Poster Abstract: A Design of Data-Driven Energy-Use Profiling in Residential Buildings

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ABSTRACT

In this paper, we designed a method for data-driven energy-use profiling using smart-meter data in residential buildings. The process includes a model-based energy disaggregation, appliance rate-of-use statistics, and inter-appliances association mining. Our goal is to provide the energy-use profile which includes what appliances, when did they use, and the relationship between them. These results can be used for further help in the design of building energy management systems for adaptive and transactive energy control.

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1 INTRODUCTION

In recent years, many research has been conducted on the development of building energy management systems (BEMS) for adaptive and transactive energy control which include home and building automation, electrical load forecasting, and demand response application [1, 4, 5]. However, the effectiveness of systems usually depends on the human behavior inside the building. Therefore, the need for real-time information of energy-use profile that gives insight into what appliances, when did they use, how much energy they consume, and the relation of usage among them is indispensable.

One of the earliest methods to profile the energy-use behavior is using activity data. This method requires a conversion procedure from the activity probability to the appliance usage pattern. However, since most of the conversion is not rigorously investigated, this method sometimes problematic [2]. Hence the need to directly estimate appliance usage patterns is unavoidable.

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Generally, appliance sensor data is used to record the power signature, either using a single-appliance sensor or plug-sensor which record one or more appliances that connected directly to the plug. However, this method is costly and requires much amount of time of implementation. Therefore, the usage of a smart-metering device to record aggregate energy consumption from all appliances inside a building is proposed. In this paper, we designed a method for data-driven energy-use profiling using smart-meter data in residential buildings.

2 PROPOSED METHOD

Our energy-use profiling process includes a model-based energy disaggregation, appliance rate-of-use statistics, and inter-appliances association mining as depicted in Figure 1.

2.1 Energy Disaggregation

The task of energy disaggregation in this process is to infer

(1) the energy contribution e_t^i appliance $i \, \epsilon \{1,2,....,N\}$ at time $t = \{1,2,....,T\}$,
(2) from the sequence of aggregation energy consumption data $D = \{D_1, D_2, ..., D_T\}$.

$$D_t = \sum_{i}^{N} e_t^i + \sigma(t) \tag{1}$$

as depicted in equation 1, where $\sigma(t)$ represent any contribution from appliances not accounted for measurement noise.

In the initial stage of our research, we develop a simple ON/OFF model to define the state of each appliance. This model describes how much energy that each appliance consumes and how long is active. This simple ON/OFF model includes two states, the ON state draws some fixed power active S_t^{ON}, and the OFF state draws zero or minimal amount of energy usage S_t^{OFF}. To construct this model, we use NILMTK [1], an open-source toolkit designed to help researchers evaluate their algorithm while determining the appropriate values of S_t^{ON} and S_t^{OFF}.

2.2 Rate-of-Use Statistics

In this step, we expected to present a matrix of probabilities for each appliance state ON/OFF in a specific time of period, for example

[1]http://nilmtk.github.io/

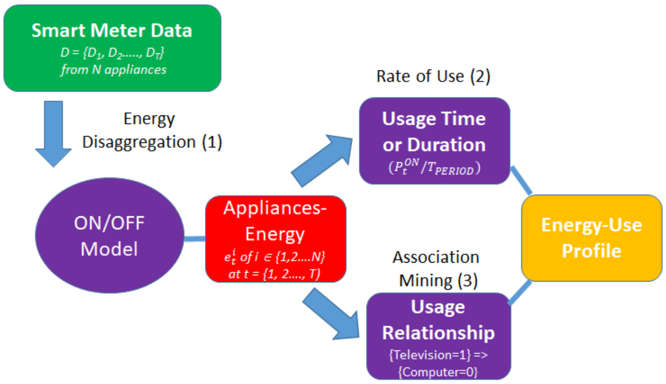

Figure 1: Energy-Use Profiling Process from Smart-Meter Data

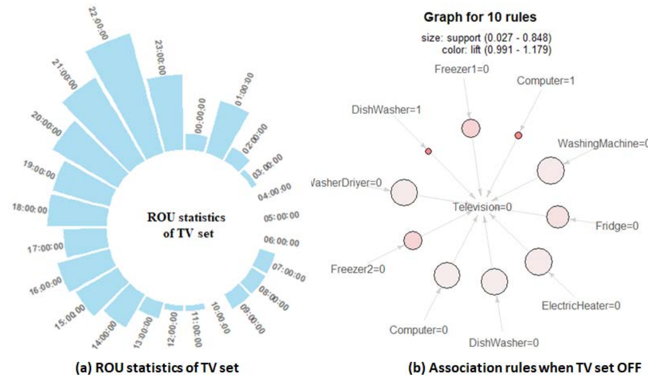

Figure 2: Initial Result

in a specified month or during a winter season. Using the ON/OFF model from energy disaggregation step, we then apply the rate-of-use (ROU) statistics to define ON/OFF rate of an appliance. We denote value 1 represents ON state and value 0 represents OFF state.

The portion of time that the appliance is ON P_t^{ON} over a specific time-period T can be calculated using the following equation

$$P_t^{ON} rate = \frac{1}{T} \sum_{T=1}^{T} S_t^{ON} \times 100\% \qquad (2)$$

2.3 Inter-Appliances Association Mining

In this step, we analyze inter-appliance usages to find what appliances that are relatively used together and the strength of their relationship. We investigate the most relevant set of association rules by use of apriori principle in association mining.

Consider in a single residential building with N set of active appliances at each sampling time t. $i \epsilon N$ represents the set of active appliances at given sampling point. The association rule $A \Rightarrow B$ expresses an if/then relationship between those appliances. The support, confidence, and lift values can be measured by following equations

$$Support\{A\} = \frac{|i \epsilon N; A \subseteq t|}{|N|} \qquad (3.1)$$

$$Confidence\{A \Rightarrow B\} = \frac{support(A, B)}{support(B)} \qquad (3.2)$$

$$Lift\{A \Rightarrow B\} = \frac{support(A, B)}{support(A) \times support(B)} \qquad (3.3)$$

3 INITIAL RESULT AND ANALYSIS

We run our experiment using the REFIT dataset [3], one of the publicly available data for energy consumption measurement. This dataset includes data from 20 residential buildings in the Loughborough area, UK, in two years of periods (2013-2014). Each building has a smart-metering data and nine appliances data. For example, in the building 1, they have one fridge appliance, two freezer appliances, one washer dryer, one washing machine, one dishwasher, one computer, one television set, and one electric heater.

Using this dataset, we can profile the energy-use for each-building or inter-building (neighborhood) behavior in adaptive and transactive energy network. However, we provide only the result of the intra-building analysis in current work. We selected the television (TV) set appliance as the first example. This appliance is the most frequent consumer electronics use in the daily living. We begin the experiment with two questions.

a) When and how long does the occupant of each residential buildings is watching TV in each time of day?

b) At the time of watching TV, what appliances are also active together?

Figure 2 depicted example of our initial result. From the recorded data, we conclude that the TV was OFF when the Dish Washer or the Computer was ON, and the highest probability of the TV was ON at 08:00 to 10:00 PM with rate 79.31% in the building-1.

4 CONCLUSION AND FUTURE WORKS

Using an energy disaggregation technique, combined by the ROU statistics, and an association mining algorithm we can provide the energy-use profile which includes what appliances were used, when did they use, the amount of the appliances energy consumption, what appliances that were used together, and the strength of their relationship. However, for the better profiling result, we need to enhance the ON/OFF model in the future of our work, not only limited to binary states.

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