Energy & Buildings 176 (2018) 95–108

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

Interactive visualization for NILM in large buildings using non-negative matrix factorization

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ARTICLE INFO

Article history:
Received 5 February 2018
Revised 24 May 2018
Accepted 28 June 2018
Available online 20 July 2018

Keywords:
Energy efficiency
Visual analytics
Building energy consumption
NMF
Energy disaggregation
Interactive displays

ABSTRACT

Non-intrusive load monitoring (NILM) techniques have recently attracted much interest, since they allow to obtain latent patterns from power demand data in buildings, revealing useful information to the expert user. Unsupervised methods are specially attractive, since they do not require labeled datasets. Particularly, *non-negative matrix factorization* (NMF) methods decompose a single power demand measurement over a certain time period into a set of components or "parts" that are sparse, non-negative and sum up the original measured quantity. Such components reveal hidden temporal patterns which may be difficult to interpret in complex systems such as large buildings. We suggest to integrate the knowledge of the user into the analysis in order to recognize the real events inside the electric network behind the learnt patterns. In this paper, we integrate the available domain knowledge of the user by means of a visual analytics web application in which an expert user can interact in a fluid way with the NMF outcome through visual approaches such as *barcharts, heatmaps* or *calendars*. Our approach is tested with real electric power demand data from a hospital complex, showing how the interpretation of the decomposition is improved by means of interactive *data cube* visualizations, in which the user can insightfully relate the NMF components to characteristic demand patterns of the hospital such as those derived from human activity, as well as to inefficient behaviors of the largest systems in the hospital.

1. Introduction

One interesting approach in energy efficiency is the improvement of electric consumption strategies by means of power demand monitoring tools. Thanks to the growing amount of smart meters installed recently, a lot of measurements of power demand are being gathered today in buildings, household and industrial systems, containing useful hidden information that can help in making efficient decisions if it is extracted and presented intuitively. Thus, developing techniques that are able to extract characteristic patterns of how energy is being consumed from large volumes of demand data, as well as methods to visualize these patterns in an efficient and intuitive way have become promising research topics. A suitable approach with these features is *visual analytics* (VA) [1,2]. VA exploits the insightful synergies between *intelligent data analysis* (IDA), *data visualization* and *interaction* mechanisms, allowing the user to get knowledge from efficient visualizations of raw data and the IDA outcome. By means of interaction mechanisms, the user is brought into the analysis, being able to modify according to his expert knowledge of the system both the visualization and the IDA analysis.

Applying techniques based on IDA algorithms, it is possible to address issues that require a certain learning from the data such as forecasting energy consumption [3–5], getting temporal patterns in electric power demand [6] or the factorization of a total electric power demand into consumptions downstream that have not been measured individually. Decomposing a total consumption, in a sensorless way, is called in the literature *non-intrusive load monitoring* (NILM) [7–9]. This kind of techniques, that can be considered a parts-based representation of total energy, increases the energy awareness of the user, since the obtained components can provide insightful information of how the electric consumptions are distributed temporally and spatially in the network.

Despite recent efforts to develop novel NILM systems, few approaches have explored the NILM outcome within the VA paradigm. NILM techniques are suitable analysis tools for VA, since the obtained disaggregated consumptions reveal temporal patterns

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https://doi.org/10.1016/j.enbuild.2018.06.058

bearing insight when they are represented using suitable data visualizations such as week [10] or calendar [11] heatmaps.

NILM techniques can be classified into supervised and unsupervised methods. In supervised methods, optimization algorithms [12] are applied, and their principal disadvantage is that a labeled dataset is required. In many cases, obtaining labeled data can increase set-up costs of NILM systems, making unsupervised methods more suitable. Within unsupervised NILM techniques, *blind source separation* (BSS) and *factorial hidden Markov models* (FHMM) are the most typical approaches as it is explained in [13]. We choose to apply *non-negative matrix factorization* (NMF) [14] as BSS technique, due to the positive nature of electric power demand and because the imposed constraints on the resulting components may improve their interpretability. NMF techniques aim to separate total power demand into sources of consumption which can be associated with characteristic events or recognizable consumption patterns downstream. In large buildings, where there are many complex systems, the interpretation of the resulting decomposition is often difficult and may require an expert knowledge of the system.

In our work, we propose to apply state-of-the-art NMF techniques to energy-based data of a hospital complex within an interactive framework which allows to integrate the user knowledge in the analysis, showing that NILM methods combined with efficient visualization and interaction mechanisms result in an insightful power demand monitoring tool for large buildings. In Section 2, we formulate our approach and we describe the real electric consumption dataset from a hospital complex on which our approach is tested. Then, in Section 3, we define how to apply NMF to electric measurements and how to integrate NMF in an interactive visualization. Finally, in Section 4, the proposed power demand monitoring application is presented, showing different cases of study.

2. Problem formulation

In this section, we will introduce the two pillars of our work: NILM analysis and the specifications of the interactive data visualization. Then, we will explain the particular problem that will be addressed in Section 4.

2.1. NILM analysis

Several studies [7,15,16] suggest that an improvement in energy efficiency can be achieved through the increase of energetic awareness by means of feedback mechanisms. The extended deployment of smart meters is an example that getting feedback about demand has become a key factor in energy efficiency strategies. Based on this, we propose not only a simple visual supervision of the measured energy data, but also consider the integration of NILM techniques in a visual interface to reveal hidden patterns of how the energy is spent, providing a more detailed feedback information.

The idea of NILM was introduced three decades ago by Hart in [12]. Its application to time series of electrical demand results in the decomposition of the following parts

$$\mathbf{p}(t) = \mathbf{p}_1(t) + \mathbf{p}_2(t) + \ldots + \mathbf{p}_n(t) \quad (1)$$

where the electric power demand at time t is the sum of the n consumptions $\mathbf{p}_i$ corresponding to the appliances connected downstream. Note that if the network lacks generative systems, the components $\mathbf{p}_i$ are always positive. This non-negative nature of the components suggests that each $\mathbf{p}_i$ is a part of a whole. Getting insight into an object through learning its parts individually is an operation that occurs in the human perception process as it is shown in [17,18]. Thus, the parts-based representation expressed in Eq. (1) is potentially a highly interpretable feedback for the user.

A well-known decomposition method which attempts to learn the parts of a whole from the input data is *non-negative matrix factorization* introduced in [14]. NMF was conceived to address fundamentally image processing, being able to learn different parts from example images of an object. In recent years, more successful applications of NMF have been addressed in different fields, such as text analysis [19] or environmental data analysis [20], but few approaches have explored the possibilities of applying NMF to electric power demand data. In this paper, we suggest how to apply NMF techniques to energy consumption analysis in a large building, discussing their advantages and limitations as unsupervised NILM methods.

2.2. The need for interactive visualization

Energy demand monitoring tools in large buildings are based on the energy-based data gathered from smart meters. These measurements involve different kinds of attributes apart from the electric variables, such as time factors (hour, day, week, year), spatial factors (buildings, floor), environmental factors (temperature, humidity, occupancy) or even variables of characteristic processes or systems where a large demand is involved. Thus, energy demand analysis is a *multiway* problem. If all these factors are efficiently presented in an intuitive representation, an expert user can discover hidden insightful correlations between all these factors, thereby improving his knowledge about how the energy is spent. In this scenario, many applications suggest that the user can find these correlations visually by means of well designed visual encodings to transform information into appropriate visual representations. Most of the visual energy demand approaches are based on static 2D representations which can only plot a few factors. Through interaction, the user can explore a multiway dataset, setting a scenario by means of a number of conditions and using the visual feedback to confirm or reformulate hypotheses, by retuning the conditions, focusing on specific factors or modifying the visual encodings. This process has been modeled in [2] as an iterative process that improves the knowledge of the user through several cycles of interaction and visualization. It is known that the more fluid [21] the process of interaction is, the better immersion in the problem, increasing the chances to obtain useful knowledge as well as confidence in the results.

One example of interactive data exploration tool based on electric power demand is [22], where the multiway problem of energy demand analysis in several public buildings is addressed through a fluid interaction between coordinated views of the factors. In order to achieve the required fluidity in the interaction, the information from the buildings is structured according to the *data cube* approach [23,24]. The data cube provides mechanisms to create new hypotheses through filters on different attributes of the data which can be established quickly by means of Javascript implementations [25], receiving an immediate visual feedback (latencies $<$ 16 ms).

The *visual analytics* paradigm suggests that the gained knowledge about the problem not only comes from the fluid interaction between data and the user, but also from the outcome of IDA algorithms. The integration of IDA outcomes in the interactive visualization reinforces them, since they can be visually confronted with the rest of the attributes by the user in an intuitive way. The newly discovered knowledge inspires the user to change the specifications both in data visualization and in IDA, closing the cycle.

In our approach, we propose to integrate the outcome of NILM techniques in an interactive visualization based on the data cube framework, considering design principles which improve both the fluid interaction and the efficient perception of the attributes.

2.3. Monitoring power demand in a hospital complex

The concepts explained above will be tested with real electric power demand data obtained from a hospital complex, which in-