Reducing the Intrusiveness of Energy and Water End-Use Disaggregation via Social Media and Users Interactions

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Abstract

Water end-use disaggregation from smart-metered water consumption data is key to design water demand management strategies. Yet, despite large investments for smart metering networks, few water utilities are actually exploiting the potential of end-use-based consumer profiling. This is mostly due to the intrusiveness of existing disaggregation algorithms, which require intensive and time consuming human interaction for extracting appliance-specific information and estimating the end-use patterns. We propose to explore the potential for social media in facilitating the interactions between water utilities and water users in order to collect consumption diaries. The evaluation of the value of this user-generated information is performed by using the collected diaries as input for a disaggregation algorithm, which is shown to attain acceptable performance in reproducing the end-use patterns.

Introduction

The growth of human population by the end of the century and the increasing number of mega-cities will boost the demand for natural resources, particularly energy and water (Gerland et al. 2014). To face pressure on these finite resources, a variety of demand management strategies have been applied in different contexts, including promotion of cost-effective water-saving technologies, revised economic policies, appropriate national and local regulations, and education. The effectiveness of demand management strategies relies on the level of understanding we have about users' behaviors and the associated consumption patterns at different spatial and temporal resolutions. The effectiveness of customized demand management strategies has been demonstrated to benefit from appliance-specific information (Carrie Armel et al. 2013): timings, peak-hours, and frequencies of use of electric and water devices represent a key information for better targeting demand management strategies (e.g., deferring the use of some appliances to peak-off hours).

These challenges have motivated large investments for the deployment of smart metering networks (Neenan and Hemphill 2008), which made available consumption data at very high spatial (household) and temporal (from several minutes up to few seconds) resolution, enabling the application of big data analytics tools to develop accurate characterizations of end-use consumption patterns. In parallel, research efforts have focused on developing dis-

aggregation algorithms to breakdown the total consumption data registered at the household level into the different end-use categories (Hart 1992). Several disaggregation algorithms have been proposed in the literature, mainly in the energy sector (for a review, see (Zoha et al. 2012; Cominola et al. 2015b) and references therein).

Despite promising results, the large-scale application of these approaches has been strongly limited by the rate of intrusiveness of the data sampling process (Goncalves et al. 2011) as most disaggregation techniques require large datasets collected at the appliance level for the initial off-line training of the algorithm. Several studies have been conducted in the last two decades using a variety of single or mixed disaggregation methods, often requiring time consuming expert manual processing and intensive human interactions via surveys and event diaries, where the users are requested to register their consumption habits (Desmedt, Vekemans, and Maes 2009). This process, however, may significantly benefit from the use of social media in terms of facilitating the interactions with energy and water users and, particularly, of engaging them in filling in a consumption diary.

In this work, we explore the potential of social media in prompting active users participation to support the non-intrusive acquisition of consumption events at the appliance level by means of consumption diaries, used for disaggregation algorithms that estimate end-use consumption patterns.

Problem Statement

Disaggregation estimates the contribution of each appliance to the total consumption metered at the household level. Formally, it solves a blind identification problem searching for the consumption trajectories of each appliance that minimize the error between estimated $\hat{Y}_t$ and observed $\bar{Y}_t$ trajectories:

$$[B^*, x^*] = \arg \min_{B^i x^i} \left[\sum_{t=1}^{H} (\bar{Y}_t - \hat{Y}_t)^2 \right]$$

where: $\bar{Y}_t = \sum_{i=1}^{N} y_t^i + e_t$ is the total measured power consumption, N is the total number of appliances, $y_t^i = B^i x_t^i$ is the consumption of the i-th appliance given as the product of its consumption basis B^i related to each operational state and the corresponding activation vector x^i, e_t is the measure noise.

Most disaggregation algorithms require a supervised learning phase to collect the end-use consumptions representing typical consumption patterns (the so-called signatures) of the N appliances. These are needed for calibrating the consumption basis B^i and other method-specific parameters. However, the intrusiveness of this phase, which would require installing one meter per device for few weeks, often hampers the wide usability of su ch algorithms in real world case studies. Such intrusiveness can be reduced by replacing the observation of device-level consumption with the collection of information about a single-event signature, retrieved from the total consumption trajectory for a time window in which the considered appliance is working without other appliances interference. This time window can be identified through the use of consumption diaries where the users annotate specific consumption events for a limited time.

Experimental Setup

Our approach plans to acquire user-generated data on single device usage by means of a mobile application, allowing the compilation of consumption diaries with minimum effort thanks to a concise user interface with a small set of fields and toggles to register water-consuming actions. The goal of the app is to build a user-generated water-consumption diary, associating to each day a set of temporal ranges in which a single appliance is used. A well-formed diary contains, within a day, a certain number of events exclusively characterizing a time range. The time range can be defined a-priori, possibly associated to the metering resolution.

The app features two form-based components, a descriptive component and an underlying *diary-builder* engine. The first form-based component gathers data, such as appliances types and quantities, family composition, number of bathrooms and personal attitude towards environment. Once the required information is collected, the user can access the second component, which provides interactive views to easily register appliance usages. The input of events is made with simple widgets, such as buttons, time and date pickers and selectors. For some actions whose duration plays a crucial role (e.g. showers), a start/stop toggle helps register the event and its duration with one touch. An agenda-view makes the diary available for consultation and let the user deleting or correcting registered actions.

The *diary-builder* engine performs validation, excluding actions registered in the same time range. It can also inform the user on the lack of recorded actions associated to certain appliances. When a validated diary reaches the required size (in terms of days, defined by developers at design-time), the engine notifies the user, who can send the report to data server. To complete the loop, the effectiveness of the app is validated by sending to the users the computed trajectories, asking for confirmations of estimated actions.

We assess the utility of collected information, i.e. a single-event signature for each appliance, by testing the Hybrid Signature-based Iterative Disaggregation algorithm (Cominola et al. 2015a) against the AMPds dataset (Makonin et al. 2013). This dataset contains power consumption readings for five devices (i.e., heat pump,

forced air furnace, clothes dryer, kitchen fridge, and security/network equipment) at 1 minute resolution for a single house located in the Vancouver region (Canada). Despite the limited amount of information for calibrating the algorithm, preliminary results show an acceptable performance in the characterization of the end-use patterns. The accuracy in classifying the operating states of the considered appliances is higher than 70% for four out of five appliances. Moreover, the errors in assigning the power consumption to the different appliances is lower than 10%.

Conclusion and future work

We explore the potential of social media and user interaction for collecting consumption diaries that allows reducing the intrusiveness of energy and water end-use disaggregation. The estimated end-use patterns are crucial for designing customized demand management strategies. As future work, the designed app will be used for a large scale application for collecting water consumption diaries in the city of Valencia, as part of the SmartH2O Project (http://www.smarth2o-fp7.eu/), reaching hundreds of thousands water users.

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