Learning to Be Energy-Wise: Discriminative Methods for Load Disaggregation

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ABSTRACT

In this paper we describe an ongoing project which develops an automated residential Demand Response (DR) system that attempts to manage residential loads in accordance with DR signals. In this early stage of the project, we propose an approach for identifying individual appliance consumption from the aggregate load and discuss the effectiveness of load disaggregation techniques when total load data also includes appliances that are unmonitored even during the training phase. We show that simple discriminative methods can directly predict the appliance states (e.g. *on, off, standby*) and the predicted state can be used to calculate energy consumed by the appliances. We also show that these methods perform substantially better than the generative models of energy consumption that are commonly used. We evaluated the proposed approach using publicly available REDD data set, and our experimental evaluation demonstrates the improvement in accuracy.

Categories and Subject Descriptors

I.5.2 [**Design Methodology**]: Pattern Analysis

General Terms

Algorithms, Performance, Design, and Verification

Keywords

Energy management, non-intrusive, data mining, context-awareness and ubiquitous computing

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1. INTRODUCTION

Since electricity cannot be stored effectively in large quantities, power grids must continuously match supply and demand. This can be challenging because power must be generated and supplied to each customer as it is called for instantly, in quantities that vary rapidly. Meeting these fluctuating demands requires keeping a vast array of expensive transmission, distribution and generation equipment on constant standby. The amount and size of these equipment must be sized to meet peak demand rather than the average. As a result, the power grids usually suffer from low load factor and are underutilized most of the time. For example, the US national load factor is about 55%, and 10% of generation and 25% of distribution facilities are used less than 400 hours per year, i.e., 5% of the time [2]. Shaping the demand to reduce the peak and smooth the variation can greatly improve power system efficiency and yield huge savings [6].

Demand response (DR) programs encourage end consumers to alter their electricity consumption in response to DR signals such as incentives and real-time electricity prices so that peak demand may be reduced [20]. Reducing peak demand preempts the need to invest in additional generation capacity that gets utilized only during narrow peak periods, thereby minimizing costs and added environmental pollution. Studies indicate that even minor shifts in peak demand have major implications in terms of savings for both consumers and utilities [19]. A Lawrence Berkeley National Lab report estimates that during 2006-08, the potential size of peak load reduction from existing DR resources in the US was as much as 5-5.8% of peak national demand [4]. As per another study, DR programs alone could achieve up to half of EU's 2020 targets concerning energy savings and CO_2 emissions [5].

Traditionally, only industrial customers have been participating in DR programs. However, facilitating the participation of residential consumers as well is likely to result in considerable savings given that this is a growing sector and accounts for a sizable portion of the total energy consumed. For instance, in EU-27 nations, the domestic sector consumed 24.6% of total energy in 2007 while the sector grew by 8% from 1990 and 2007 [9]. Despite the savings possible through DR, the success of these programs essentially hinges upon user participation and their timely response to DR signals. One of the main barriers in involving households to participate in DR is the lack of systems that can automatically respond to DR signals [1, 3]. Automating DR is not straightforward as home appliances must be managed in accordance with DR signals without compromising the comfort of consumers. A deep and accurate understanding of user's energy consumption patterns in relation to their regular activities is crucial for automatic DR Systems [11, 7], as well as for undertaking studies that focus on inducing long-term sustainable behaviors at a societal level [8].

To address this need, we are developing *Wattzup*, a context-aware automated DR system. This system, to minimize consumer inconvenience, aims to manage residential loads while respecting the context[1] of residential consumers. In this paper, we present only one component of *Wattzup* that identifies active appliances at specific time and appliance level consumption details using only the aggregated (household level) consumption data. We also discuss the effectiveness of load disaggregation techniques when total load data also includes appliances that are unmonitored even during the training phase.

The rest of the paper is organized as follows. Section 2 gives an overview of *Wattzup*. Section 3 describes our approach for identifying appliance usage from aggregated consumption data and Section 4 presents the evaluation results of our approach. Finally, Section 5 concludes the paper with a summary of the results and a discussion on load disaggregation effectiveness.

2. WATTZUP OVERVIEW

The conceptual design of our proposed system, *Wattzup*, is shown in Figure 1. There are two major components or processing stages in the system. The first component is designed to recognize and determine which appliances are in use at a specific time. While this is reasonably simple when all appliances and circuit breakers have monitoring sensors attached to them, we believe that this needs to also be feasible in contexts where appliance monitoring sensors are limited or only aggregate smart meter data is accessible. We then generate set of patterns that imply the energy/appliance usage behavior of the occupants, and record these patterns as the baseline (normal) patterns and keep them as basic rules of the system.

The second component focuses on understanding the context that underpins the specified usage pattern. We aim to extract the correlations between the appliance usage patterns and consumer context such as occupant's demographics (e.g. age, gender), external factors (e.g. weather and temperature), major events (e.g. popular sport matches), and location information from mobile phones and/or social media (if available and accessible). A very simple example is the fact that television usage patterns may differ significantly from their normal baseline usage during major sporting events/natural disasters.

Our objective for understanding correlations between demand patterns and context is developing automated DR programs that can manage loads without inconveniencing consumers. Moreover, such correlations can also be useful for accurate prediction of residential demands.

[1]We refer to 'context' in the pervasive computing sense information that pertains to the what, where, when and why of a particular user and her activities [18].

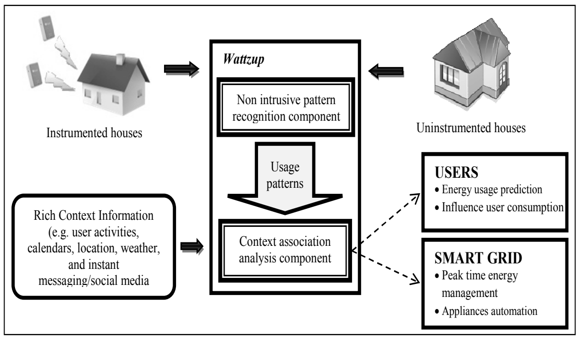

Figure 1: *Watzzup* System Overview

3. APPLIANCE USAGE RECOGNITION

Currently we are in the first stage of this project that focuses on learning the normal patterns of energy consumption. We start this stage by recognizing active and inactive appliances based on Non-intrusive Appliances Load Monitoring (NALM) concept introduced by Hart [10]. Past and recent NALM works on real and reactive power (macro) data falls into two categories. The first group of approaches typically analyzes changes in power to determine which appliance is changing state (e.g. from on to off) [17, 14, 16]. While these approaches give significant accuracy in detecting most consumptive appliances e.g. heating, ventilation and air conditioning (HVAC) appliances, common problems arise when there are two or more appliances with similar energy consumption characteristic [17] and the interval between two aggregate meter readings is large [14]. The second group of algorithms disaggregates total load consumption by analyzing snapshot data [13, 12]. The value of using snapshot data is that the accuracy remains similar when data stream is interrupted or unavailable for a specific interval. Thus, in this paper, we propose a disaggregation method based on snapshot data.

Load disaggregation problem is defined as given $\bar{y}$ be a discrete sequence of observed aggregate power readings of n number of individual appliance $\bar{y} = \{\bar{y}_1, \bar{y}_2, ..., \bar{y}_T\}$, $\bar{y}_t = \sum_{i=1}^{n} y_t^{(i)}$,$i = 1, ..., n$, $t = 1, ..., T$, determine the operational state/load of each appliance in a specific time $\hat{y}_t^{(i)}$ [13]. In real condition, the total household consumption data $\bar{y}$ may include energy consumption from unmonitored household appliances since appliance level sensors deployment does not cover all appliances inside the house due to cost and installation issues. This condition has significantly increased the challenge of providing high accuracy load disaggregation models when compared with other research in the area that assumes that aggregate data is the sum of appliance level data.

4. EARLY EXPERIMENTS AND RESULTS

Unlike other NALM based systems which use generative models of energy consumption to determine which appliance goes on or off, we focus on discriminative approach that predicts the most likely or possible appliance state configuration from total power consumption in a specific time period using simple non parametric classification algorithms. In our model, we first automatically discretize each appliance's load $y^{(i)}$ into z states where $z \geq 2$, since each appliance has at least 2 states, *on* and *off*. When real power consumption of an appliance at specific time is 0, we can consider this appliance is not in use or in *off* state. So, for any number of z, we assign all $y_t^{(i)} = 0, y_t^{(i)} \in y^{(i)}$ as *off*. We then use EM algorithm [15] to cluster the non-zero appliance load into z-1 clusters and label those clusters sequentially based on the cluster mean. As an example, if $z = 3$ (*on, off, standby*), we assign all $y_t^{(i)} = 0$ as *off*, then we cluster $y_t^{(i)} \neq 0$ into two clusters. For descriptive clarity, a cluster that has highest mean of power consumption is labelled as *on* cluster and the other cluster is labelled as the *standby* cluster. We keep each cluster mean as state power demand and use it to recalculate the appliance power consumption from predicted state.

Having discretized our training data set, we then run kNN algorithm to build the predictive model. For each aggregate load $\bar{y}_t$ in the test data, we find k nearest neighbors from the training data based on their Euclidean distance of aggregate load, day and time of the day attributes. Each neighbor has a combination of appliances' state as a result of previous discretization process. We then decide the most possible state combination from those neighbors based on the majority/voting approach.

One important point of emphasis is that simple 'Subset-Sum' type techniques, where we find the set of appliances that sum up to the observed consumption, do not work well on this data set since a large portion of the home energy consumption is not monitored directly. The primary characteristics of our method that are important to emphasize are: (i) The discriminative machine learning approach we use is based directly on historical consumption data which consists of each monitored appliance's consumption data and total household consumption that includes both monitored and unmonitored appliances energy consumption; (ii) The method does not directly predict consumption levels, but activity or state, and then uses historical data to predict usage level. This seems to improve accuracy substantially compared to previous approaches that directly estimate consumption levels; (iii) The method is simple and computationally efficient while offering high enough accuracy for the next steps of a complete DR system.

To validate our approach two main evaluations have been performed. Firstly, we identify the accuracy in terms of identifying state of each appliance based on aggregate load to measure the performance of the proposed approach in detecting active and inactive appliances. Secondly, we compare the performance of our approach with other algorithms that run on similar data set. From the best of our knowledge there are two other approaches that have been tested on this data set, Kolter and Johson [13] and Parson et al [16]. Kolter and Johnson implement a generative Factorial HMM to model and test all appliances within the houses. Parson et. al. identify most energy consuming appliances (refrigerator, microwave, and clothes dryer) by implementing unsupervised iterative hidden markov model. Our experiment is similar to Kolter and Johnson's supervised algorithm, thus we compare our result to their published supervised approach results on the same dataset.

Our approach have been evaluated on the publicly available REDD data set [13]. The REDD data set contains 6 houses energy consumption data that contains both appliance and total consumption level data. However, the data is historical and static (there are no updates) and only 4 houses consist of at least two weeks data. In our experiment we focus on these houses. Over these two weeks data, we use first week data as training set and second week data as test set. We aggregate both circuit (appliance) level and total household consumption data into 10 seconds interval. The total household load comprises all monitored appliances energy consumption and additional load of unmonitored appliances.

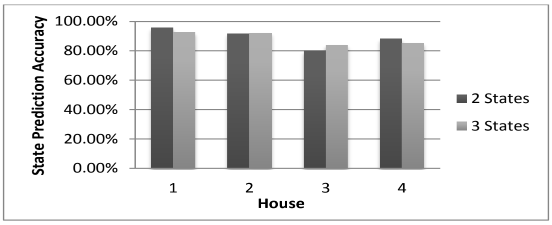

Figure 2: State Prediction Accuracy

The experimental evaluation demonstrates the improvement of accuracy in identifying the appliance states and predicting the total energy as shown in Figure 2 and Figure 3 respectively. Figure 2 shows our state prediction accuracy. Both 2 states discretization and 3 states discretization achieve around 88% average accuracy on states detection. This result shows that our proposed algorithm is reasonably effective in recognizing active (*on/standby*) and inactive (*off*) appliance. Having reasonably good accuracy in predicting state of appliances, we then recalculate the energy consumption of each appliance based on the predicted states and calculate the accuracy of total energy being correctly assigned. We use Kolter and Johnson's [13] performance evaluation formula to calculate the accuracy.

$$Acc = 1 - \frac{\sum_{t-1}^{T} \sum_{i=1}^{n} \left| \hat{y}_t^{(i)} - y_t^{(i)} \right|}{2 \sum_{t-1}^{T} \bar{y}_t}$$

As can be seen in Figure 3, our 3 states discretization approach achieves more than 80% accuracy for each house. These results compare favorably with Kolter and Johnson's supervised approach, which achieves on average 42.7% using simple means and 64.5% using FHMM [13]. This significant improvement in terms of total assigned energy accuracy is due to the appliance state discretization techniques and the additional context features (time and day) that we use. This initial evaluation provides us with evidence that there is scope to significantly improve on the prediction accuracy of NALM techniques in a condition where only few number of the appliance level sensors installed on major appliances.

5. DISCUSSION

This project proposes an automated DR system that combines sensor based appliance data analysis and publicly available rich context data to maximize the energy savings within residential premises. In this very early stage of the project, we propose a very simple discriminative approach to disaggregate energy load which gives fine-grained information of active and inactive appliances from only total household

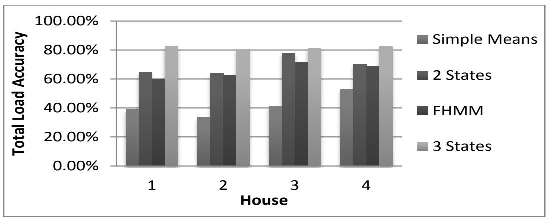

Figure 3: Total Load Accuracy

consumption even when only a subset of appliances are monitored during the training phase. Experiments show that the proposed approach achieves a reasonably good accuracy in state prediction and a significant accuracy improvement in total energy prediction.

In practical deployments, the measured total consumption will include unmonitored household appliances since appliance level sensors deployment will not cover all appliances, due to cost and installation issues. Thus, the most important challenge to be addressed is 'Can energy disaggregation methods be useful even when only a few appliances are monitored even in the training phase?'. If the answer to this question is 'Yes', then it helps attain an understanding of appliance usage despite the absence or the limited number of the appliance level sensors and make the case that effective demand response is possible with just the monitoring of a few important devices.

Additionally, while most previous attempts at appliance disaggregation have build generative models of appliance usage we see that discriminative methods that attempt to classify appliances that are *on* or *off* directly from total usage are simple to implement yet very successful in practice as shown here. This is complementary to the discriminative methods in [12] where it is assumed that the measured loads form majority of the total load. They also rely on time series of usage while we see that even time slot by time slot classification performs very well in practice.

The final topic of discussion raised by our work is 'What is the NALM accuracy required for successful DR systems?'. The 88% accuracy in state prediction becomes an important milestone for the subsequent stage of the project. Moreover, having 82% accuracy in total energy correctly assigned, we intend to use this aggregation technique for our future work.

Our immediate focus is on analyzing the level of accuracy required to have reliable DR system, developing the unsupervised load disaggregation method and discovering effective techniques for leveraging situation awareness through external/rich context information.

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