$$

where the $p(\mathbf{y}_t \mid \mathbf{x}_t)$ is the likelihood PDF given by the measurement model of the system. The Kalman filter [16] can be used to solve the integrals in (1) and (2) if the system is linear with additive white Gaussian noise. In contrast, if the physical systems are nonlinear, then these integrals are intractable. Often, nonlinear state estimation methods such as PF are used to approximate these integrals.

### B. Particle Filter (PF)

PF calculates weighted particles or Monte Carlo samples to approximate the PDFs as in (1) and (2). Particles are propagated over time to obtain new particles and the weights, resulting in a series of PDF approximations. The approximation of the PDF becomes more accurate with an increasing number of samples. In many cases, the sampling of the required PDF is not possible. In such cases, the samples drawn from a different PDF (importance PDF) are used to approximate the required PDF. It is called importance sampling. Let $\{\mathbf{x}^i_{0:t}, \mathbf{w}^i_t\}^{Np}_{i=1}$ be the set of random samples, $x^i_{0:1}$, drawn from the importance density $q(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t})$ and their associated weights, $w^i_t$, for $1 \ldots N_p$ where $N_p$ is the number of particles. Then the required PDF can be approximated as

$$p(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t}) \approx \sum_{i=1}^{Np} \mathbf{w}^i_t \delta\left(\mathbf{x}_{0:t} - \mathbf{x}^i_{0:t}\right) \quad (3)$$

where $\delta$ is the unit dirac function and the weights are defined as

$$\mathbf{w}^i_t = \frac{p\left(\mathbf{x}^i_{0:t} \mid \mathbf{y}_{1:t}\right)}{q\left(\mathbf{x}^i_{0:t} \mid \mathbf{y}_{1:t}\right)}. \quad (4)$$

In the case of sequential importance resampling (SIS) [16], the samples and corresponding weights $\{\mathbf{x}^i_{0:t-1}, \mathbf{w}^i_{t-1}\}^{Np}_{i=1}$, which approximate $p(\mathbf{x}_{0:t-1} \mid \mathbf{y}_{1:t-1})$ are known at time $t$. If the importance density for approximating $p(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t})$ is chosen in such a way that

$$q(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t}) = q(\mathbf{x}_t \mid \mathbf{x}_{0:t-1}, \mathbf{y}_t) q(\mathbf{x}_{0:t-1} \mid \mathbf{y}_{1:t-1}) \quad (5)$$

then the new samples $x^i_{0:t} \approx q(x_{0:t}|y_{1:t})$ can be obtained by augmenting the existing samples $x^i_{0:t-1} \approx q(x_{0:t-1}|y_{1:t-1})$ with the new state $x^i_t \approx q(x_t|x_{0:t-1}, y_{1:t})$. The corresponding weight update equation is given as

$$\mathbf{w}^i_t = \mathbf{w}^i_{t-1} \frac{p\left(\mathbf{y}_t \mid \mathbf{x}^i_t\right) p\left(\mathbf{x}^i_t \mid \mathbf{x}^i_{t-1}\right)}{q\left(\mathbf{x}^i_t \mid \mathbf{x}^i_{0:t-1}, \mathbf{y}_t\right)}. \quad (6)$$

Now, the required PDF at time $t$ can be approximated as

$$p(x_{0:t}|y_{1:t}) \approx \sum_{i=1}^{Np} w^i_t \delta\left(x_t - x^i_{0:t}\right). \quad (7)$$

However, the SIS algorithm suffers from the degeneracy problem in which all but a few particles have negligible weights. Due to the degeneracy, large computational effort is expended for updating the particles with less contribution to the approximation of the required PDF. One solution to overcome degeneracy is resampling. The resampling process eliminates particles with negligible weights by replacing them with particles with large weights $\{\mathbf{x}_{0:t}^{*i}, \mathbf{w}_t^{*i}\}_{i=1}^{Np}$. Several resampling techniques are proposed in [16]. Then, the PDF can be approximated as

$$p(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t}) \approx \sum_{i}^{Np} w_t^{*i} \delta\big(\mathbf{x}_t - \mathbf{x}_t^{*i}\big). \tag{8}$$

The PF algorithm is given as: at time $t$, $\{\mathbf{x}_{t-1}^{*i}, \mathbf{w}_{t-1}^{*i}\}_{i=1}^{Np}$ are known. The new samples are generated by

$$\mathbf{x}_t^i \sim p\big(\mathbf{x}_t \mid \mathbf{x}_{t-1}^{*i}\big)\big|_{i=1}^{Np}.$$

The weights are updated by

$$\mathbf{w}_t^i = p\big(\mathbf{y}_t \mid \mathbf{x}_t^i\big)\big|_{i=1}^{Np}.$$

*1) Resampling:* The particles are resampled using the auxiliary resampling [16] as

$$\big\{\mathbf{x}_t^{*i}, \mathbf{w}_t^{*i}\big\}\big|_{i=1}^{Np} = \text{Resampling}\big\{\mathbf{x}_t^i, \mathbf{w}_t^i\big\}\big|_{i=1}^{Np}.$$

The state estimate is given by the sample mean of the resampled particles $\mathbf{x}_t^{i*}$.

### C. Particle Filter-Based Load Disaggregation—PALDi

PF is an alternative choice to disaggregate power loads for several reasons. Firstly, to model appliances and their usage in a realistic way, a probabilistic modeling method such as a HMM is necessary. To infer the most probable state of the HMM for each appliance, the posterior density of the whole appliance state space has to be estimated according to the observation. This could be estimated online by particle filtering (PF). The advantage of PF in the sense of aggregated power loads is the fact that PF can handle large state spaces as in the case of several appliances with multiple operation states. Moreover, PF could be used as an approximation technique for the FHMM. Second, ON/OFF and multistate appliances behave in a linear way whereas a continuous behaving appliance such as a drill or dimmer show nonlinear behavior. This motivates the usage of PF to make the proposed NILM approach usable for all kinds of appliance types. Thirdly, the appliance model generated by the HMM and household power consumption established by the FHMM suffer from non-Gaussian noise. In particular, the used appliance could suffer from noise due to inaccuracies and the aggregated power consumption could be disturbed. Considering the aggregated power consumption, all appliance and corresponding power draws are regarded as non-Gaussian noise if these appliances are not known by the estimation process. In detail, each HMM represents an appliance with its hidden appliance states $x_t$ and its recognizable power consumptions as observation value of the HMM. For each HMM, it is necessary to describe offline, the structure, the transition matrix and the observations. All appliance HMMs are conducted by the FHMM, where all hidden appliance states of the HMMs are aggregating their power consumptions to the total household power consumption. The total household demand is represented by the observation of the FHMM. The PF is used to estimate the posterior density of the FHMM according to the appliance models and the observed household power consumption. The outputs of the PF are power values for each appliance, which are aggregated at each point in time. The PF has the characteristics to randomly adjust the estimated power observation for each appliance in predefined ranges. The reason for that is to estimate and to compensate for appliance inaccuracy in the appliance power consumption. However, the PF itself is not providing the information as to in which state an appliance is operating; it delivers power values which are given to a decision-making process. The decision-making process has knowledge of the power demand of each appliance operation state. It decides, accordingly, in which state each appliance is at each point in time by a simple thresholding approach.

## IV. Evaluation Settings

In the following section, the evaluation settings for the simulations on synthetic data are described and the evaluation metric for the proposed approach is defined.

### A. Settings on Synthetic Data

To generate a synthetic total power load $P(t)$, ON/OFF appliances are modeled by their power demand $p_d$, the average usage time $t_{\mathrm{ON}}$, and the average occurrence frequency of an appliance $f_{\mathrm{ON}}$. This parameter $\{p_d, f_{\mathrm{ON}}, t_{\mathrm{ON}}\}$ is initialized as follows.

1) Power demand $p_d$ is a uniformly distributed variable in the range $p_d \in \{100, 3000\}$ in Watts (W).
2) Average usage time $t_{\mathrm{ON}}$ is a uniformly distributed variable in the range $t_{\mathrm{ON}} \in \{60, 3600\}$ in seconds (s).
3) Average occurrence $f_{\mathrm{ON}}$ is a uniformly distributed variable in the range $f_{\mathrm{ON}} \in \{1, 10\}$ in average number of occurrences per day.

The information of $\{p_d, f_{\mathrm{ON}}, t_{\mathrm{ON}}\}$ is fed into the transition matrix $A$ and the observation matrix $B$. Thus, for an ON/OFF appliance, the ON probability is $p_{\mathrm{ON}} = f_{\mathrm{ON}}/T$, where $T = 86\,400$ s and the OFF probability $p_{\mathrm{OFF}} = 1/t_{\mathrm{ON}}$. The observation matrix is built up by $B = \{0, p_d\}$, where $B = 0$ belongs to the appliance OFF state and $B = p_d$ belongs to the ON state. Multistate appliances are defined in a similar way. The transition matrix $A$ is defined in a way that the ON probability is chosen equivalently for ON/OFF appliances. The transition states from one state to the other state are defined by $t_{\mathrm{ON}}$ and is the same for each transition from one state to another state. The probability of staying in the same state is calculated by 1 minus the sum of all other transition probabilities. The observation power demand matrix $B_m$ is defined by the power demand values for each appliance state. Unless stated otherwise, we used a sampling frequency of 1 s, one simulation run corresponds to one day of 86 400 s, and in general, 100 simulation runs for each test scenario and configuration were computed.

### B. Real-World Dataset: REDD

We decided to use the REDD dataset as real-world dataset because the data were recorded for several appliances and houses over several days [13] and it is well known in the research community. For our evaluations, we used house 1, where each appliance is defined by the recorded apparent power. We choose six different appliances that are common in households and are affecting the energy consumption of a household in a significant way [3]. The REDD dataset offers submetered power profiles, i.e., the devices are known and the load is already disaggregated. We calculated an overall power profile based on the submetered data which were fed into PALDi.[2] PALDi is a model-based state estimation approach, thus for each used appliance, the transition matrix $A$ and the observations matrix $B$ have to be determined. For this, we used the matrix laboratory (MATLAB) preprogrammed HMM functions to construct the matrices $A$ and $B$. According to the appliance types, we used ON/OFF appliances and multistate appliances, where we give the algorithm the possibility to adjust its used power demand for each iteration. The used sampling frequency is 1 s.

### C. Evaluation Metrics

To evaluate the performance and the precision of the proposed approach, we use the normalized root-mean-square error (RMSE) and the accuracy of the classification. The normalized RMSE is formulated as

$$\mathrm{RMSE} = \frac{\sqrt{E((\hat{\Theta} - \Theta))^2}}{\max(\Theta) - \min(\Theta)} \tag{9}$$

where $\Theta$ represents the true total power load, $\hat{\Theta}$, the estimated total power load produced by PALDi, and $\max(\Theta)$ and $\min(\Theta)$, the maximum and minimum power values of the total power load. To be able to formulate the accuracy of the classification process, the following classification terms have to be defined such as TP (number of times an appliance is correctly detected as ON), FP (number of times an appliance is wrongly detected as ON), FN (number of times an appliance is wrongly detected as OFF), and TN (number of times an appliance is correctly detected as OFF). The classification terms TP, FP, FN, and TN are straightforward for ON/OFF appliances. Considering multistate appliances, we remark that we consider only the operating state if an appliance is ON or OFF and not, if a device is in a certain operating state. With the mentioned classification terms, the overall classification result is calculated by combining TP, FP, FN, and TN to the accuracy metric

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \in [0, 1] \tag{10}$$

where ACC represents how accurate appliance states can be detected by the proposed approach. Both presented metrics are computed by the mean of the achieved metric value for each simulation run whereas the metric value for each simulation run is computed by means of the reached metric values at the appliance level.

[2]The submetered power profiles have a varying sampling frequency and are partially out of order, which makes it necessary to adjust the sampling frequency on an equal level using interpolation.

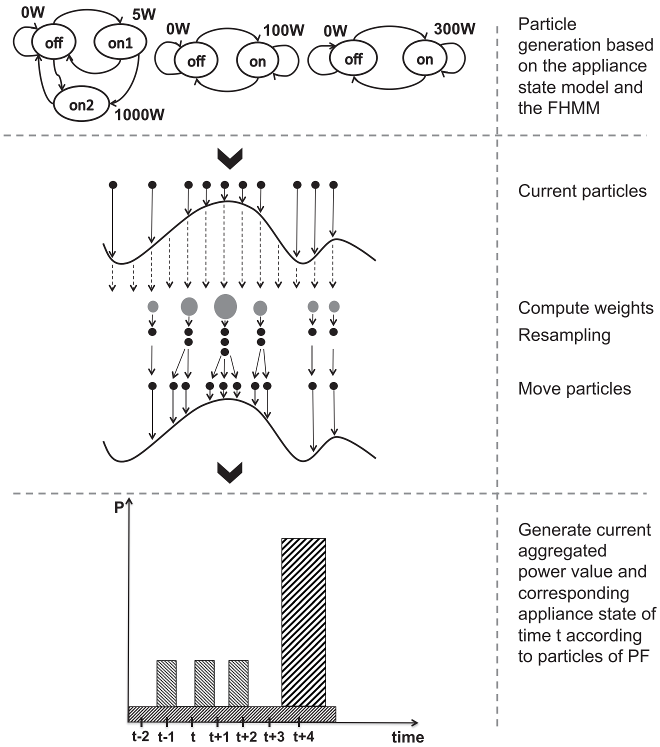



Fig. 2. General algorithm sequence of the PF.

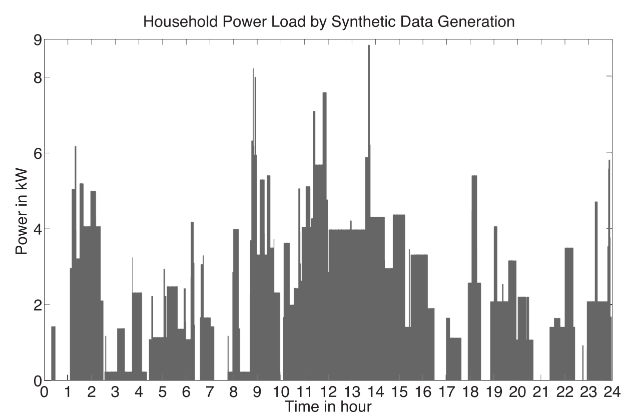



Fig. 3. Household power load of one day generated by the synthetic HMM model.

## V. Evaluation Scenarios

### A. Synthetic Dataset

In the following, different test scenarios are described. The used appliance model is defined by the synthetic HMM model of Section IV-A. An example for the power load generation by the FHMM household model is shown in Figs. 2 and 3.

*1) Scenario for a Varying Number of Aggregated Appliances:* The number of active appliances in a house depends on the time of day, weekday, and season as well as on personal variances, since every person has different appliances and usage habits. Therefore, we simulated 100 different

TABLE I

SELECTION OF TYPICAL ON/OFF AND MULTISTATE APPLIANCES DESCRIBED BY THE POWER DEMAND FOR EACH STATE, AVERAGE USAGE TIME AND AVERAGE OCCURRENCE PER USED OBSERVATION WINDOW. IT FURTHER SHOWS THE ACCURACY AT THE APPLIANCE LEVEL, IN TOTAL, AND THE REACHED RMSE OF PALDi FOR A DIFFERENT NUMBER OF PARTICLES $N_p \in \{100, 1000\}$

| Name | $P_{state1}$ | $P_{state2}$ | $P_{state3}$ | $P_{state4}$ | avg. run time | avg. occurrence | Accuracy $Np = 100$ | Accuracy $Np = 1000$ |
|---|---|---|---|---|---|---|---|---|
| Watter Kettle | 1980 | 0 | - | - | 120 | 10 | 0.9987 | 0.9996 |
| Stove | 870 | 0 | - | - | 1200 | 5 | 0.9452 | 0.9955 |
| Freezer | 170 | 0 | - | - | 120 | 100 | 0.9408 | 0.9756 |
| Iron | 1430 | 0 | - | - | 1800 | 2 | 0.9870 | 0.9946 |
| Refrigerator | 78 | 0 | - | - | 300 | 150 | 0.9349 | 0.9569 |
| Toaster | 700 | 0 | - | - | 250 | 2 | 0.9931 | 0.9976 |
| Vacuum Cleaner | 1100 | 0 | - | - | 800 | 2 | 0.9581 | 0.9986 |
| Air Condition | 1000 | 0 | - | - | 200 | 200 | 0.9817 | 0.9898 |
| Hair Dryer | 1530 | 0 | - | - | 600 | 2 | 0.9944 | 0.9948 |
| Boiler | 1300 | 0 | - | - | 1200 | 4 | 0.9849 | 0.9830 |
| Waffle Iron | 950 | 0 | - | - | 600 | 2 | 0.9492 | 0.9851 |
| Curling Iron | 90 | 0 | - | - | 100 | 3 | 0.9871 | 0.9929 |
| Mixer | 80 | 0 | - | - | 180 | 2 | 0.9892 | 0.9872 |
| Coffee Machine | 10 | 1150 | 0 | - | 120 | 5 | 0.9660 | 0.9155 |
| Clothes Dryer | 250 | 1800 | 0 | - | 3600 | 1 | 0.9161 | 0.9131 |
| Clothes Washer | 170 | 650 | 0 | - | 3600 | 1 | 0.9278 | 0.9192 |
| Microwave | 5 | 1650 | 0 | - | 300 | 4 | 0.9268 | 0.9608 |
| Dishwasher | 5 | 200 | 1200 | 0 | 3600 | 2 | 0.9323 | 0.9817 |
| Total $ACC$ | - | - | - | - | - | - | 0.9619 | 0.9745 |
| RMSE | - | - | - | - | - | - | 0.1099 | 0.0395 |

appliance compositions, the sizes of which vary in the range $N \in [9, 12, 15, 18]$ in the case of ON/OFF appliances. We compute the accuracy and the RMSE of PALDi with a particle number of $Np = 100$.

*2) Scenario for the Influence on a Varying Number of Used Particles:* The efficiency of the particle filter is mainly dependent on the number of used particles. In this test scenario, the dependence on the particle number in the range of $N_p \in \{100, 200, 500, 1000\}$ is evaluated. To make an assumption on how the particle parameter $Np$ influences the performance of PALDi, we compute the accuracy and RMSE. The experiment is made for ON/OFF appliances on synthetic appliance models. The number of used appliances is $N = 12$.

*3) Scenario for the Influence on an Imperfect Appliance Model:* In this paper, the used appliance model is dependent on the transition matrix $A$ and the observation matrix $B$. Matrix $A$ consists of the parameters $p_{\mathrm{ON}}$, $p_{\mathrm{OFF}}$, and the matrix $B$ is dependent on the average power demand $p_d$. In case of the power demand $p_d$, the used value can vary from appliance to appliance and from time to time due to the imperfect manufacturing process of a device and the environmental circumstances. Accordingly, we modify the used power demand of each appliance proportional to its size in the range $\sigma_p \in \{5\%, 10\%, 20\%\}$; we give the particle filter the knowledge that the power demand is changing and approximate the current disturbed power value by the particle filter estimation. The evaluation is done for ON/OFF appliances ($N = 12$). Furthermore, the appliance model is dependent on the frequency of occurrence, which is represented by $f_{\mathrm{ON}}$ and depends on the average running time represented by $t_{\mathrm{ON}}$. The values $f_{\mathrm{ON}}$ and $t_{\mathrm{ON}}$ define the ON and OFF probabilities of each device. Thus, we evaluate the estimation behavior on varying $f_{\mathrm{ON}}$ and $t_{\mathrm{ON}}$ by doubling the usual and saved parameter values. We change the values for $f_{\mathrm{ON}}$ and $t_{\mathrm{ON}}$, where PALDi does not have any information about the imperfect appliance model. Our approach modifies and compensates for naturally imperfect model probabilities by scanning the search space with different particles. The variation for $f_{\mathrm{ON}}$ and $t_{\mathrm{ON}}$ simulates the human behavior to choose independently at any time either to use or not to use an appliance. The simulations are done for $N = 12$, $N_p = 100$ for ON/OFF appliances generated by synthetic data.

*4) Scenario for the Extension From ON/OFF to Multistate Appliances: The General Load Disaggregation Issue:* The general and the most simple appliance model is the ON/OFF appliance model. However, many appliances are working in a multistate manner having several states with a specific amount of power for each state. By considering multistate devices in load disaggregation, the problem of identifying appliances gets more complicated. We introduce a set of realistic devices in Table I, where we represent the appliances with their power demand for each operating state, the average run time $t_{\mathrm{ON}}$, which specifies the mean number of seconds to run in a state and the average frequency of occurrence $f_{\mathrm{ON}}$, which indicates how often a device is turned on per day.[3] For the evaluation of PALDi, the accuracy in total and at the appliance level and the RMSE are listed in Table I. In total, ten whole days were simulated where 12 random appliances out of all devices were chosen for each day. The number of used particles is $N_p \in \{100, 1000\}$.

*5) Scenario for Analyzing the Run-Time Performance of PALDi:* In this scenario, we assess the execution time of our algorithm on 1000 data samples. We ran PALDi and measured the mean run-time of one sample computation. We vary the number of particles in the range $N_p \in$

[3]The times $f_{\mathrm{ON}}$ and $t_{\mathrm{ON}}$ are assumed to be the same for each appliance state. Thus, the running time of state 1 and state 2 of a desired device are the same.

TABLE II
ACCURACY AND NORMALIZED RMSE ERROR FOR VARYING NUMBER OF APPLIANCES $N \in \{9, 12, 15, 18\}$

| $N$ | 9 | 12 | 15 | 18 |
|---|---|---|---|---|
| Accuracy | 0.9538 | 0.9365 | 0.9190 | 0.8964 |
| $RMSE$ | 0.1137 | 0.1677 | 0.1966 | 0.2413 |

$\{100, 200, 500, 1000\}$ and the number of appliances in the range $N \in \{6, 8, 10, 12, 14, 16\}$. The used appliance models are based on the devices in Table I. We used a MacBook Pro 2.8 GHz Dual Core i7, 8 GB and Mac OS operating system to execute the algorithm for this scenario.

### *B. REDD Dataset*

In this test scenario, PALDi is applied on real data from the well-known REDD dataset. In the evaluation, we compute the accuracy and the RMSE, where the RMSE indicates, on the one hand, the estimation precision, and on the other hand, how good multistate appliances can be detected. We used three variations of PALDi:

1) without noise adaptation behavior where the PF uses the exact power demand of the observation matrix of the HMM;
2) noise adaptation behavior where the PF varies the power demand of the observation matrix in predefined ranges to compensate for inaccurate appliance models;
3) resetting behavior where the PF is setting its posterior estimations to a random composition of samples each expired minute.

The number of particles is chosen as $N_p = 100$.

## VI. EXPERIMENTS

### *A. Synthetic Dataset*

*1) Scenario for a Varying Number of Aggregated Appliances:* In this scenario, we are evaluating the accuracy and the RMSE of PALDi for a varying number of appliances $N \in \{9, 12, 15, 18\}$. We calculate the mean values over 100 simulation runs and over all used appliances. Table II shows that the accuracy is decreasing by an increasing number of appliances. In addition, the RMSE increases by an increased number of appliances. As reason, we assume that our household power load generated by synthesis shows a high degree of overlapping appliances. This could be observed in Fig. 3, where a produced power profile generated by synthetic data is shown. Power peaks up to 8kW are shown, where several appliances are running at the same time.

*2) Scenario for the Influence on a Varying Number of Used Particles:* We simulated 100 different appliance compositions to be able to make an assumption as to how the number of used particles influences the accuracy and RMSE of PALDi. Thus, in Table III, the accuracy and RMSE versus the number of used appliances is listed. It is apparent that with increasing particle number, the accuracy is increasing and the RMSE is decreasing. We also claim that for the problem of 12 different appliances, a particle number of 500–1000 is sufficient. By increasing the number of devices, we recommend increasing the number of particles as the accuracy with an increased number of appliances is decreasing (Table II) and an increased number of particles improves the load disaggregator result in both, reached accuracy and RMSE value (Table III).

TABLE III
ACCURACY AND NORMALIZED RMSE FOR VARYING NUMBER OF PARTICLES $N_p \in \{100, 200, 500, 1000\}$

| $Np$ | 100 | 200 | 500 | 1000 |
|---|---|---|---|---|
| Accuracy | 0.9365 | 0.9445 | 0.9586 | 0.9599 |
| $RMSE$ | 0.1677 | 0.1292 | 0.0889 | 0.0831 |

TABLE IV
ACCURACY AND NORMALIZED RMSE FOR NOISE INTERFERED POWER MAGNITUDES IN THE RANGE $\sigma_p$ IN {0%, 5%, 10%, 20%}

| $\sigma_p$ | 0 | 5 | 10 | 20 |
|---|---|---|---|---|
| Accuracy | 0.9365 | 0.9027 | 0.8693 | 0.8430 |
| $RMSE$ | 0.1677 | 0.2470 | 0.3025 | 0.3340 |

TABLE V
ACCURACY AND NORMALIZED RMSE FOR NOISE INTERFERED $\hat{f}_{\mathrm{ON}}$ AND $\hat{t}_{\mathrm{ON}}$

| $\sigma_{don}$ | no influence | $\hat{f}_{on} = 2 \cdot f_{on}$ | $\hat{t}_{on} = 2 \cdot t_{on}$ |
|---|---|---|---|
| Accuracy | 0.9365 | 0.8939 | 0.9229 |
| $RMSE$ | 0.1677 | 0.1 | 0.0693 |

*3) Scenario for the Influence on an Imperfect Appliance Model:* The first part of this scenario deals with imperfect modeling of the power demand $p_d$ for a used appliance model. The power demand $p_d$ is changed by $\sigma_p \in \{0\%, 5\%, 10\%, 20\%\}$ in positive and negative directions. PALDi has the possibility to vary the estimated power value from the appliance model set power demand in *a priori* determined ranges to improve the estimation result. In Table IV, the accuracy and the RMSE for the simulations are shown.

The performance is decreasing by a varying appliance model. Moreover, an additional problem for the algorithm is that similar consuming appliances can be confusing to the approach if the power demand difference between two devices is in the range of the imperfect appliance power demands. Furthermore, to consider also the frequency of appliance occurrence $f_{\mathrm{ON}}$, we change this parameter by $\hat{f}_{\mathrm{ON}} = 2 \cdot f_{\mathrm{ON}}$ to simulate a common appliance usage frequency per day. The accuracy and the RMSE is presented in Table V.

Our proposed approach has a decreased accuracy if $f_{\mathrm{ON}}$ is not the same as the true predefined value. However, the proposed algorithm tries to compensate for this by probabilistic scanning of the appliance state space from sample to sample each time. The minor loss of accuracy is acceptable considering that PALDi has no information about the model difference. In addition to the probability to switch a device ON, an important parameter of the appliance model is when to switch an appliance OFF. Therefore, the parameter $t_{\mathrm{ON}}$ is varied which defines the average running time of an appliance. We change the parameter by $\hat{t}_{\mathrm{ON}} = 2 \cdot t_{\mathrm{ON}}$ and evaluate the performance of PALDi. Accuracy and RMSE are shown in Table V.

TABLE VI

COMPUTATION TIME IN MILLISECONDS FOR THE CALCULATION OF ONE TIME SAMPLE OVER THE NUMBER OF USED PARTICLES $N_p \in \{100, 200, 500, 1000\}$ AND THE NUMBER OF USED APPLIANCES $N \in \{6, 8, 10, 12, 14, 16\}$. THIS EVALUATION WAS DONE WITH MATLAB SIMULATION ON THE APPLIANCE OF TABLE I

| $t/ms$ | $Np = 100$ | $Np = 200$ | $Np = 500$ | $Np = 1000$ |
|---|---|---|---|---|
| $N = 6$ | 0.69 | 1.55 | 5.95 | 22 |
| $N = 8$ | 0.88 | 1.64 | 6.22 | 22 |
| $N = 10$ | 0.97 | 1.79 | 7.02 | 22 |
| $N = 12$ | 1.14 | 2.02 | 7.37 | 22.5 |
| $N = 14$ | 1.29 | 2.16 | 7.8 | 24.2 |
| $N = 16$ | 1.44 | 2.44 | 8.3 | 25 |

*4) Scenario for the Extension From ON/OFF to Multistate Appliances. The General Load Disaggregation Issue:* In the previous scenarios, the proposed approach was evaluated according to synthetic data of ON/OFF appliances. In this scenario, the accuracy and RMSE of ON/OFF and multistate appliance according to Table I are evaluated. In this table, the simulation results for the accuracy and the RMSE are shown. Accordingly, the algorithm works with simple ON/OFF appliances and with multistate appliances.

*5) Scenario for Analyzing the Run-Time Performance of PALDi:* An important as well as critical point of using PF for the estimation process is the runtime. Therefore, we made this evaluation where the runtime for varying number of appliances and varying number of particles is reviewed. Table VI shows a linear behavior of run time in relation to the number of appliances and the number of used particles. This evaluation is based on MATLAB simulations and reaches running times in millisecond range on desktop hardware. To improve the computation, it is necessary to implement PALDi in a higher performance programming language such as C. Using the MATLAB C-converter, we could improve the runtime by a factor of 5 on the same personal computer. Therefore, the algorithm can also work in real-world applications on a low-cost hardware such as a Raspberry Pi.

### B. REDD Dataset

To test the proposed approach on real data, we used the REDD dataset, where a composition of appliances was chosen to be detected. We choose general household appliances, which are listed in Table VII. In Table VII, the accuracy results at the appliance level, in total, as well as the RMSE are also presented. We tested the standard PF case with noise adaptation, with no noise adaptation, and with resetting behavior. The best accuracy and RMSE are achieved with noise adaptation[4] and resetting behavior.[5] Noise adaptation overcomes appliance model inaccuracies and the resetting behavior improves the dynamic behavior of PALDi. The results also show that similar appliances such as oven and microwave or dishwasher and kitchen outlet have a decreased accuracy which is due to the fact that the PF has no possibility to distinguish between consuming appliances and identical consumption behavior. The most important feature for the PF is the power demand which is, for similar appliances, nearly the same. Moreover, Table VII shows that a multi-state appliance model such as in the case of the dishwasher (three operation states) can be detected with PALDi. In Fig. 4, an example for a power load with the REDD data set is shown and Fig. 5 presents the estimated power load by our approach PALDi. The minor difference between the power loads is visible.

[4]Power estimated by PF can vary in the range of 10 W.

[5]The posterior density is reset every second.

TABLE VII

ACCURACY IN TOTAL AND AT THE APPLIANCE LEVEL AND NORMALIZED RMSE ERROR FOR PALDi ON THE REDD DATA SET FOR HOUSE 1

| | House1 noise-adapt. | no noise-adapt. | resetting | multi-state |
|---|---|---|---|---|
| Oven | 0.9697 | 0.9538 | 0.9909 | - |
| Fridge | 0.8049 | 0.8503 | 0.7886 | √ |
| Dishwasher | 0.5943 | 0.5690 | 0.7712 | √ |
| Kitchen Outlet | 0.7062 | 0.6428 | 0.9832 | - |
| Microwave | 0.3489 | 0.3593 | 0.8833 | √ |
| Washing Dryer | 0.9873 | 0.9868 | 0.9953 | - |
| Total | 0.7352 | 0.7270 | 0.9021 | - |
| $RMSE$ | 0.167 | 0.207 | 0.0296 | - |

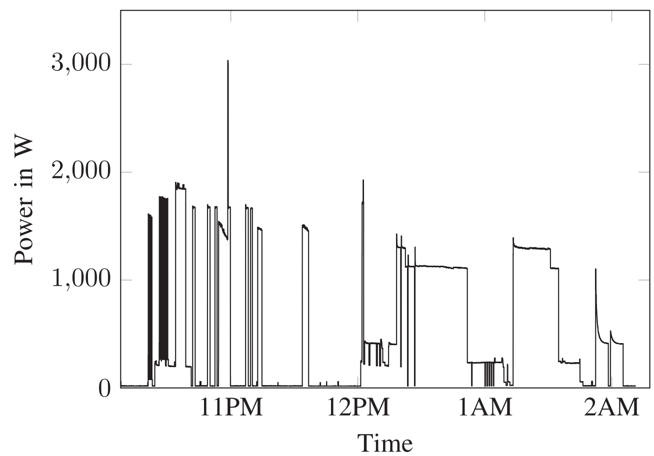



Fig. 4. Total power load of six appliances of the REDD data set for a time slice of several hours.

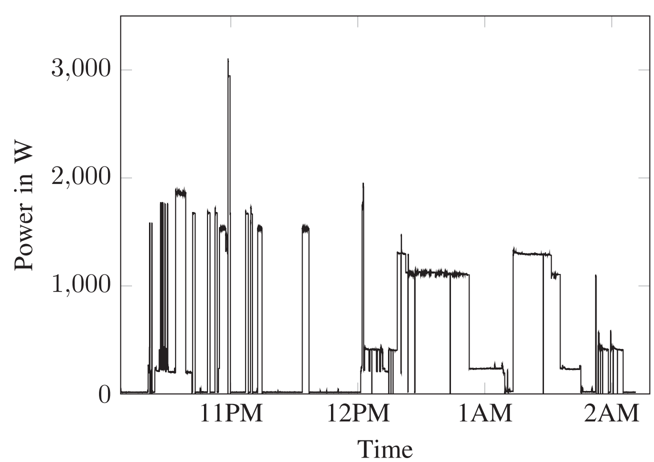



Fig. 5. Estimated total power load by PALDi of the power load, as in Fig. 4, with noise adaptation and resetting behavior.

## VII. DISCUSSIONS

In the previous sections, different evaluation scenarios were presented. We showed that the algorithm is dependent on the number of used particles. The higher the number of particles, the higher the reached accuracy (Table III) is. With the variation of the particle number, it is also possible to overcome the loss of accuracy (Table II) if the number of appliances is increased. Moreover, the algorithm has the characteristics to compensate for imperfect appliance models. Power demand differences of 5% are common power demand variation of appliances, where we showed that PALDi can handle this situation by randomly changing the output of the particle filter in predefined ranges. The observation value of each HMM represented by the observed power demand of each appliance state can fluctuate within limits to compensate for irregularities in the appliance power demand. Considering the modeling of the appliance HMM, our evaluations show that an imperfect modeling of the appliance switching frequency has a decreasing effect on the accuracy of the load disaggregator whereas an imperfect modeling of the average usage time of a device has a minor to null effect on the performance of PALDi (Table V). Therefore, the learning of the appliance model is simplified. PALDi can work with general appliance models with known structure such as ON/OFF appliance or multistate appliance (Tables I and VII) and common transition probabilities on synthetic and real-world data. In addition, the common power demand of each appliance state should be known. Our approach not only handles the detection if a device is ON or OFF, it also detects the current operation state of the appliance. However, PALDi is dependent on the choice of power demand of the appliance. The power demand is the main feature used for the estimation process. Accordingly, if appliances with similar power demands are presented in the same household, PALDi could not work properly any more, since it has no feature and no hint to decide as to which appliance the current power demand belongs to. This is a general problem for NILM algorithms which can be solved by improving the distinctive features such as improving the used sampling rate (e.g., from steady-state to transient behavior) to add further features such as reactive power measurements or to modify the sample-by-sample approach to a windowing approach. Finally, a very important point to evaluate the performance of a NILM approach is the degree of overlapping power draws. The more devices are running simultaneously and are aggregating their power profiles, the more complex the disaggregation problem becomes. We showed this as well as the ability to perform sufficient estimation results for power draws with high degree of overlapping power by simulations on synthetic data (Tables I and II).

## VIII. RELATED WORK

In general, NILM approaches can be divided into supervised and unsupervised approaches [17]. The supervised approach needs a labeled data set to train a classifier and can be divided into optimization and pattern-recognition-based algorithms [18]. In the optimization-based approaches, the problem of aggregated power profiles is modeled into an optimization problem. A total power consumption and a database of known power profiles of appliances are given. With this knowledge, a random composition of database power profiles is selected to approximate the total power consumption with minimal error [19]–[22]. In case of pattern recognition approaches, the proposed methods can be divided into clustering approaches [4], neural networks algorithms [23], and support vector machine-based algorithms [23], [24]. The disadvantage of the supervised classification approach is the required *a priori* information. Accordingly, recent research in NILM is more concerned with unsupervised algorithms, which is using unlabelled data. Unsupervised algorithms do not need any training data. Recent algorithms are based on blind source separation [25], on HMM [26], [27], on FHMM [11], different variants of FHMM [10], [28] and on source separation via non negative tensor factorization [29]. Moreover, Shaw and Laughman [30] use Kalman filtering instead of PF for NILM. As mentioned in Section I, the work of Hart was the first NILM approach which used active and reactive power records to establish an appliance model based on finite state machine (FSM) by clustering. He used this information to infer an appliance to be ON or OFF. The proposed approach uses a deterministic appliance model which is not appropriate as a realistic appliance model because of its deterministic behavior representation. Thus, a probabilistic appliance model based on HMM is advantageous and occupies recent research [10], [11], [26]–[28]. For example, Kim *et al.* [28] report an average accuracy of 83% for up to ten appliances with a 3 s sampling interval. Reference [10] obtains an average accuracy of 87% for seven appliances with a 60-s sampling interval. The most related work is presented in [11]. It shows an average accuracy of 90% for ON/OFF appliances and 80% for multistate appliances (five appliances were tested) with a 3 s sampling interval. It defines ON/OFF and multistate appliances and estimates the appliance state space. Our proposed approach differs from [4] and [11], as we use only the active or apparent power as estimation feature[6] instead of using several feature combinations of active power, reactive power, apparent power, or power factor as in [11], and we tested our approach on synthetic and real-world power draw. Moreover, we tested PALDi on common household appliances in which the number of aggregated appliances was six for real-world data and up to 18 for synthetic consumption data in contrast to the work of Zoha which used up to five appliances.

Unfortunately, there currently exists no accepted and approved evaluation test case and metric, which makes a numerical comparison between approaches complicated. Thus, a qualitative evaluation is possible, as a fulfillment of the Zeifman requirements.

## IX. CONCLUSION

We propose an evaluation on the feasibility of particle filtering on the problem of disaggregated power loads in households. We tested ON/OFF and multistate appliances modeled by HMM superimposing their power draws by the use

[6]The use of one appliance feature is advantageous because of its applicability to recent smart meters.

of a FHMM. We suggest using PF as NILM algorithm because PF is applicable to estimate the inference of FHMM and is suitable for nonlinear problems with non-Gaussian noise. PF is beneficial because of its characteristics to improve the estimation performance by increasing the number of particles and to search through the possible search space to compensate for imperfect appliance model assumptions. In Section I, the requirements of a method useful for NILM problems are reviewed. We compare these requirements with the results of the proposed approach.

1) The used appliance model and household model are defined by its power and time characteristics. A device is characterized by its active power demand in 1-s resolution.
2) The total accuracy of PALDi is higher than 90% for real data.
3) No training during operating of PALDi is necessary. The algorithm needs a general knowledge of the structure and power demand of the used devices in the household. The algorithm is only dependent on the previous state and not on historic data.
4) The algorithm is real-time capable with a running time smaller than the measurement sampling time.
5) The complexity of the proposed approach is based on the direct proportional relation between the number of particles and the number of used appliances. The higher the number of particles, the better is the result of PALDI, and the higher the number of appliances with constant number of particles the lower is the accuracy of PALDI. Thus, the number of particles has to be chosen appropriately depending on the number of appliances.
6) The proposed algorithm depends on the used appliance model. Currently, the algorithm was tested with ON/OFF and multistate appliances and will be extended and tested with other appliance types like continuous consuming appliance types.

In summary, the contribution of this paper is the fulfillment of the requirements presented in [6] by keeping the algorithm and the appliance model as simple as possible and by evaluating the proposed approach with synthetic and real-world data.

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**Dominik Egarter** (S'13) received a B.Sc in Information Technology from Alpen-Adria University Klagenfurt, Klagenfurt, Austria in 2010 and the Dipl. Ing. degree in Information Technology from Alpen-Adria University Klagenfurt, Klagenfurt, Austria in 2012. He is currently pursuing the Ph.D. degree with Alpen-Adria University Klagenfurt, and the Lakeside Labs GmbH, Klagenfurt.

He has been with Alpen-Adria University Klagenfurt and Lakeside Labs GmbH, since 2012, as a researcher. His current research interests include energy-efficient applications in smart homes with special focus on smart metering and load disaggregation.

**Venkata Pathuri Bhuvana** received the B.E degree from Acharya Nagarjuna University, Gunthur, India and the Dipl.-Ing. degree form Alpen-Adria University, Klagenfurt, Austria in 2012, where he is currently pursuing the Ph.D. degree in adaptive signal processing and estimation with the Erasmus Interactive and Cognitive Environments Program, Embedded and Signal Processing Group.

His current research interests include robust state estimation and adaptive signal processing.

**Wilfried Elmenreich** (SM'02) received the Ph.D. (Hons.) degree in computer science from the Vienna University of Technology, Vienna, Austria, in 2002.

He was a Visiting Researcher with Vanderbilt University, Nashville, TN, USA, in 2005, and the CISTER/IPP-Hurray Research Unit, Polytechnic Institute of Porto, Porto, Portugal, in 2007. In 2007, he joined Alpen-Adria-Universität Klagenfurt, Klagenfurt, Austria, as a Senior Researcher. From 2012 to 2013, he was a Professor of Complex Systems Engineering with the University of Passau, Passau, Germany. Since 2013, he has been a Professor of Smart Grids with the Institute of Networked and Embedded Systems, Alpen-Adria-Universität Klagenfurt. He is also with Lakeside Labs, Klagenfurt, a research and innovation cluster on self-organizing networked systems. He is the Editor of five books, and has authored over 100 papers in the field of networked and embedded systems.

Prof. Elmenreich is a Senate Member of Alpen-Adria-Universität Klagenfurt and Counselor of the Klagenfurt's IEEE student branch. He was granted venia docendi in the field of computer engineering from the Vienna University of Technology in 2008.