Non-intrusive load monitoring by using active and reactive power in additive Factorial Hidden Markov Models

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HIGHLIGHTS

● NILM is performed by using the active and reactive power in the FHMM framework.
● Appliance models are represented by bivariate HMMs.
● The proposed approach outperforms both AFAMAP and Hart's algorithm on the AMPds dataset both in the denoised and in the noised scenarios.

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ABSTRACT

Non-intrusive load monitoring (NILM) is the task of determining the appliances individual contributions to the aggregate power consumption by using a set of electrical parameters measured at a single metering point. NILM allows to provide detailed consumption information to the users, that induces them to modify their habits towards a wiser use of the electrical energy. This paper proposes a NILM algorithm based on the joint use of active and reactive power in the Additive Factorial Hidden Markov Models framework. In particular, in the proposed approach, the appliance model is represented by a bivariate Hidden Markov Model whose emitted symbols are the joint active-reactive power signals. The disaggregation is performed by means of an alternative formulation of the Additive Factorial Approximate Maximum a Posteriori (AFAMAP) algorithm for dealing with the bivariate HMM models. The proposed solution has been compared to the original AFAMAP algorithm based on the active power only and to the seminal approach proposed by Hart (1992), based on finite state machine appliance models and which employs both the active and reactive power. Hart's algorithm has been improved for handling the occurrence of multiple solutions by means of a Maximum A Posteriori technique (MAP). The experiments have been conducted on the AMPds dataset in noised and denoised conditions and the performance evaluated by using the \( F_1 \)-Measure and the normalized disaggregation metrics. In terms of \( F_1 \)-Measure, the results showed that the proposed approach outperforms AFAMAP, Hart's algorithm, and Hart's with MAP respectively by + 14.9%, + 21.8%, and + 2.5% in the 6 appliances denoised case study. In the 6 appliances noised case study, the relative performance improvement is + 25.5%, + 51.1%, and + 6.7%.

1. Introduction

In the recent years, the public awareness on energy saving themes has been constantly increasing. Indeed, the consequences of global warming are now tangible and studies have demonstrated that they are directly related to humans activities and their inefficient use of energy and natural resources [1–3]. The response of governments and public institutions to counteract this trend is to promote policies for reducing energy waste and intelligently use natural resources. The electricity grid is a key component in this scenario: the original electromechanical grid, where the information flow was one-directional, is transforming into the new digital smart grid [4] where the information flows from the energy provider to distributed sensors and generator stations and vice versa. Part of this change involves the integration of smart meters in the grid in order to provide detailed consumption information both to the consumers and to the energy provider.

Indeed, recent studies demonstrated that this fine-grained information is able to provide significant energy savings [5]. On the consumers side, the knowledge of the energy consumption of individual appliances establishes a virtuous behaviour towards a wiser use of

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electric energy \[6,7\]. Studies showed that this can lead to savings greater than 12% with specific appliance feedback and personalised recommendations \[5,8–10\]. On the energy provider side, fine-grained information enables the prediction of the power demand, the application of management policies and the prevention of overloading or blackouts over the energy network \[11\].

Providing detailed consumption information without installing several dedicated meters requires intelligent methods able to infer the energy consumed by individual appliances with minimal metering points. Non-intrusive load monitoring (NILM) denotes the class of methods and algorithms able to perform this task by using the electrical parameters measured in a single-point \[5,12,13\]. Originally developed in the seminal work by Hart \[14\], NILM has been an active area of research in the last years. The most promising approaches recently presented in the literature are based on machine learning algorithms, and their general scheme consists in extracting significant features from the measured electrical parameters and then estimating the appliance specific active power signal by using a supervised or unsupervised algorithm \[15,12,16\].

The electrical parameters are usually represented by active power, reactive power, voltage or current. The majority of appliances is characterised by a finite number of operating states \[14\] and they are analysed by observing the values of the signals \textit{after a state transition} has completed (steady state approach \[14,17–27\]) or \textit{during a state transition} (transient state approach \[28–33\]). Usually, the latter requires higher sampling rates with respect to steady state analysis (respectively in the order of kHz and of Hz) and more complex and costly hardware equipment \[16\]. This explains why the scientific community devoted particular attention to steady state approaches.

The necessity of the user intervention for creating appliance models distinguishes supervised from unsupervised approaches. The first ones require the availability of the individual signals of each appliance. In a real operating scenario, this translates into requiring support by the user, that should sequentially switch on the appliance of interest and switch off the remaining \[14\]. In a recent work by the authors \[34\], this requirement has been partially relaxed by using selected appliances (e.g., the fridge) to remain operational while signatures of the other appliances are being created.

Unsupervised techniques provide the means to automate the learning process, thus being completely transparent to the user \[15\]. Furthermore, they are capable of dynamically adapting to the power system changes over time (i.e., addition, removal, or substitution of appliance) \[35\]. However, their major shortcoming is represented by the inability to apply an appropriate label to the disaggregated signals. Different approaches try to overcome these limitations by exploiting the information contained on a generic labelled dataset and generalising to unseen household data by using an unsupervised algorithm \[21\].

As aforementioned, machine learning techniques have become a popular choice for NILM, since they showed significant disaggregation performance: in particular, Factorial Hidden Markov models (FHMMs) \[17,36,21,18,25,37,19,20,27,38–40\], Neural Networks (NN) \[22–24,31\], graph-based signal processing \[26\], Support Vector Machines (SVM) \[41\], k-Nearest Neighbours \[41\], and Decision Trees \[42\] have been successfully employed for NILM.

This paper proposes a disaggregation algorithm based on FHMMs and active and reactive power measured at low sampling rates. The paper describes the HMM models of the appliances and the proposed solution for obtaining their parameters from a training dataset. Load disaggregation is performed by proposing a reformulated version the Additive Factorial Approximate Maximum a Posteriori (AFAMAP) algorithm \[18\] that allows a straightforward extension to the bivariate case. The experimental evaluation has been conducted on the Almanac of Minutely Power dataset (AMPds) dataset \[43\] in noised and denoised scenarios, and the proposed solution has been compared to AFAMAP based on the active power only and to two variants of Hart’s algorithm \[14\] both based on active and reactive power. The results show that in terms of $F_2$-Measure the proposed approach provides a significant performance improvement with respect to the comparative methods.

The remainder of this section provides an overview of recent works on NILM based on FHMMs and illustrates the contribution of this paper with respect to them.

1.1. Related work

Among unsupervised approaches, the ones based on FHMMs have been devoted particular attention in the last years. One of the earliest work on the topic has been presented in \[17\] by Kim and colleagues. The key idea is to model each appliance with independent parallel HMM each contributing to the aggregate power. The framework is assessed by using the steady-state real power signal, but it allows multidimensional features as input. In \[21\], the authors employ HMMs in a Bayesian framework in order to combine multiple models and form a general model of an appliance. Labelled data are required in the training phase and then appliance specific models are tuned on aggregate data without requiring user intervention. In the literature, particular attention has been devoted to the algorithm proposed by Kolter and Jaakkola \[18\], since it showed noteworthy performance with a reasonable computational complexity. The Additive Factorial Approximate Maximum a Posteriori (AFAMAP) algorithm is an efficient method, based on an optimization problem, for the inference of the working states combination in the Factorial Hidden Markov Model framework. The authors introduced the AFAMAP algorithm, where they constrain the posterior probability to require only one HMM change state at any given time. Semi-Markov models are combined with Hierarchical Dirichlet Process in \[39\] for inferring both the state complexity of the models and the duration of the distributions. The authors use the active power as input feature and evaluate the performance on the five most consuming appliances of the REDD dataset \[40\]. Makonin and colleagues in \[38\] proposed the sparse Viterbi algorithm for disaggregating the active power online and in real-time. Sparse Viterbi exploits the matrix sparsity in HMMs and it was evaluated on the AMPds \[43\] and REDD \[40\] datasets. Aiad and Lee \[44\] augmented FHMMs with additional chains for modelling possible interactions among the appliances. The algorithm operates on the active power input feature and it was evaluated on the REDD dataset. The work in \[25\] introduces an FHMM model with unbounded number of chains, and states for each chain as well. In \[37\] the authors introduce Hierarchical FHMM with the aim of overcoming the device independence assumption and the one-at-time condition. The algorithm operates on the steady-state active power signal by clustering the signals of correlated devices and then by training HMM models on the identified clusters (denoted as “super devices”). In the disaggregation phase, inference is performed with AFAMAP on the super devices, and the result is mapped back to the original device by using the state relation table learned during the training phase. Compared to the original AFAMAP algorithm on the REDD and Pecan datasets, the method proposed by the authors provides significant performance improvements. Zhong et al., \[19\] incorporate domain knowledge in the FHMM in the form of signal aggregate constraint. In the NILM scenario, this translates into constraining the total energy consumed in a day by an appliance to be close to a predefined value. The algorithm was assessed on the Household Electricity Survey dataset and compared to the Additive Factorial HMM and the AFAMAP algorithms. The results showed that the method indeed achieves better performance in terms of disaggregation error. In a different work \[20\], the same authors introduce interleaved factorial non-homogeneous hidden Markov model (IFNHMM), where the transition probabilities of the models are supposed time variant in order to represent the different pattern of usage of an appliance during the day. In addition, at each time step only one chain is allowed to change. The algorithm presented in \[27\] combine FHMM and Subsequence Dynamic Time Warping (SDTW). The FHMM is employed in the first stage to identify only the ON and OFF state of each appliance. SDTW, then, is applied iteratively to extract the final output. The authors propose both a supervised and semi-supervised version of the algorithm, with the latter employing the aggregate signal and consumption diaries to extract the appliance signatures.

The works presented so far perform load disaggregation by using the
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