Appliance Usage Profiling for Energy Management and Healthcare

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1. INTRODUCTION

Residential energy consumption is steadily increasing year after year and this constitutes a siginificant proportion of the total buildings energy consumption. With this in mind, analyses of electricity consumption in residential households have grown in the recent years. Prediction of energy usage and estimating energy usage behavior in general, is an important aspect of energy management solutions; from the end of the utility providers this will help the estimation of the demand for energy and from the energy consumers end this will help to generate appropriate advice for significant energy/cost savings. There have been a number of recent efforts for analyzing user behaviors, learning user preferences and predicting user activities. The goal of the work presented in this paper is to study the energy consumers' behavior in terms of appliance usage. By using the past energy data for the individual appliances in a household, this work tries to build profiles for appliance use for each household and these profiles may vary for different days of the week, for different months/ seasons and so on depending on the household occupants' routine. The constructed appliance usage profiles will provide a wealth of information relating to the routines and lifestyles of the occupants (e.g. wake up times, meal times, habits such as frequent television viewing, cooking and eating behavior etc.). The profiling method can also be generally applied for analyzing other behaviors such as sleeping profiles. Such profiles once identified, will provide a valuable input towards the development of effective energy management and home automation systems, for providing energy saving tips and for taking appropriate automated control action. This knowledge will not only be useful in an energy management viewpoint, but also from a healthcare management viewpoint. For instance, this can point to unhealthy lifestyles (for example identifying constant television viewing even in good weather) or the change of behavior patterns for elderly occupants that may cause concern. In such cases, relevant health officials can be informed as appropriate and/ or preventive advice and action can be taken.

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2. APPLIANCE USAGE PROFILILNG

In this work, we are aiming to find for an individual household and for each individual appliance, the usage behavior for the different classes of days (termed as Appliance Usage Profile). This will indicate, for the 24 hour period of the day, the probability of the appliance being used in a given time. The different 'classes' (of days) can vary depending on the appliance concerned and the routines of the individual households. For example, for a household with a single occupant, who is full-time employed in routine work, this can correspond to a week-day and week-end. However, this is likely to vary hugely depending on the lifestyles of the occupants involved and numerous other factors such as weather, season, events etc. In order to extract the appliance usage profiles, we need for each given time, the energy data indicating whether the appliance was on or off, i.e. whether it is being used or not. The granularity of energy data we consider in this work is minutely.

Let $a \in A$ denote an appliance in a given household where A denotes the set of appliances in the household. Daily usage for appliance a will be the usage data over a 24 hour period, and for this study we consider the frequency of available data to be every one minute. Thus, the daily use will be a function $d_a = \{(x, y)|x = \{1, 2, \ldots, 1440\}, y = \{0, 1\}\}$, representing used/ not used behavior of the given appliance for each minute of the day. For each appliance a, the clustering approach will identify a set of clusters $C_a = \{c_{a_1}, c_{a_2}, \ldots, c_{a_n}\}$, where c_{a_k} identifies a group of Daily Usages d_a where usage of appliance a is similar and n_a is the number of clusters associated with appliance a. The appliance usage profile for a given appliance a (P_a) will consist of a number of sub-profiles such that $P_a = \left\{p_{a_{c_{a_1}}}, p_{a_{c_{a_2}}}, \ldots, p_{a_{c_{a_n}}}\right\}$ where $p_{a_{c_{a_k}}}$ identifies the profile associated with the kth cluster c_{a_k} for the appliance. Each sub-profile is a function $p = \{(x, y)|x = \{1, 2, \ldots, 1440\}, y = (0, 1)\}$, which is obtained by computing the average over the Daily Usages d that were included in the cluster c_{a_k}. That is:
$p_{a_{c_{a_k}}} = \left\{(x, y)|x = \{1, 2, \ldots, 1440\}, \frac{1}{m} \sum_{k=1}^{m} d_a(x, z)\right\}$ where d represents the daily usages associated with the cluster c_{a_k} and m is the number of days included in the cluster. A given sub-profile $p_{a_{c_{a_k}}}$, will identify the most likely usage behavior for a day that will fall into the cluster c_{a_k}. This effectively will indicate the probability of the use of the appliance a, for each minute of a day in that given cluster.

Table 1: Households used in the experiment and Demographics.

	House1	House2	House3
Appliance monitored	Computer Lounge-lamp Kettle Microwave	TV Dishwasher	TV Cooker Kettle
No. of Adults	1	1	2
No. of Children	0	1	2
Employment status	Retired	Part-time employed	Part-time employed/ Unemployed
Type of house	Semi-detached	Semi-detached	Mid-terraced

2.1 Experiment and Results

The 3eHouses dataset (3eHouses European Union FP7 Project : http:// www. 3ehouses.eu/) was used in this experiment, which covers energy data obtained from over 100 houses and each house's data contains energy data coming from several appliances. For the purpose of this experiment, three households were chosen with each house containing a varying number of appliances. The relevant details of the households used in the experiment are shown in Table 1. For the profiling process, five months of data was used as a training set. The detailed results obtained for the appliances are not included in this paper, however, Figure1 provides a graphical illustration of a sub-profile obtained for one of the appliances. In this graph, the x axis shows the 24 hour time of day, and the y axis shows the probability of the appliance being used, which will range between 0 and 1. As apparent from profiles obtained for the individual appliances, these can disclose a wealth of information regarding the occupants such as: their wake-up times, meal times, television viewing patterns, meal types they usually have (the amount of cooker using time or microwave use may link to home cooked meals/ ready meals / eating out) and other lifestyle facts. Although we intuitively expect to see a weekly pattern in the appliance usage, this wasn't present in some appliances. This is probably due to the lifestyles and work routines of the household occupants concerned in this experiment. Where a weekly pattern is apparent, this can be used to predict the appliance usage for a future date.

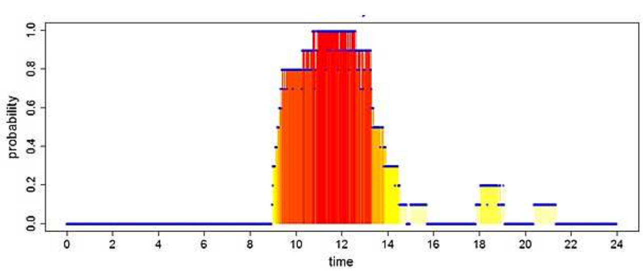

Figure 1: Sub-profile corresponding to the use of Cooker on Sundays for House-3

3. USING APPLIANCE USAGE PROFILES

As mentioned earlier, the usage of certain appliances showed a weekly cycle. Where the appliance use can be linked to weekly cycle, the associated sub-profiles can be used for effectively predicting the appliance usage for a future date. That is, given the appliance usage profiles obtained from historic data, for a given future day and for each hour of the day, a prediction is made as to whether the appliance will be used or not. Please note, that the prediction is done on an hourly basis here, which is more reasonable than trying to predict on a minutely basis. The first step in the prediction process is to construct the hourly sub-profiles for each cluster (which is different to sub-profiles explained in the previous section, which are minutely). Once the hourly sub-profiles are obtained this is used to derive a prediction corresponding to each such hourly sub-profile. This is done using a probability threshold t, and if the probability of use in a given hour is greater than this threshold as indicated in the hourly sub-profile, the prediction is that the appliance will be used, otherwise the prediction will be, that appliance will not be used. We have constructed the usage profiles using 5 months (March 2012 - July 2012) of data as the training data set. For prediction, we use as test data, the days in the month of May 2013. We have applied the prediction approach for 4 of the appliances in Table 1. The detailed results of prediction cannot be discussed here due to limited space, however, the prediction resulted in good rates of accuracy (ranging between 78% and 97% for the four appliances).

In addition to appliance usage prediction, another potential benefit and application of appliance usage profiles, is the use of this knowledge in generating customized energy advice. Also, the energy usage behavior profiles disclose many aspects relating to the lifestyle of the occupants. Therefore, if the behavior profiles indicate an unhealthy lifestyle, it will be in the best interests of the occupants to offer them advice about changing their behavior and to inform them of possible consequences if the unhealthy behaviors are continued.

4. CONCLUSIONS AND FURTHER WORK

In this paper we have proposed an approach for profiling appliance usage of a household's occupants by making use of energy consumption data collected from individual appliances. The approach has been validated on energy data collected from 3 households and the results demonstrate the usefulness of the approach in understanding the user behavior. Also, it has been shown, how the constructed profiles can be used for predicting appliance usage for a future day. The initial results of the prediction approach shows encouraging results with good rates of accuracy.

However, consideration of the other factors (such as the work routines of the individual occupants, weather and external events) other than the profiles obtained from the energy data alone, will be beneficial in improving the prediction results. Also, more research and experimentation needs to be carried out on more varied data sets, with more occupants having different demographics and lifestyles. This will enable the results of findings to be interpreted and validated.