STOCHASTIC MODELING AND DISAGGREGATION OF ENERGY-CONSUMPTION BEHAVIOR

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ABSTRACT

This paper focuses on stochastic modeling and energy disaggregation based on conditional random fields (CRFs) using real-world energy consumption data. Firstly, energy-consumption activities modeling aims at understanding and identifying energy-consumption activities using behavior models based on observed energy signals. Our ultimate goal is to suggest ways to modify human behavior activities in order to conserve energy by optimizing the use of energy. Preliminary analysis of energy consumption data clearly shows the potential effectiveness of activity behavior changes on the changing energy consumption behavior. Secondly, energy disaggregation aims at breaking up the total energy signal into its component appliances. This is very useful since it can provide home owners with feedback about the way they use electrical energy, and can also motivate users to conserve significant amounts of energy. In the current study, we focus on activity/event disaggregation using the total energy-consumption signal.

Index Terms— Energy consumption, energy activity behavior model, CRFs, HMMs, energy disaggregation.

1. INTRODUCTION

Energy conservation is one of the main challenges facing our society. Studies have shown that residential and commercial buildings consume 40% of our total energy resources [1], and that 20% of this consumption can be efficiently reduced [2] by changing human energy consumption behavior [3]. In this study, energy consumption behavior is examined by employing stochastic energy-consumption behavior models along with signal processing methods.

The task of energy disaggregation is to break up total energy signals into usage by its component appliances. This can provide home owners with useful feedback about how they use electrical energy, and can also motivate users to save significant amounts of energy. Several energy disaggregation methods have been introduced, including sparse coding [4], detection and clustering based approaches [5, 6], pattern recognition [7], factorial HMMs, and difference HMMs and variants [8–10]. Our method differs from those of previously reported studies in that it uses CRF-based energy-consumption behavior modeling [11] to classify usage activities using only total energy consumption.

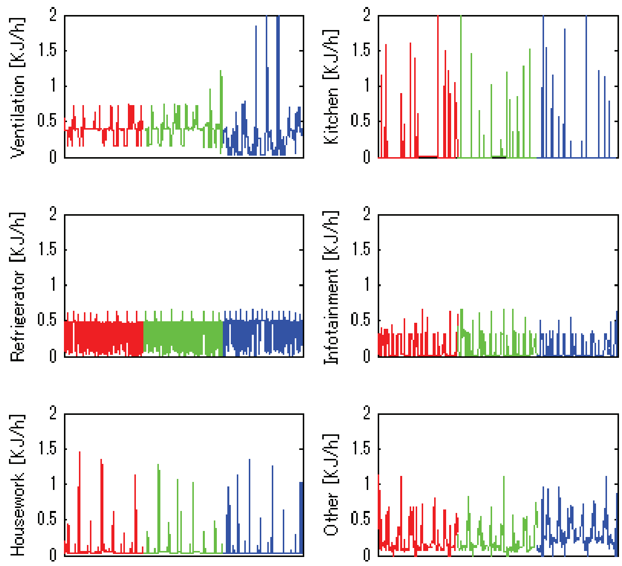

Fig. 1. Energy signals for three consecutive weeks.

One of the main objectives of the current study is to discover better methods for estimating energy consumption activities from consumption signals. We address this problem by employing a behavior model to estimate usage activities from energy-consumption signals. Previous studies have accomplished estimation tasks using eigenvalue decomposition [12], non-linear time series analysis of arrival times [13] and variable order Markov models [14]. In the current study, however, a discrete CRF-based behavior model was used and experimentally evaluated.

In the current study, several factors (e.g., region, season, number of family members, etc.) that affect energy behavior are investigated and analyzed. Figure 1 shows six energy usage signals for three consecutive weeks. As the figure shows, repetitive patterns can be observed from day-to-day

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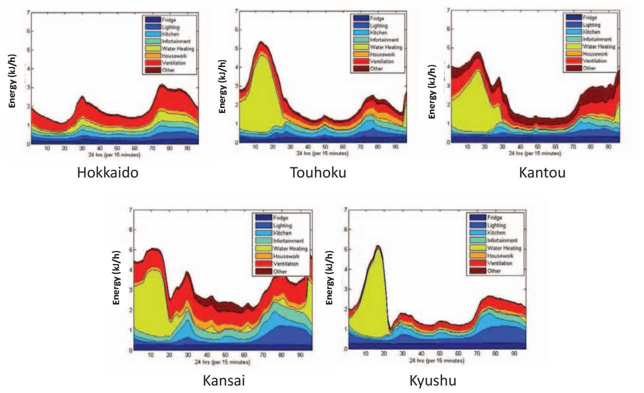

Fig. 2. Average total energy consumption in five regions in Japan.

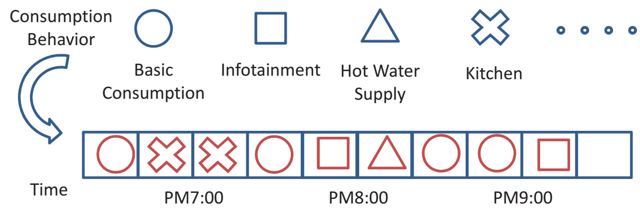

Fig. 3. Discrete behavior model for energy-consumption activity prediction

and week-to-week. Also, some activities are more clearly divided into discrete acts (e.g.,kitchen, housework), while other activities display more continuous behavior (e.g., ventilation, infotainment). It can be observed that the ventilation signals display three typical kinds of usage; during the day there is low usage, in the evening there is high usage, and at night there is medium usage.

In addition to energy disaggregation, we investigate estimation of energy activities, energy consumption analysis, and use of Artificial Neural Networks (ANN) [15] for the prediction of energy consumption using previous observations.

Recently, many researchers are also focusing on electricity price forecasting, which is an important issue for home owners, governments, and systems operators. Electricity price forecasting methods include time-series predictors [16, 17], neural networks [18–20], the nearest-neighbor approach [21], and QP with outage combinations [22].

2. METHODS

2.1. Database

The publically available database used in this study was collected by Niigata University, Japan [23]. Energy usage data was collected in six different areas of Japan from November, 2002 to March, 2005. The six areas selected for data collection were: Hokkaido, Tohoku, Kanto, Hokuriku, Kansai, and Kyushu. In each of the six areas, eight sensors were used in nine households. The following sensors were used: ventilation, water heating, lighting, kitchen, refrigerator, infotainment, housework, and others. A sampling rate of 15 minutes was used for data collection. Figure 2 shows the average energy consumption for selected households in each of the six regions. As we can see, higher energy consumption was observed early and late in the day. This figure also shows differences in energy consumption among regions. In the Tohoku and Kyushu areas, similarities in energy consumption patterns can be observed.

2.2. Prediction of Energy Consumption

In this baseline experiment/analysis, energy consumption by a particular activity is predicted based on previous observations. For example, using the energy consumption data of the previous day, we attempt to predict energy consumption for the current day. In this experiment, a method based on artificial neural networks modeling, specifically, a multi-layer perceptron (MLP), was applied. The MLP estimates energy consumption at a particular time using past observations. The previous day's energy consumption data from the six sensors (i.e., ventilation, house work, infotainment, kitchen, refrigerator, and others) were used, and the energy consumption readings from these sensors for the following day were predicted. Energy signal, weekday/weekend, and bias values (ones) were used as features. This method was evaluated for each of the sensors of one household using Normalized Mean Square Error (NMSE).

2.3. Activity prediction

An experiment for activity prediction based on CRF modeling was also conducted. CRF avoids the need for the assumption of independence between observations, and can model the conditional probability of the label sequence rather than the joint probability of both the labels and observations.

At each point in time, total energy consumption is comprised of several different energy-using activities, with few activities dominating the energy load. Therefore, energy consumption behavior can be modeled by a set of distributions representing consumption activities. In this experiment, an activity occurring at time t is predicted from patterns of activity sequences by observing the activities sequence after waking up and employing a CRF-based behavior model. The main energy-consuming activity is assigned based on the energy consumption that dominates that particular time slot. Eight activities are assumed to occur. Experiments were conducted for estimating cooking and housework activities using two-state CRF and HMMs [24]. Energy signal, weekday/weekend, and bias value (ones) were used as features. Figure 3 illustrates the proposed method.

2.4. Activity/Event disaggregation

Total energy consumption was composed of various energy signals and various energy-consumption activities as shown in Figure 2. In the current study, a method is proposed to determine a particular consumption activity from the observed total energy consumption only. For each 15-minute time slot (t), total energy consumption, ΔEnergy and the time of the day are extracted and used as features. The number of extracted feature vectors was 35,136 (i.e., a 366 day collection period with 96 feature vectors per day). Half of the data were used for training, and half for testing. For clustering, all the feature vectors were used.

In this study, two assumptions are made; it is assumed that only a single activity is defined within each time slot, and that each activity will generate feature vectors which will form compact and disjoined clusters in the feature space. The proposed method consists of three main steps:

- Assign activities based on the pattern of energy signals to obtain an activity ID or label sequence.
  Our proposed energy disaggregation method assumes that the total energy signal is composed of k hidden activities. Since the number of activities is unknown, an unsupervised Dirichlet Process Mixture Model (DPMM) clustering method [25] is applied, which does not require the number of mixture components to be determined in advance. The number of mixture components is determined instead by the model and the data. The applied DPMM clustering resulted in K classes. Following clustering, decoding is performed and each feature vector is assigned to a cluster (i.e., 1-k) resulting in the label sequence required for the training of the behavior model.
- Train a CRF-based behavior model using the training data and the assigned ID label sequence for each time slot.
- Test and map a set of activities to represent a particular activity of interest.
  First, a small threshold is selected empirically to remove some biases and exclude outlier data. This threshold is adjusted to maximize accuracy. Following this, a histogram of the IDs is created in order to group a set of activities representing a particular activity of interest. To group the histogram IDs with activities, we assign a threshold and track the frequency counts of activities of interest that are greater than the threshold. In this experiment, a typical (i.e., uniform) threshold is used.

Figure 4 shows the proposed method for energy disaggregation.

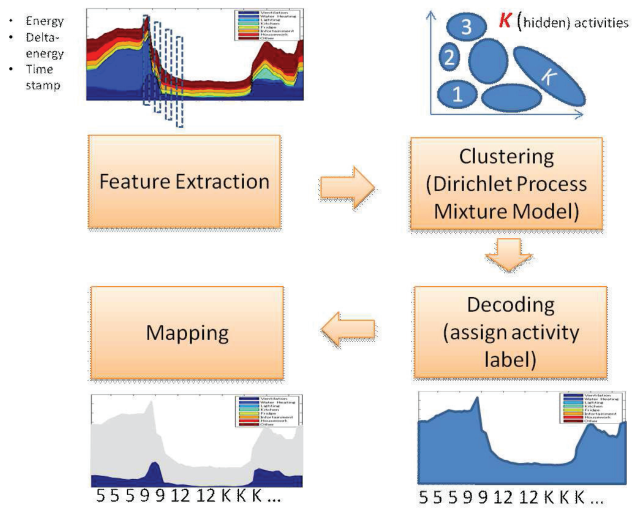

Fig. 4. The proposed method for event/activity disaggregation.

3. RESULTS

In our analysis, several factors which affect energy consumption behavior were considered. Energy consumption behavior was analyzed according to the time of occurrence (e.g., early or late in the day), the kind of activity (e.g., infotainment, kitchen), lifestyle changes, and regional variations. Several other factors (e.g., family size, type of family members, etc.) that affect energy consumption behavior were also considered and analyzed. Energy consumption behavior can be categorized into the following types:

- Type I

  Routine/Frequent Repetition/Typical Behavior:

  Daily Routine; Life Style

  Seasonal Behavior
- Type II

  Special Events/Atypical Behavior

  Short-term; one day to a few days/weeks

Type I energy consumption behavior is easier to predict and control, while Type II behavior is more difficult to predict and control.

Figure 5 shows energy consumption of infotainment and ventilation for a 24-hour period (upper figures), and for the whole collection period (lower figures). Regarding infotainment energy consumption, regular patterns can be observed, but the amount of energy usage noticeable decreased later in the year. In the case of ventilation, it can be observed that there is higher energy consumption during the winter months.

Figure 6 the results for prediction of energy consumption for the current day using energy usage values of the previous

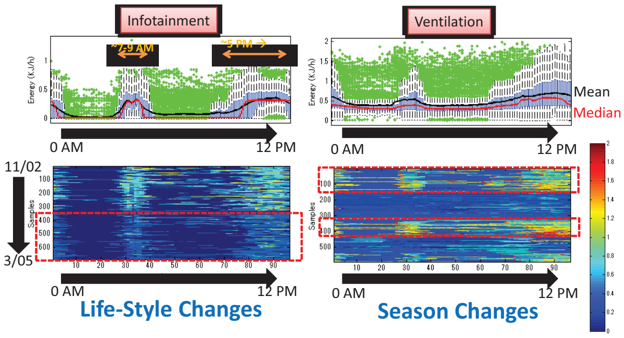

Fig. 5. Energy consumption of infotainment and ventilation.

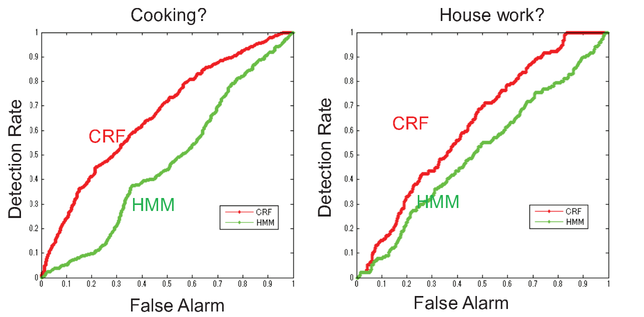

Fig. 7. ROC curves for cooking and house work prediction based on a discrete behavior model.

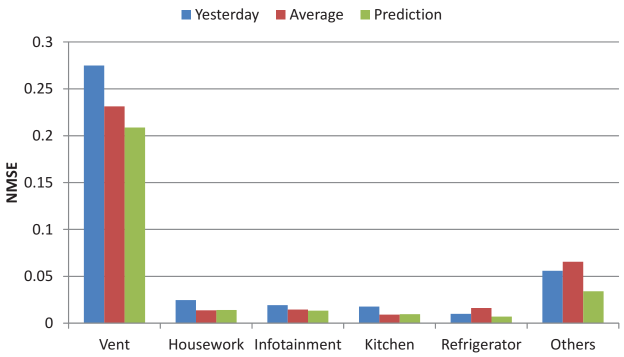

Fig. 6. Prediction of energy consumption based on ANN.

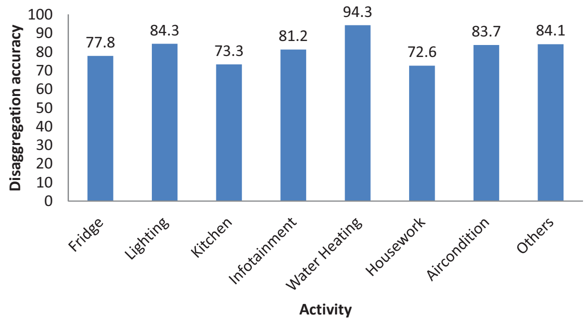

Fig. 8. Energy disaggregation accuracies based of the proposed method.

day. These results indicate that the use of ANN for predicting energy consumption using previous observations is promising.

Figure 7 shows the receiver operating characteristic (ROC) curves, when cooking and housework were predicted using the proposed method. The results show that CRF-based prediction performs better than HMM-based prediction. This may be because HMMs are frame-independent and do not consider the whole label sequence, in contrast to the CRFs.

The proposed method of energy disaggregation was evaluated for all houses in all regions. For activity ID classification using total energy consumption only, a 63.6% classification accuracy rate was achieved. Figure 8 shows the disaggregation accuracies for all energy-consumption activities based on our CRF model. As shown, the proposed method was highly accurate. For instance, in the case of water heating, the disaggregation accuracy rate was 94.3%. The average disaggregation accuracy rate for all activities was 81.4%, which is a very promising result.

4. CONCLUSION

We modeled energy-consumption behavior and disaggregated energy usage using real world energy-consumption data. Our approach was based on stochastic behavior modeling using CRFs and HMMs. A baseline analysis experiment using ANN was conducted to predict energy consumption for the current day using previous energy consumption data. In another experiment, a discrete activity behavior model based on CRFs was employed to estimate activity sequences, with promising results. We also proposed a novel method for the disaggregation of energy usage activities, using a method based on CRFs. This method was able to identify energy usage activities with a high degree of accuracy. Specifically, the proposed method achieved an average accuracy rate of 81.4% when disaggregating eight different energy usage activities.

Acknowledgements

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