PALDi: Online Load Disaggregation via Particle Filtering

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

***Abstract*---Smart metering and fine-grained energy data are one of the major enablers for the future smart grid and improved energy efficiency in smart homes. By 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 a NILM approach, where the appliance states are estimated by particle filtering (PF). PF is used for non-linear and non-Gaussian disturbed problems and is suitable to estimate the appliance state. On/off appliances, multi-state appliances, or combinations of them are modeled by hidden Markov models (HMM) and their combinations result in a factorial hidden Markov model (FHMM) 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*---Particle filter, load disaggregation, non-intrusive load monitoring, hidden Markov model, factorial hidden Markov model, 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 the consumers not only gets the overall cost of his/her consumption, 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 for 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 on 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.

Smart meters provide the possibility to show the consumers not only when and what quantity of power is consumed, it is also possible to provide information about which appliance is consuming which amount of power at which 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 on appliance level [2]. One possible way to provide energy data on 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 based on a single sensor monitoring the overall energy consumption of a house[1] on the grid connection point was introduced by G. Hart [4] and was designated firstly under the name nonintrusive 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 in [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:

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

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

This work was supported by Lakeside Labs GmbH, Klagenfurt, Austria and funding from the European Regional Development Fund and the Carinthian Economic Promotion Fund (KWF) under grant KWF-20214 | 22935 | 24445.

D. Egarter and W. Elmenreich are with the Institute of Networked Embedded Systems, Alpen-Adria-University Klagenfurt, Klagenfurt, e-mail: {*name.surname*}@*aau.at*

V.P. Bhuvana is with the Department of Marine Engineering, electrical, electronics, and telecommunications, University of Genova, Genova, e-mail:{venkata.pathuri}@aau.at

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

appliance models based on HMM. We model our household consumption using the FHMM. The problem of disaggregating aggregated appliances is computationally complex and suffers on non-linearity if instead of on/off and multi-state appliance, non-linear appliances such as a drill are used. It suffers from non-Gaussian noise according to appliances which 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 which are stressing this topic are based on approximating FHMM interference by Kolter [10] or make use of structural variational approximation methods by Zoha [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 1 second granuality. 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 non-linear 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 which meets 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 basic knowledge of particle filtering and how particle filtering can be used to estimate appliance states using measured data, followed by Section IV, which 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 work in Section IX.

II. Household and Appliance model

The load of a household is characterized by the power profiles of household's 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, 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]. An HMM is probabilistic graphical model describing time series as a Markov model in which the states are not directly observable. The state of an HMM are 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 $s = \{s_1, \dots s_n\}$ 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 terms x_t are the states 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 $z = \{z_1, z_2 \dots z_t\}$ is the result of the hidden states $x = \{x_1, x_2, \dots x_t\}$, 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 $P(x_{t+1} \mid x_t, x_{t-1} \dots x_1) = P(x_{t+1} \mid x_t)$. In Figure 1, an example for a general model of an on/off appliance model to generate the hidden states is shown. In this work we consider on/off devices and multi-state 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 which 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.

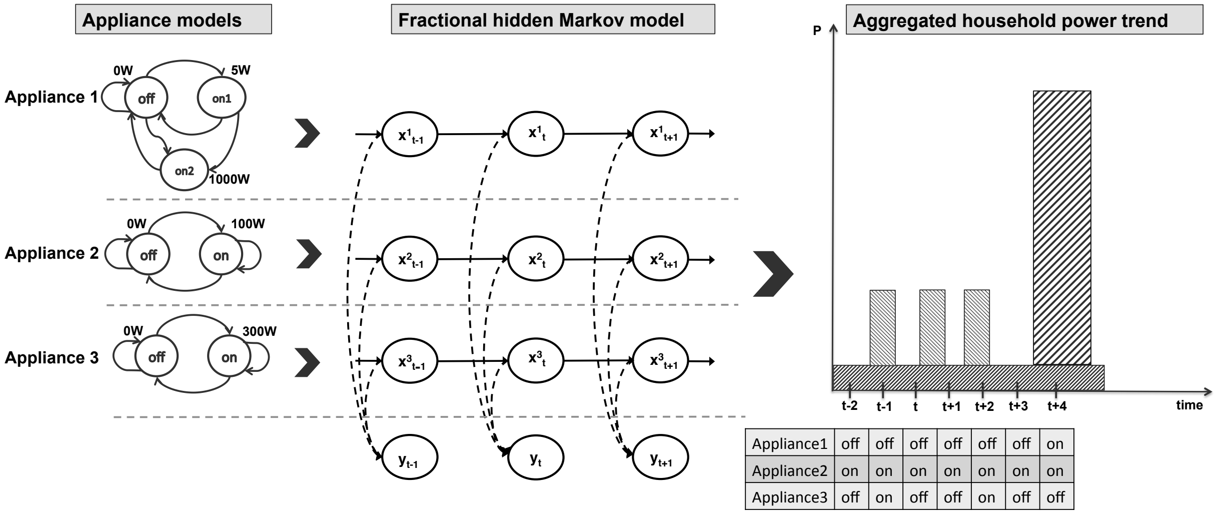
The household power profile can be observed as the aggregate power profile of N different appliances such as $Y = \{y_1, y_2, \dots y_t\}$ and is generated by the state sequence of $x = \{x^{(1)}, x^{(2)}, \dots x^{N}\}$, which is the superposition of the appliance states at each time slice $x^{(n)} = \{x_1^{(n)}, x_2^{(n)} \dots x_t^{(n)}\}$. 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 Figure 1.

III. State Estimation

In the following sections, we discuss background information on particle filtering and how to apply particle filtering to the problem of appliance state estimation. We start with Bayesian estimation, explain the shortcomings of using Bayesian estimation with non-linear 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



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: In this figure the appliance models for on/off or multi-state appliances, a sketch of the FHMM model and the power draw of the aggregated power trends for 3 appliances are presented.

time t. The sequential Bayesian estimation has two primary steps at every time instance t:

- State prediction predicting the state as the expectation of the prediction PDF
$$p\left(\mathbf{x}_t \mid \mathbf{y}_{t-1}\right)=\int p\left(\mathbf{x}_{t-1} \mid \mathbf{y}_{t-1}\right) p\left(\mathbf{x}_t \mid \mathbf{x}_{t-1}\right) d\mathbf{x}_{t-1}, \quad (1)$$
where $p\left(\mathbf{x}_{t-1} \mid \mathbf{y}_{t-1}\right)$ is the posterior PDF available from time t-1 and $p\left(\mathbf{x}_t \mid \mathbf{x}_{t-1}\right)$ is the state transition probability given by the system process model.
- Measurement update where upon receiving the measurement, the predicted state is computed as expectation of the posterior PDF

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

where the $p\left(\mathbf{y}_t \mid \mathbf{x}_t\right)$ is the likelihood PDF given by the measurement model of the system. The Kalman Filter (KF) [16] can be used to solve the integrals in Eq. 1 and Eq. 2 if the system is linear with additive white Gaussian noise. In contrast, if the physical systems are non-linear, then these integrals are intractable. Often, non-linear 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 Eq. 1 and Eq. 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 $\left\{\mathbf{x}_{0:t}^i, \mathbf{w}_t^i\right\}_{i=1}^{Np}$ be the set of random samples, $x_{0:1}^i$, drawn form the importance density $q\left(\mathbf{x}_{0:t} \mid \mathbf{y}_{1:t}\right)$ and their associated weights, w_t^i, for $1 \ldots N_p$ where N_p is the number of particles. Then the required PDF can be approximated as

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

where δ is the unit dirac function and the weights are defined as
$$\mathbf{w}_t^i=\frac{p\left(\mathbf{x}_{0:t}^i \mid \mathbf{y}_{1:t}\right)}{q\left(\mathbf{x}_{0:t}^i \mid \mathbf{y}_{1:t}\right)}. \quad (4)$$

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

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

then the new samples $x_{0:t}^i \approx q(x_{0:t}|y_{1:t})$ can be obtained by augmenting the existing samples $x_{0:t-1}^i \approx q(x_{0:t-1}|y_{1:t-1})$ with the new state $x_t^i \approx q(x_t|x_{0:t-1}, y_{1:t})$. The corresponding weight update equation is given as
$$\mathbf{w}_t^i=\mathbf{w}_{t-1}^i \frac{p\left(\mathbf{y}_t \mid \mathbf{x}_t^i\right) p\left(\mathbf{x}_t^i \mid \mathbf{x}_{t-1}^i\right)}{q\left(\mathbf{x}_t^i \mid \mathbf{x}_{0:t-1}^i, \mathbf{y}_t\right)}. \quad (6)$$

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

$$p(x_{0:t}|y_{1:t}) \approx \sum_{i=1}^{Np} w_t^i \delta(x_t - x_{0:t}^i). \quad (7)$$

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 $\left\{\mathbf{x}_{0:t}^{*i}, \mathbf{w}_t^{*i}\right\}_{i=1}^{Np}$. Several resampling techniques are proposed in [16]. Then, the PDF can be approximated as

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

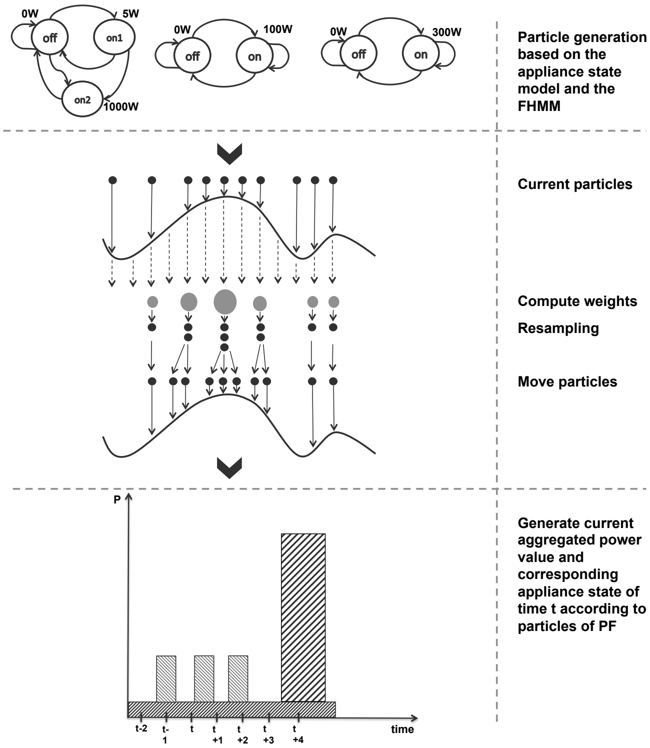


Fig. 2: In this figure the general algorithm sequence of the PF.

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

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

The weights are updated by

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

Resampling: The particles are resampled by using the auxiliary resampling [16] as

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

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. Secondly, on/off and multi-state appliances behave in a linear way whereas a continuous behaving appliance such as a drill or dimmer show non-linear behavior. This motivates the usage of PF to make the proposed NILM approach usable for all kinds of appliance types. Third, the appliance model generated by the HMM and household power consumption established by the FHMM suffers from non-Gaussian noise. In particular, the used appliance could suffer from noise due to inaccuracies as well as 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 output of the PF are power values for each appliance which are aggregated at each point in time. The PF has the characteristic to randomly adjust the estimated power observation for each appliance in predefined ranges. The reason for that is to estimate and to compensate appliance inaccuracy in the appliance power consumption. However, the PF itself is not providing the information 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, the evaluation settings for the simulations on synthetic data are described and the evaluation metric for 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_{on} and the average occurrence frequency of an appliance f_{on}. This parameters $\{p_d, f_{on}, t_{on}\}$ are initialized as follows.

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

The information of $\{p_d, f_{on}, t_{on}\}$ is fed into the transition matrix A and the observation matrix B. Thus, for an on/off appliance the on probability is $p_{on} = f_{on}/T$, where $T = 86400$ and the off probability $p_{off} = 1/t_{on}$. 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. Multi-state 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_{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 second, one simulation run corresponds to one day of 86400 seconds 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 was 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 6 different appliances which are common in households and are affecting the energy consumption of an 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 was 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 has to be determined. For this we used the MATLAB pre-programmed HMM functions to construct the matrices A and B. According to the appliance types, we used on/off appliances and multi-state appliances, where we give the algorithm the possibility to adjust its used power demand for each iteration. The used sampling frequency is one second.

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

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

where Θ 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 value 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 multi-state 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,

[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

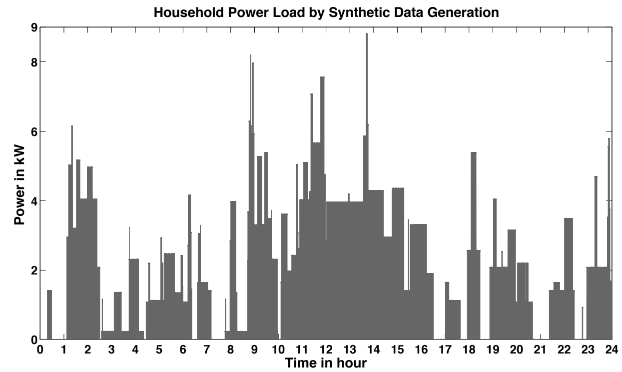


Fig. 3: Household Power Load of one day generated by the synthetic HMM model.

the overall classification result is calculated by combining TP, FP, FN and TN to the accuracy metric

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

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 mean of the reached metric values on appliance level.

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 Figure 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 wells as on personal variances, since every person has different appliances and usage habits. Therefore, we simulated 100 different appliance compositions, whose size varies 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 $Np \in \{100, 200, 500, 1000\}$ 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_{on}, p_{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_{on} and depends on the average running time represented by t_{on} . The values f_{on} and t_{on} define the on and off probabilities of each device. Thus, we evaluate the estimation behavior on varying f_{on} and t_{on} by doubling the usual and saved parameter values. We change the values for f_{on} and t_{on}, where PALDi does not have any information about the imperfect appliance model. Our approach modifies and compensates naturally imperfect model probabilities by scanning the search space with different particles. The variation for f_{on} and t_{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 $N = 12$, $Np = 100$ for on/off appliances generated by synthetic data.

4) Scenario for the extension from on/off to multi-state appliances. The general load disaggregation issue: The general and most simple appliance model is the on/off appliance model. However, many appliances are working in a multi-state manner having several states with a specific amount of power for each state. By considering multi-state 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_{on}, which specifies the mean number of seconds to run in a state and the average frequency of occurrence f_{on}, which indicates how often a device is turned on per day[3]. For the evaluation of PALDi, the accuracy in total and on appliance level and the RMSE are listed in Table I. In total, 10 whole days were simulated where 12 random appliances out of all devices were chosen for each day. The number of used particles is $Np \in \{100, 1000\}$.

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 $Np \in \{100, 200, 500, 1000\}$ 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 multi-state appliance can be detected. We used three variation of PALDi:

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

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

TABLE II: Accuracy and normalized RMSE error for varying number of appliances $N \in \{9, 12, 15, 18\}$.

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

TABLE III: Accuracy and normalized RMSE error for varying number of particles $Np \in \{100, 200, 500, 1000\}$.

- without noise adaptation behavior where the PF uses the exact power demand of the observation matrix of the HMM
- noise adaptation behavior where the PF varies the power demand of the observation matrix in predefined ranges to compensate inaccurate appliance models
- 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 $Np = 100$.

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 increased number of appliances. Also 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 seen in Figure 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 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 also the accuracy is increasing and theRMSE is decreasing. We also claim that for the problem of 12 different appliances a particle number of 500 to 1000 is sufficient. By increasing the number of devices we recommend also to increase the number of particles as the accuracy with an increased number of appliances is decreasing (see Table II) and a increased number of particles improves the load disaggregator result in both, reached accuracy and RMSE value (see Table III).

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 direction. PALDi has the possibility to

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

TABLE I: A selection of typical on/off and multi-state appliances described by the power demand for each state, average usage time and average occurrence per used observation window. It further shows the accuracy on appliance level, and in total and the reached RMSE of PALDi for a different number of particles $Np \in \{100, 1000\}$.

σ_p	0	5	10	20
Accuracy	0.9365	0.9027	0.8693	0.8430
$RMSE$	0.1677	0.2470	0.3025	0.3340

TABLE IV: Accuracy and normalized RMSE error for noise interfered power magnitudes in the range σ_p in $\{0\%, 5\%, 10\%, 20\%\}$.

σ_{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

TABLE V: Accuracy and normalized RMSE error for noise interfered $\hat{f}_{on}$ and $\hat{t}_{on}$

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_{on}, we change also this parameter by $\hat{f}_{on} = 2 \cdot f_{on}$ to simulate a commonly appliance usage frequency per day. The accuracy and the RMSE is presented in Table V. Our proposed approach has a decreased accuracy if f_{on} is not the same as the true predefined value. However, the proposed algorithm tries to compensate this by probabilistic scanning 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. Beside 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_{on} is varied which defines the average running time of an appliance. We change the parameter by $\hat{t}_{on} = 2 \cdot t_{on}$ and evaluate the performance of PALDi. Accuracy and RMSE are shown in Table V.

4) Scenario for the extension from on/off to multi-state 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 multi-state 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 multi-state 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 are 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. By using the MATLAB C-converter, we could improve the runtime by a factor of 5 on the same PC. 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 this table also the accuracy results on appliance level and in total as well as the RMSE are 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]

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

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

TABLE VI: Computation time in milliseconds for the calculation of one time sample over the number of used particles $Np \in \{100, 200, 500, 1000\}$ 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.

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

TABLE VII: Accuracy in total and on appliance level and normalized RMSE error for PALDi on the REDD data set for House 1.

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 with identical consumption behavior. The most import 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 (3 operation states) can be detected with PALDi. In Figure 4 an example for a power load with the REDD data set is shown and Figure 5 presents the estimated power load by our approach PALDi. The minor difference between the power loads are visible.

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 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 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 no 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 multi-state appliance (Tabel I and VII) and common transition probabilities on synthetic and real-world data. Additionally, also 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 in which operation state the appliance is currently. 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 proper any more, since it has no feature and no hint to decide 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 (Table II and I).

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 [18] based algorithms. In the optimization based approaches, the problem of aggregated power profiles is modelled 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, 20, 21, 22]. In case of pattern recognition approaches, proposed methods can be divided into clustering approaches [4], neural networks algorithms [23] and support vector machines 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, the work of [30] uses 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

[5]The posterior density is reseted every second

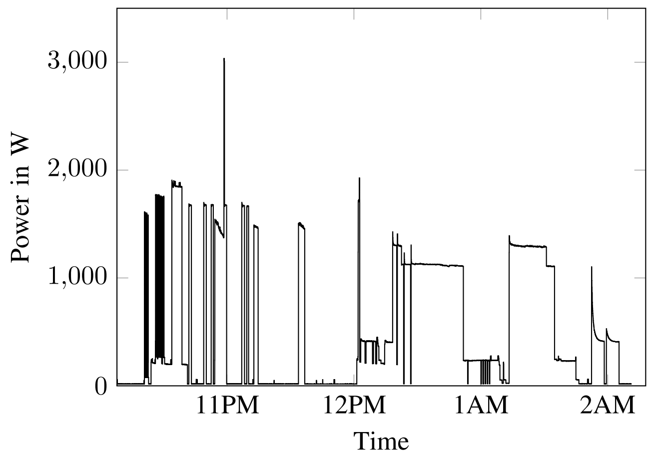


Fig. 4: Total power load of 6 appliances of the REDD data set for a time slice of several hours

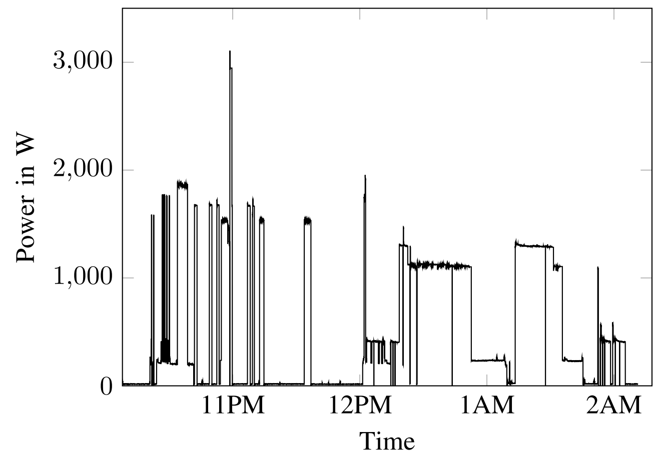


Fig. 5: Estimated total power load by PALDi of the power load as in Figure 4 with noise adaptation and resetting behavior.

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 [26, 27, 11, 10, 28]. For exmple the work of [28] reports an average accuracy of 83% for up to 10 appliances with a 3 second sampling interval. The work of [10] obtains an average accuracy of 87% for 7 appliances with a 60 second sampling interval. The most related work is presented by Zoha [11]. It shows an average accuracy of 90% for on/off appliances and 80% for multi-state appliances (5 appliances were tested) with a 3 second sampling interval. It defines on/off and multi-state appliances and estimates the appliance state space. Our proposed approach differs from [11] and the initial work of Hart [4], 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 6 for real world data and up to 18 for synthetic consumption data in contrast to the work of Zoha which used up to 5 appliances.
Unfortunately, there exists currently no accepted and approved evaluation test case and metric, which makes a numerical comparison between approaches complicated. Thus, a qualitative evaluation is possible, as the 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 multi-state appliances modeled by HMM superimposing their power draws by the use of a FHMM. We suggest to use PF as NILM algorithm, because PF is applicable to estimate the inference of FHMM and is suitable for non-linear 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 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:

- The used appliance model and household model is defined by its power and time characteristics. A device is characterized by its active power demand in $1s$ resolution.
- The total accuracy of PALDi is higher than 90% for real data.
- 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.
- The algorithm is real-time capable with a running time smaller than the measurement sampling time.
- 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 appropriate depending on the number of appliances.
- The proposed algorithm depends on the used appliance model. Currently, the algorithm was tested with on/off and multi-state 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 the fulfilment of the requirements presented by Zeifman [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.

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

References

[1] L. Peretto, ''The role of measurements in the smart grid era,'' *IEEE Instrum. Meas. Mag.*, vol. 13, no. 3, pp. 22--25, June 2010.

[2] K. C. Armel, A. Gupta, G. Shrimali, and A. Albert, ''Is disaggregation the holy grail of energy efficiency? The case of electricity,'' *Energy Policy*, vol. 52, no. 0, pp. 213 -- 234, 2013.

[3] D. R. Carlson, H. S. Matthews, and M. Berges, ''One size does not fit all: Averaged data on household electricity is inadequate for residential energy policy and decisions,'' *Energy and Buildings*, vol. 64, no. 0, pp. 132 -- 144, September 2013.

[4] G. Hart, ''Nonintrusive appliance load monitoring,'' *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870--1891, December 1992.

[5] M. Zeifman and K. Roth, ''Nonintrusive appliance load monitoring: Review and outlook,'' *IEEE Trans. Consum. Electron.*, vol. 57, no. 1, pp. 76 --84, February 2011.

[6] M. Zeifman, ''Disaggregation of home energy display data using probabilistic approach,'' *IEEE Trans. Consum. Electron*, vol. 58, no. 1, pp. 23--31, 2012.

[7] D. Egarter, V. P. Bhuvana, and W. Elmenreich, ''Appliance state estimation based on particle filtering,'' in *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings BuildSys*, November 2013, pp. 24:1--24:2.

[8] G. Forney, ''The Viterbi algorithm,'' *Proceedings of the IEEE*, vol. 61, no. 3, pp. 268--278, March 1973.

[9] S. Geman and D. Geman, ''Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images,'' *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 6, no. 6, pp. 721--741, November 1984.

[10] Z. Kolter and T. Jaakkola, ''Approximate inference in additive factorial HMMs with application to energy disaggregation,'' in *Proceedings of the International Conference on Artifical Intelligence and Statistics*, vol. 22, 2012, pp. 1472--1482.

[11] A. Zoha, A. Gluhak, M. Nati, and M. Imran, ''Low-power appliance monitoring using factorial hidden Markov models,'' in *Proceedings of IEEE Conference on Intelligent Sensors, Sensor Networks and Information Processing*, April 2013, pp. 527--532.

[12] G. Rigatos, ''Particle filtering for state estimation in nonlinear industrial systems,'' *IEEE Trans. Instrum. Meas.*, vol. 58, no. 11, pp. 3885--3900, November 2009.

[13] J. Z. Kolter and M. J. Johnson, ''REDD: A public data set for energy disaggregation research,'' in *Proceedings of KDD Workshop on Data Mining Applications in Sustainability (SustKDD)*, 2011.

[14] L. R. Rabiner, ''A tutorial on hidden Markov models and selected applications in speech recognition,'' vol. 77, no. 2, pp. 257--286, February 1989.

[15] O. Parson, S. Ghosh, M. Weal, and A. Rogers, ''Non-intrusive load monitoring using prior models of general appliance types,'' in *Proceedings of the Twenty-Sixth Conference on Artificial Intelligence (AAAI-12)*, July 2012, pp. 356--362.

[16] M. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, ''A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,'' *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174--188, February 2002.

[17] A. Zoha, A. Gluhak, M. A. Imran, and S. Rajasegarar, ''Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey,'' *Sensors*, vol. 12, no. 12, pp. 16 838--16 866, 2012.

[18] S. Shaw, S. Leeb, L. Norford, and R. Cox, ''Nonintrusive load monitoring and diagnostics in power systems,'' *IEEE Trans. Instrum. Meas.*, vol. 57, no. 7, pp. 1445--1454, July 2008.

[19] J. Liang, S. Ng, G. Kendall, and J. Cheng, ''Load signature study, part i: Basic concept, structure, and methodology,'' *IEEE Trans. Power Del.*, vol. 25, no. 2, pp. 551--560, April 2010.

[20] M. Baranski and J. Voss, ''Genetic algorithm for pattern detection in NIALM systems,'' in *Proceedings of IEEE International Conference on Systems, Man and Cybernetics*, vol. 4, October 2004, pp. 3462--3468 vol.4.

[21] D. Egarter, A. Sobe, and W. Elmenreich, ''Evolving non-intrusive load monitoring,'' in *Proceedings of the Applications of Evolutionary Computation Conference*, April 2013, pp. 182--191.

[22] K. Suzuki, S. Inagaki, T. Suzuki, H. Nakamura, and K. Ito, ''Nonintrusive appliance load monitoring based on integer programming,'' in *Proceedings of SICE Annual Conference*, August 2008, pp. 2742--2747.

[23] D. Srinivasan, W. S. Ng, and A. Liew, ''Neural-network-based signature recognition for harmonic source identification,'' *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 398--405, January 2006.

[24] G. Lin, S. Lee, J. Y.-J. Hsu, and W. Jih, ''Applying power meters for appliance recognition on the electric panel,'' in *Proceedings of IEEE Conference on Industrial Electronics and Applications (ICIEA)*, June 2010, pp. 2254--2259.

[25] H. Goncalves, A. Ocneanu, and M. Berges, ''Unsupervised disaggregation of appliances using aggregated consumption data,'' in *Proceedings of KDD Workshop on Data Mining Applications in Sustainability (SustKDD)*, 2011.

[26] A. A. Zaidi, F. Kupzog, T. Zia, and P. Palensky, ''Load recognition for automated demand response in microgrids,'' in *Proceedings of Annual Conference on IEEE Industrial Electronics Society (IECON)*, November 2010, pp. 2442--2447.

[27] T. Zia, D. Bruckner, and A. Zaidi, ''A hidden Markov model based procedure for identifying household electric loads,'' in *Proceedings of Annual Conference on IEEE Industrial Electronics Society (IECON)*, November 2011, pp. 3218--3223.

[28] H. Kim, M. Marwah, M. Arlitt, G. Lyon, and J. Han, ''Unsupervised disaggregation of low frequency power measurements,'' in *Proceedings of the 11th SIAM International Conference on Data Mining*, 2011.

[29] M. Figueiredo, B. Ribeiro, and A. de Almeida, ''Electrical signal source separation via nonnegative tensor factorization using on site measurements in a smart home,'' *IEEE Trans. Instrum. Meas.*, vol. 63, no. 2, pp. 364--373, February 2014.

[30] S. Shaw and C. Laughman, ''A Kalman-filter spectral envelope preprocessor,'' *IEEE Trans. Instrum. Meas.*, vol. 56, no. 5, pp. 2010--2017, October 2007.