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Time series distance-based methods for non-intrusive load monitoring in residential buildings

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ABSTRACT

Non-intrusive load monitoring (NILM) deals with the disaggregation of individual appliances from the total load at the smart meter level. This work proposes a generic methodology using temporal sequence classification algorithms. It is based on a low sampling rate unlike other approaches in this domain. An innovative time series distance-based approach in the temporal classification domain is compared with a standard NILM application based on the hidden Markov model (HMM) algorithm. The method is validated over a data-set of 100 houses for a duration of 1 year (with a 10 min sampling rate). A qualitative analysis of the database is also conducted, allowing to segment it into four major clusters based on discussed features.

1. Context

1.1. Introduction

The smart power meter is becoming one of the fundamental and elementary units of the smart grids, as many further applications rely on the availability of fine-grained information for local energy consumption but also production. We are aiming to a better monitoring of the appliances (loads) present in buildings, from households to tertiary buildings.

These appliances may be, finally, controlled by a local energy management system (private or aggregating many consumers) responding to regional grid manager flexibility requests (through automatically shutting downs, shifting or shading the loads) [1]. In order for the inhabitants to let that happen, economic incentives will have to be proposed (real time pricing, financial compensation, etc.) [2,3].

1.1.1. Monitoring the loads

Load monitoring instrumentation used to involve complex data-gathering hardware but more simple software mechanisms. All the appliances of interest were directly monitored using wires or power-line carrier techniques or radio signaling connected to a central data-gathering unit [4]. Conversely, a non-intrusive load monitoring (NILM) system consists of a simpler hardware part and more complicated software mechanisms: devices can be identified from the global load profile of the house without having to monitor their individual behavior [5,6]. It is called *load disaggregation* or *separation* [7]. The challenges encountered by a NILM problem are both technical and social.

Technical. It is built on top of the premise that the study of how the variation over time of the global energy consumption of a building can lead to information about the appliances that have advocated these changes. Most of the approaches were based on signal processing at a high sampling rate (less than 1 s typically) to evaluate the appliance load signature and subsequently to use pattern recognition techniques for identification from previously trained classifiers.

This requires the installation of a sensor for each appliance within the house and is then naturally restricted to the deployment of this physical system of sensors (without speaking about the installation and maintenance cost). Furthermore, the cost benefit for the user has to be carefully analyzed before developing this kind of solution. The appliance usage being different from one user to the other, the variability of consumption patterns is not systematically compatible with benefits.

Social. A major hurdle in the NILM research is the privacy concerns of the user as the appliance usage can be co-related with user

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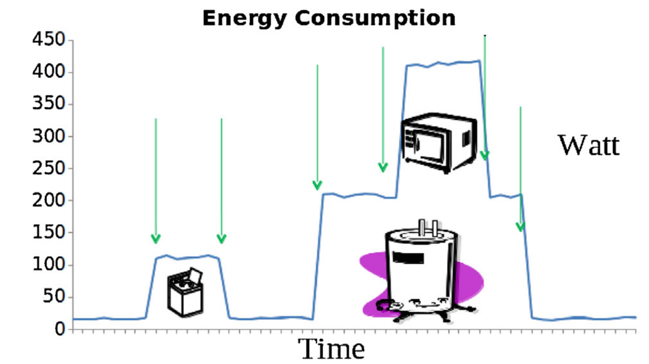
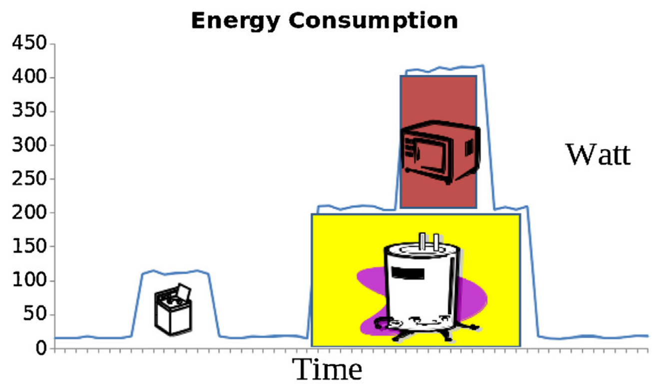


(a) Event-based method



(b) Non event-based method

Fig. 1. Non intrusive load monitoring methods.

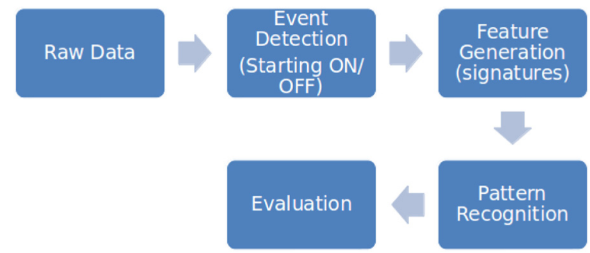


Fig. 2. Non-intrusive load monitoring work flow.

behavior. For example, the time at which the lights are shut down can be assumed to be the sleeping time of the inhabitant [8].

1.1.2. Load disaggregation

Load disaggregation methods can be classified based on the intrusiveness of the training process and the nature of the classification algorithm (*event-based* or *non event-based*). As illustrated in Fig. 1, event-based algorithm tries to detect On/Off transitions whereas non event-based methods tries to detect whether an appliance is On during the sampled duration.

The context of the training process offers two possibilities. First, using supervised machine learning methods with the assumption of the availability of prior data for training [9]. This training mechanism drastically increases the complexity of the mechanism both in terms of cost and time. Second, using unsupervised disaggregation methods where no prior training data is used. This requires a post-processing phase where the appliances are labeled manually. But a fully non-intrusive method which works for all the range of appliances within the house is yet to be developed.

A *non event-based* NILM approach is described in this paper. The strengths of the proposed method are its very short and non-intrusive training period, a novel data collection mechanism that can be very practically implemented due to its procedural simplicity, and an appliance state detection mechanism which is presented and compared with a more traditional NILM mechanism, hidden Markov model, HMM.

1.2. Background

Researchers have been working on the NILM problem for the last two decades. Traditionally the NILM consists of six overlapping phases of data flow analysis [10]. The first is *data acquisition* followed by *data processing*, *event detection*, *feature extraction*, *event classification* and finally *energy computation* as shown in Fig. 2.

The pioneering work in load disaggregation was started by Hart [5] in the beginning of the 1990s. His method was proposed to identify individual appliances from their On/Off transitions. Appliances transitions result in corresponding changes in the overall power consumption monitored at the power meter. This pioneering signal processing technique is shown in Fig. 3.

From that time, most of the approaches were event-based high sampling rate approaches (typically less than 1 s). This rate is required as event-based methods depend on state switching detection.

High sampling rate. There have been a considerable amount of work conducted in the last two decades regarding high sampling rate NILM methods. Each new method proposes to reduce the limitations of the previous ones both in term of appliances signatures or in term of pattern recognition techniques.

Approaches typically consist of identifying the steady state in the appliances signatures (called features) and in some cases transient state [11,12]. Subsequently, these signatures are matched with earlier learned models using a pattern recognition algorithm [13]. The drawbacks of these approaches are mainly hardware requirement due to high sampling rates and the impossibility of the process being totally non-intrusive [14,15].

Despite all the efforts, research at high sampling rate over the years lack of a comprehensive, widely accepted set of feature. Most of the proposed solution are customized for respective applications. Also, these methods do not fit well into the smart meter sampling rate, so separate device has to be installed for training, visualization and communication to the grid. This is a major drawback for these methods, commercially and practically speaking. The load separation at a high sampling rate of all the appliances also raise privacy concerns as user activity can be easily detected, interpreted and monitored [10].

Low sampling rate. At a low sampling rate, switching events are difficult to detect so non event-based methods are more suited. The major issue at low sampling rates is that low energy consuming devices are difficult to detect. However, high energy consuming appliances, such as water heater or washing machine can still be identified with reasonable precision even at a sampling rate of 15 min for example [16,17].

Considering the constraint of low sampling rates, the differentiation of the methods is directly dependent on the choice of algorithms. Some algorithms have already been implemented and tested in the field of load monitoring. For example, a method partially disaggregating total household electricity usage into five load categories has been proposed at a low sampling rate in [18] where different sparse coding algorithms are compared and a discriminative disaggregation sparse coding (DDSC) algorithm is tested. A feature-based support vector machine (SVM) classifier accuracy is also mentioned.

This method is an implementation of the blind source separation problem, which aims at disaggregating mixture of sources into its individual sources. A classic example for this would be the