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Non-intrusive load disaggregation with adaptive estimations of devices main power effects and two-way interactions

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ABSTRACT

Energy management and savings in residential homes are emerging concerns nowadays because of several challenges facing the energy sector such as energy sources limitations and environmental impacts. Non-intrusive load monitoring (NILM) was introduced as a set of methods and techniques that aim to decompose the total aggregate consumption measured by the smart meter into the consumptions by individual appliances present in the household. The detailed information on energy usage for each device were found to be a good influencing method for the residents to adopt better devices usage profiles which lead eventually to noticeable energy savings. Recent research had shown that the Hidden Markov Models (HMMs) and its extensions are effective models in the load disaggregation problem. The authors had introduced a new unsupervised approach for load disaggregation that includes the mutual devices interactions information into the Factorial Hidden Markov Model (FHMM) representation of the aggregate signal in an earlier work. In this paper, we introduce an adaptive approach for estimating devices main power consumptions and their two-way interactions during the disaggregation process. The adaptive approach is used to mimic the changes in devices consumptions and two-way interactions. The adaptive estimation process was carried out only for cases when there are four devices or less that are operating/ON instantaneously. The proposed approach was tested with data from the REDD public data set and it showed better performance in terms of energy disaggregation accuracy compared with the standard FHMM. The adaptive estimating of main factors effects (primary power consumptions) and two-way interactions during the disaggregation process provided higher disaggregation accuracy results, in general, than those with fixed factors and two-way interactions values.

1. Introduction

Several challenges and concerns have arisen nowadays in the energy sector worldwide such as limitation of resources, sustainability, integration of new resources and environmental impacts. Energy saving is becoming a vital issue in an attempt to reduce the effects of some of these challenges. Research has shown that the knowledge of the power consumed by the individual appliances in the house can influence its users and hence lead to energy savings [1]. Energy savings from 9% to 20% were observed in studies conducted (see e.g. [1,5]).

Non-intrusive load monitoring, or energy disaggregation, is a set of methods and techniques whose objective is to decompose the total consumption measurements from smart meters and break them down into the appliances individual consumption. Such information on a specific appliance consumption was found to be helpful for the inhabitants to take further actions that will eventually achieve energy savings [1]. The concept and work on non-intrusive load monitoring was first proposed by Hart in 1992 [2]. Formally, the energy disaggregation problem can be defined as follows: Given the total measured power consumption $p(t)$ at any time instant t, we have

$$p(t) = \sum_{j=1}^{N} p_j(t) \tag{1}$$

The problem is to estimate each $p_j(t)$, the individual power drawn by the device j at time instant of t, where $j = 1, 2, \ldots N$, $t = 1, 2, \ldots T$ and N is the total number of the operating appliances within the disaggregation period T [3]. The NILM process makes use of the total aggregate readings from the smart meter. There is no need for sub-metering or to install a unique sensor for each device as done in the intrusive monitoring methods. For this reason, non-

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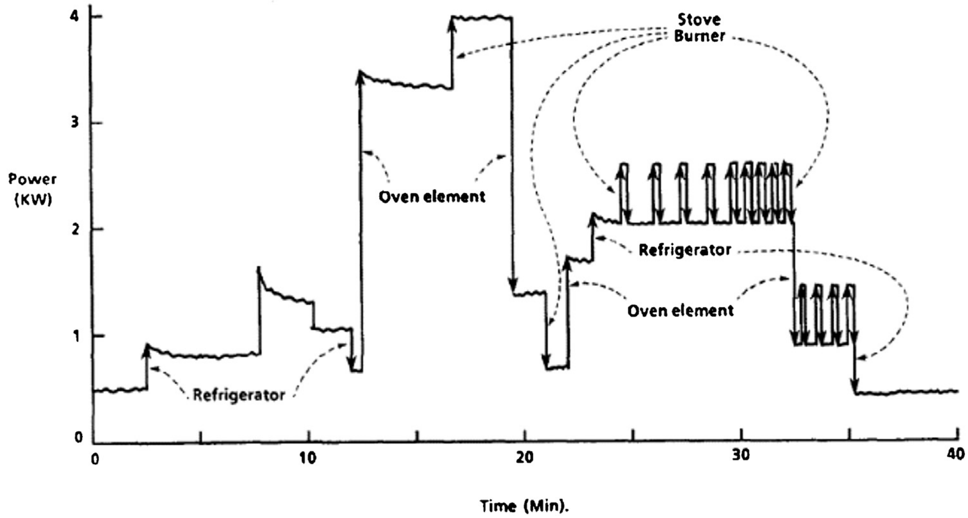

Fig. 1. Power versus time (total load) shows step changes due to individual appliance events [2].

intrusive methods gain more advantages such as applicability and lower implementation cost.

2. Background and related work

The concept and initial work of NILM was first proposed by Hart in 1992 [2]. He showed the possibility to identify the operation of individual devices using the total aggregate signal only. He suggested to perform the disaggregation process in two steps. Firstly, to estimate main devices signatures such as active and reactive power drawn when an event (a device goes ON or OFF) is detected as shown in Fig. 1 [2]. Secondly, to group elements with similar features (signatures) into clusters that represent the individual devices.

It was noticed that there are still some overlapping points between two or more clusters. This can happen between close clusters of low power consuming devices [2]. Therefore, advances in new features extraction and good performance classification methods are required to achieve more accurate energy disaggregation results [4].

The nature and number of features that can be extracted from the total aggregate signal depend significantly on the sampling frequency used in measurements. Main features that can be captured by low frequency meters (like 1 Hz smart meters) include the consumption pattern of a device and its real and reactive power consumptions. In contrast, high sampling frequency measurements (several kHz) can provide more detailed and finer information on distinct devices features such as harmonics, transients, electromagnetic interference (EMI) and noise Fast Fourier Transform (noise FFT) [3]. Even though these fine signatures are useful in the classification process, using high frequency measurement is still unreasonable since it would require installation of new and costly metering equipment rendering it an impractical solution. For these reasons, research should be directed on low frequency data obtained from the currently installed smart meters which report total consumptions at a rate of 1 Hz, for example. Sometimes it is also helpful to use non-electric features for classifications. These features are usually dependent on the users' behavior or environment factors such as outside temperature, day/time of operations, durations of use, interdependency between appliances, . . ., etc. [5].

After extracting all possible features from the aggregate consumption signal, the classification of devices can be done either by a supervised or an unsupervised learning approaches. Supervised approaches include a learning phase where a database of devices together with their distinct signatures (features) is initially built. Subsequently, the disaggregation process can be done either by optimization or pattern recognition methods. Many classification methods such as Bayesian classifiers, Artificial Neural Networks (ANNs) and Hidden Markov Model (HMM) and its extensions were used [3]. Since information on individual devices consumptions are usually unavailable, supervised learning approaches are less realistic solutions to the energy disaggregation problem. Conversely, the unsupervised learning approaches perform online training during the disaggregation process. The process is usually done based on probabilistic analysis and classification methods [5,6].

Recent research had showed that the Hidden Markov Models (HMMs) and their extensions are effective models in the energy disaggregation problem. The observations sequence in HMMs can represent the measured total consumption, while the hidden states chain represents the states of the devices in the household.

Kolter and Jaakkola [6] proposed a new approximate inference method for energy disaggregation based on Factorial Hidden Markov Model (FHMM), which is an extension of the standard HMM with several states chains evolving in parallel and the observation is a joint function of these chains [7]. They utilized two complementary models, the additive and the difference FHMM. The additive FHMM captures the total aggregate output signal while the difference FHMM encodes the signal differences between subsequent levels (when a device switches ON or OFF).

Kim et al. [5] worked on and tested four different extensions of Hidden Markov Model (HMM) for better representations and disaggregation results.

Parson [1,8] proposed an approach in which a one-time supervised learning process with already labeled data set was used to create general probabilistic models of appliances. Thereafter, these general models can be tuned to previously unseen households in an unsupervised manner. The tuning process resulted in specific models of devices that were present in the testing households.

The lack of public data sets was one of the main challenges for researchers to be able to test their new proposed algorithms. Currently, few data sets are available for research goals such as those discussed in [8]. The largest and detailed public data set available is the Reference Energy Disaggregation Data Set (REDD) [9]. REDD includes both individual devices and total consumption measurements of six real houses for an approximate period of two weeks. Individual appliances consumptions can be used for training in supervised approaches and for algorithms validation and accuracy calculations.