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Unsupervised approach for load disaggregation with devices interactions

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ABSTRACT

Energy savings is one of the hottest issues and concerns nowadays due to high oil prices and global warming as a result of CO_2 emissions. Non-intrusive appliances load monitoring (NIALM) is a methodology that aims to breakdown the total power consumption measured by the smart meter in each household into the power consumed by the individual appliances. These detailed information on individual appliances consumptions can influence the users to follow better energy usage profiles so as to achieve energy savings. We introduce a novel energy disaggregation model that considers mutual devices interactions and embeds the information on devices interactions into the Factorial Hidden Markov Model (FHMM) representations of the aggregated data. The hidden states in the FHMM were inferred by means of the Viterbi algorithm. Devices' interaction is a power quality issue that affects the measured power consumed by a device when there are other devices connected to the network. We tested our model using a selected house from the REDD public data set. Our proposed approach showed enhanced results when compared with the standard FHMM. Devices interactions, when observed, enabled us to disaggregate and assign energy consumption for individual devices more accurately.

1. Introduction

It is becoming an established fact that the world faces many challenges regarding energy matters such as resources limitation, sustainability, carbon emissions, etc. Therefore, techniques for energy savings and energy management are necessary to assist in resolving some of these issues.

In residential homes, energy smart meters give information about the total aggregated household consumption of energy. This information is insufficient to inform inhabitants about consumption by individual devices. It is believed that giving detailed information about the energy consumed by each device will influence users on energy usage that would lead eventually to the decrease in energy consumption [1]. Studies conducted had shown energy savings from 9% to 20% (see e.g. [1,6] in this aspect). Energy disaggregation, or non-intrusive appliance load monitoring (NIALM), is the task of decomposing the aggregate consumption readings of a house smart meter into its individual devices consumptions.

Formally, this problem can be defined as follows: Given the total power consumption $p(t)$ at any time instant t, we have

$$p(t) = p_1(t) + p_2(t) + \cdots + p_n(t) \tag{1}$$

The problem is to estimate each $p_j(t)$, the individual power consumption of the device j at time instant t, where $j = 1, 2, \ldots n$, $t = 1, 2, \ldots T$ and n is the total number of active devices within the time period T [2]. Applications of load disaggregation also include energy management systems and faults troubleshooting [3].

To simplify the task of load disaggregation, a load inside a house is considered to fall into one of the following four categories [4]:

- Base load or always ON devices: these are loads which are operating at all time instants. These devices do not switch to the OFF state and they usually have constant active and reactive power draws. Smoke detector is a typical example for this category.
- ON/OFF devices: these are loads with only two possible states (operating/not operating). Examples of such devices include light bulb, television, toaster, etc.
- Finite State Machines (FSM): these are appliances with finite number of possible states. An appliance in this category usually draws different amount of power at each state. Examples of this category include stand and ceiling fans, washing machine, etc.

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- Continuously variable devices: these are loads without fixed number of states and consumes variable amount of power based on their usage manner. An example of this category is the light dimmer.

It is important to notice that in the NIALM process, there is no need to install additional sensors to report devices states because we deal directly with the total measurements from the main smart meter. In intrusive load monitoring techniques, the installations of sensing devices made the energy disaggregation process more costly, complex and less practical in applications [2].

2. Background

Non-intrusive load monitoring was first proposed by Hart in 1992 [5]. His study showed the possibility to detect appliances operations by inspecting their signatures in the total consumption signal. The main work of disaggregation consisted of two steps. Firstly, to measure significant features whenever an event is detected (devices switch ON or OFF) as shown in Fig. 1 [5]. Then, to cluster these features (distinct signatures) into different clusters or groups that represent different appliances. It was observed that high power consuming devices are easier to be classified since they are placed far from other devices in the features space. Meanwhile, there are overlapping points in low power consuming devices, which require additional decision criteria to assign them correctly into devices clusters.

Influenced by Hart's work, researchers started to extend the work by investigating new methodologies to enhance disaggregation accuracy. There are mainly two paths to improve the disaggregation process: extracting new significant features and improving the clustering algorithms [4].

2.1. Low and high frequency sampling features

The number and nature of features that can be extracted from the aggregated total signal obtained from the smart energy meter depend essentially on the sampling frequency used in the measurement stage. High frequencies sampling measurements, which usually use frequencies of several kHz, can capture fine features such as harmonics, transient characteristics, voltage current V–I trajectory shapes, electromagnetic interference (EMI) and noise Fast Fourier Transform (noise FFT) [2]. Although high frequency measurements can provide more fine and detailed signatures, it is still not a practical solution due to the need of installations for new equipment. Currently installed, or to be installed, smart meters usually report power usages at low frequency intervals such as every 1 s interval. Therefore, the solutions for the energy disaggregation problem based on low frequencies signatures are more practical and promising. Main features that can be captured by low frequency measurements are generally macroscopic ones like active and reactive power measured at transition instants of states [4]. Our approach makes use of the measurements from the smart meters without the need of additional sensors installations.

Some non-electric signal features can help in the disaggregation process. These are usually related to users' behavior or outside environmental factors such as ambient temperature, time of use, duration of use, interdependency between appliances, etc. [6].

2.2. Supervised and unsupervised learning algorithms

In supervised learning algorithms, there is a training phase for the proposed models before it is set to work. In this phase, a database of all possible devices along with their features is recorded. The disaggregation process is done later either through optimization or pattern recognition approaches. In optimization methods, the system tries different combinations of known devices that will result in minimized error between actual and estimated total consumptions. In pattern recognition approaches, different methodologies were used to classify devices into their relevant groups such as Bayesian Classifiers, Neural Networks, Hidden Markov Model and its extensions [2]. Supervised learning approaches require training for the models of each device, which make it less applicable in actual system deployment since individual consumption patterns are unavailable in normal situations. Therefore, research has been directed to unsupervised approaches to gain better scalable, time and cost effective solutions [6].

Unsupervised approaches perform models training phase online while the disaggregation process is running such that whenever a new possible device is defined, it will be added to the database of devices. This process is usually done by probabilistic analysis and classification methods [6,7].

Hidden Markov Models (HMMs) and their extensions were used in many proposed disaggregation models due to their good representations of devices. The hidden states chain in HMMs represents the operation state/states of a device and the emission or observation sequences represent the measured total power consumption [8].

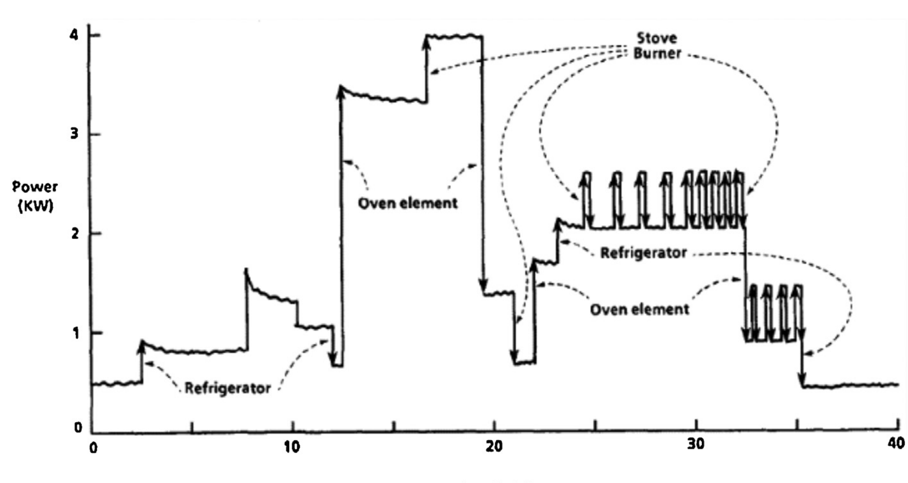

Fig. 1. Total load showing step changes due to individual appliance events [5].