Reducing energy waste in households through real-time recommendations

Conference Paper · September 2020

DOI: 10.1145/3383313.3412212

Magdalini Eirinaki
San Jose State University

Iraklis Varlamis
Harokopio University

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The energy consumption of households has steadily increased over the last couple of decades. Research suggests that user behavior is the most influential factor in the energy waste of a household. Thus, there's a need for helping consumers change their behavior to make it more energy efficient and environment friendly. In this work we propose a real-time recommender system that assists consumers in improving their household's energy usage. By monitoring the power demand of each appliance in the household, the system detects the device status (on/off) at any moment, and using pattern mining creates a household profile comprising energy consumption patterns for different periods of the day. An intuitive UI allows users to set energy consumption goals and preferences on the appliances they'd like to save energy from. Based on the household profile, the user's preferences and the actual power demand the system generates personalized real-time recommendations on which appliances should be turned off at a moment. We employ the UK-DALE (UK Domestic Appliance-Level Electricity) dataset to model and evaluate the entire process, from data preprocessing and transformation of the appliance power demand input to various pattern mining algorithms used to generate appliance usage profiles and recommendations, showing that even small changes in appliance usage behavior can lead to energy savings between 2-17%.

ACM Reference Format:

. 2020. Reducing energy waste in households through real-time recommendations. 1, 1 (June 2020), 8 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

A yearly study conducted by the EIA (U.S. Energy Information Administration) projects that energy consumed by the building sector, which includes residential and commercial structures, will increase by 65% between 2018 and 2050 [21]. As the income and standard of living increase, electricity usage goes steadily up in the residential sector. According to the Residential Energy Consumption Survey (RECS) in 2015, 31% of the U.S. households reported challenges in paying their electricity bill or sustaining adequate temperature in their house [1]. The most recent RECS found that 20% of the households choose reducing or to forgo necessities such as food or medicine to pay electricity bills [1].

The various smart home systems provide monthly aggregated reports on the energy consumption of appliances, which are not enough to motivate users to keep a long-term energy-saving behavior. This inefficiency increases the interest for smart energy-saving solutions, which focus on learning the most influential factors in the energy consumption patterns. A vast amount of research has been conducted to find out these influential factors [5], [11], [12], [20]. The research deduced that user behavior is the most influential factor in the energy consumption of a household. The repetition of energy-saving behavior is habit-forming and can naturally help reduce energy waste.

Providing real-time recommendations to save energy and change user habits into efficient energy utilization behavior is the key to solve this problem. But suggesting actions which deviate largely from the user's normal behavior will result in low acceptance rate by the user. In this work, we propose a system which learns a household's energy consumption habits and recommends actions for saving energy in real time through the day. Figure 1 depicts the proposed system

Author's address:

Manuscript submitted to ACM

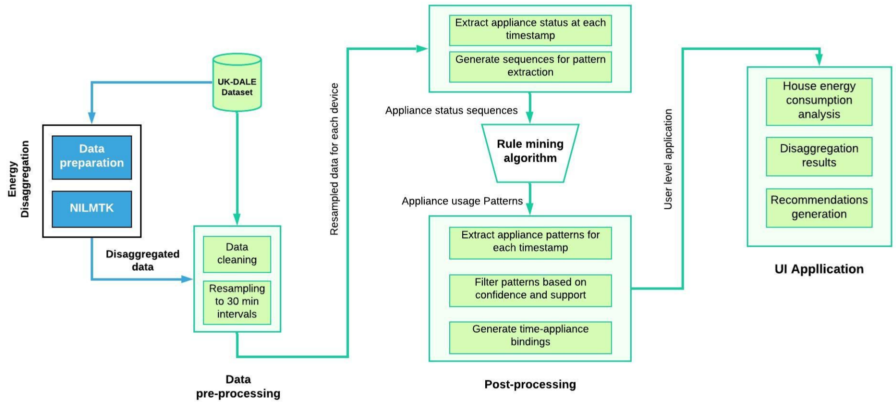

Fig. 1. Project architecture

architecture, including both the offline component of the system that performs the data preprocessing, disaggregation, and pattern mining, and the real-time component of the system that pushes recommendations through an intuitive user interface (UI).

In the absence of a smart home system with separate consumption meters for every appliance, non-intrusive load monitoring (NILM) techniques can be used, which employ a single monitor for the total energy consumption of a household and data mining algorithms to disaggregate the consumption into appliance level [2], [14], [16]. While the UK-DALE dataset that we used for our experimental evaluation and proof-of-concept (POC) prototype implementation [15], as well as some other data sets [23], record each appliance's energy demand individually, in a more realistic scenario there exists only one main meter reading for the entire house. Therefore, as part of our broader work, we have also compared various NILM techniques for energy disaggregation. Since it is out of the scope of this paper, we only provide a brief outline of this module of our system architecture here. The basic principle involved in this process is to identify step change in active and reactive power and according to the value of the step change, identify which appliances is causing it. It also helps in mapping the energy signature or footprint of an appliance. After data resampling to correct irregularities in the time intervals recorded, we performed extensive experimental evaluation of various disaggregation algorithms including Combinatorial Optimisation (CO), Factorial Hidden Markov Model (FHMM), as well as the first NILM algorithm [13], clustering techniques [19], etc., and found that FHMM performed better (as measured by RMSE) for energy disaggregation of the UK-DALE dataset [4].

In this paper we focus on the process of automatically creating personalized energy usage profiles for a household, that are employed by the energy-saving recommender system. The core module of the proposed recommender system is the pattern mining module. Pattern mining is used to create appliance usage profiles. In the absence of explicitly-set optimum electricity usage, we treat the profiles extracted from the appliance-level data as the targeted user behavior and we tailor accordingly the personalized recommendations on the appliances that must be turned on/off at any moment in each household. More specifically, we filter out the most prominent time-appliance patterns as identified by the household's previous energy consumption, indicating ideal behavior and energy consumption goals. For example, if an appliance is switched on at a time which deviates from the user's appliance usage behavior (e.g. coffee machine is on at 11pm), a recommendation is sent to turn off that device. This helps us in achieving our main goal of decreasing the power consumption of the users on a daily basis and thus optimize energy usage. These recommendations are shared with a user through a UI. As a proof-of-concept (POC), we have developed a prototype that demonstrates how these recommendations change depending on the time of day and household.

For pattern mining, we have evaluated various association rule mining approaches including Apriori and FP-Growth as well as sequential pattern mining approaches like CMRules, RuleGrowth, ERMiner and CMDeo. The challenge of applying such algorithms in the particular domain has to do with the nature of the data, that comes as fine-grained power demand readings every few seconds over several months, and have to be appropriately prepared, resampled and preprocessed in order for such algorithms to extract meaningful and useful rules that can then be used as input to the recommendation process. We discuss these steps in more detail in Section 3. Our experimental evaluation, presented in Section 4, has shown that the generated recommendations have very high recall, capturing to a big extend the household's appliance usage patterns, and can result, if followed, to reductions in energy consumption ranging between 2% and 17% for the different households used in our study.

2 RELATED WORK

As a first step towards generating recommendations for users to suggest actions for saving energy, we need to understand the appliance usage patterns. The use of association rule mining and incremental frequent pattern extraction algorithms by Singh and Yassine [22] allowed faster extraction of inter-appliance associations without checking the entire dataset for finding frequent itemsets. However, their itemsets comprise appliances that are used together at the same time, whereas we seek for appliance-time patterns that describe which appliances are to be kept on/off at particular periods in a day. Ong et al. [17] have harnessed the interconnected usage of various home appliances, using power consumption data (voltage and frequency) from 53 plug-level meters and appliance on/off events for a 3 months period. They processed data with association and sequential rule mining techniques (FPGrowth, Apriori-Inv and TRuleGrowth) and extracted rules and patterns (e.g. TV with speakers, coffee machine after using toaster etc) of high confidence (above 0.7) and varying minimum support thresholds. Rules with high support corresponded to combo usage of common devices (e.g. TV with speakers), whereas rules with low support contained rare devices and require further analysis. However, the number of obtained rules explodes for very small support thresholds, making it difficult to process the extracted patterns. However, the discovered patterns are not time-related and cannot be used as input to real-time recommendations. In order to tackle the above issues, we employ a different data engineering approach, and also evaluate the algorithms on the computational efficiency and compactness of their outputs.

In an attempt to design real-time recommender systems that provide energy-efficient recommendations based on various contexts, authors in [3, 19] propose a recommender system for changing users' habits, and reduce their energy footprint. They first apply energy disaggregation on the mains data in order to detect on/off events on the monitored appliances. Then they employ an association rule mining algorithm (Apriori) to extract usage patterns in the appliance level. Their patterns for the kitchen appliances have a support greater than 0.02 (happening more than 12 times a month). The rules depict the actual user habits, and recommendations are driven by general energy saving rules connected to external conditions such as temperature, humidity, user presence etc. The focus is on sending the recommendations in the correct time context for the user in order to maximize acceptance. On the contrary, the focus of our work is on the generation of personalized recommendations that match a household's appliance usage profile and help them achieve their energy footprint reduction goals by eliminating unnecessary energy consumption.

3 APPLIANCE USAGE RECOMMENDATIONS

One of the main challenges faced in this application domain has to do with the nature of the data that is used as input to the recommendation process. The system receives power demand readings as input, but needs to generate recommendations on which appliances need to be turned on/off in a given time of the day. In addition to data preprocessing and engineering, the pattern mining algorithm needs to be selected such that it provides a concise yet comprehensive set of patterns in a time efficient manner. In this section, we discuss in detail our process as well as our findings in evaluating different pattern mining algorithms. We assume that data comes in disaggregated form (either through the use of AIMs, or after applying NILM).

3.1 Data Preprocessing

Among the various datasets used in the literature (see [23]) we choose UK-DALE for the POC implementation and evaluation, mainly because it is the only dataset that records the power both at appliance and household level in a very fine level of detail. This allows to evaluate different energy disaggregation approaches (available in the NILMTK library [6]), and extract appliance-appliance and appliance-mains associations. The 14Gb dataset contains recordings of the active power drawn by each appliance and the entire house every 6 seconds. This is done for 5 households containing from 4 to 52 different appliances, for a varying time period (2 months to 5 years) [15].

In order to extract usage patterns for appliances, it is important to detect when they are switched on or off and be able to detect co-occurring on/off actions in the same period. For this, we resampled the initial data in 30 minute intervals taking the mean of all the readings (per appliance) in that time period, which resulted in 48 values per device per day. This increased the system scalability and added flexibility to the extracted patterns, which now assume that users do turn on/off actions on multiple devices in the same half hour.

Detecting which appliance is on or off is not as trivial as seeing some energy consumed by an appliance, as many appliances consume energy when plugged in, even when they are not turned on. We therefore have to identify the range of power demand profile that signifies that a particular appliance is on. This range is unique to each household appliance. In our first approach to tackle this, we used a mean-based threshold value, which would categorize a given reading into an on or off state, using the following equation: $threshold = \frac{maxReading - minReading}{meanReading}$. If the current reading is more than the threshold value, we labelled the appliance "on" for that segment of the day otherwise the appliance is marked as "off". This approach was very error-prone for appliances that are not used very frequently. They were detected as always on since the small surge in energy usage was being neglected.

To improve the classification accuracy, we used K-Means clustering (using K=2). K-Means divided the entire appliance readings' data for each appliance into two clusters. The cluster with lower value readings was marked as the "off" state cluster and cluster with higher value readings was marked as "on" state cluster. Using K-Means for identifying appliance on/off status proved to be better than using the threshold approach as the less-frequently used appliances were being categorized properly.

3.2 Household Profile Generation

Once we have the appliance on/off data for each segment of the day for every day, we can create an appliance usage profile. This profile is unique to each household (user) and includes the appliances switched on at each day segment, for all the days in the training data set. In order to detect recurring usage profiles across all days, we can process the lists of appliances used in the same day segment during all days.

In our POC we extracted household profiles out of the entire dataset. If we need to generate season-specific or month-specific recommendations, we can easily incorporate seasonality using each season's power demand readings for extracting the household's season profile. We have implemented and evaluated several association rule and sequential pattern mining algorithms to identify prevailing patterns in the household power usage profile. We discuss some of our observations guiding our final selection in what follows.

3.3 Appliance Usage Pattern Mining

Our system supports several association rules and sequential pattern mining algorithms for extracting patterns of appliance usage from the household profiles. The three algorithms that were the most efficient in terms of scalability and compactness of model without sacrificing coverage were Apriori, FPGrowth (both as implemented in [18]) and TRuleGrowth [10]. Apriori and FPGrowth find frequent itemsets (i.e. appliances used together), which we store in a time-segment based dictionary. This step can be efficiently parallelized for the different day segments, since there is no dependency between appliances switched on at different times. As a second step, we generated associations, which are rules extracted for the same day segment and can be considered as the user's appliance usage behavior for that segment.

In addition we evaluated several sequential pattern mining algorithms, from the SPMF library [24], which helped us identify appliance-time interdependencies and get the probability of an appliance being on at a particular time. The algorithms have been compared in terms of execution time and of the size of the generated set of rules. Among CMRules [8] that identifies sequential patterns based on their commonality among sequences, RuleGrowth [10] that uses a recursive pattern growth technique, TRuleGrowth [10] that uses a maximum sliding window for handling long sequences in rule generation, ERMiner [9] that uses a prefix (suffix) technique to group rules with the same antecedent (or consequent) into equivalence classes and a Sparse Count Matrix to filter the sequences in the dataset, and CMDeo, an adaptation of an algorithm originally developed for identifying patterns in a single sequence [7], we decided that TRuleGrowth works best for time-related patterns and hence is specifically good for our dataset. Run for the House 2 dataset with min support and confidence of 0.02 (2%), TRuleGrowth showed promising results, generating 44155 rules with a minimal time of 12052ms and generating a file size of around 163 MB. This complies with Viger's results [10] that TRuleGrowth provides concise, faster outputs consuming a minimum amount of memory. In addition we observed that: i) CMRules ran out of memory for support and confidence thresholds at 0.02, ii) ERMiner was 5 times faster than RuleGrowth, but has big memory issues, running out of memory (used 24.6 GB) after 4 hours and generating an incomplete output, CMDeo failed to generate all valid rules. It was only able to generate only 585 rules, iv) RuleGrowth generated 26.3 GB of data.

Out of the entire set of rules generated by the algorithm, we filter out only the ones that include a time segment and an appliance. This helps us get a concise set of rules in the form of <*time_segment* -> *appliance_channel*>, along with their confidence scores *conf*, that can be used as input to the recommendations module.

3.4 Recommendations Module

The module takes as input the time of the day and the number of recommendations to be generated. It then sorts the extracted rules that match the *time_segment* condition in descending order of their confidence *conf*. The rules are further filtered based on the requested number and type of recommendations for the user, and merged to generate the final set of recommendations. Fig. 2 shows the frequent appliance channels turned on for some time segments, which are used for generating recommendations for House 2.

Time	Recommendations
16:00:00	Modem,Laptop,Speakers,Monitor,Fridge,Router,Server,Server_hdd,Laptop2,Kettle,Rice Cooker,Running Machine,**Cooker**
16:30:00	Laptop,Modem,Speakers,Monitor,Fridge,Router,Server,Laptop2,Server_hdd,Kettle,**Cooker**,Rice Cooker,Running Machine
17:00:00	Laptop,Modem,Speakers,Monitor,Fridge,Router,Kettle,Server,Laptop2,**Cooker**,Server_hdd,Rice Cooker,Microwave
17:30:00	Laptop,Modem,Speakers,Monitor,Fridge,Router,Laptop2,Server,Kettle,Server_hdd,**Cooker**,Microwave
18:00:00	Laptop,Modem,Speakers,Monitor,Fridge,Router,Laptop2,Server,Server_hdd,Kettle,**Cooker**,Microwave,Dish Washer
18:30:00	Laptop,Speakers,Monitor,Modem,Fridge,Router,Laptop2,Server,**Dish Washer**,Server_hdd,Kettle
19:00:00	Laptop,Monitor,Speakers,Modem,Fridge,Laptop2,Router,**Dish Washer**,Server,Server_hdd,Kettle
19:30:00	Laptop,Monitor,Speakers,Modem,Fridge,Laptop2,Router,**Dish Washer**,Server,Kettle,Server_hdd
20:00:00	Laptop,Monitor,Modem,Speakers,Fridge,Laptop2,Router,Server,Server_hdd,Kettle,**Dish Washer**
20:30:00	Laptop,Monitor,Modem,Speakers,Fridge,Laptop2,Router,Server,Server_hdd,Kettle,**Dish Washer**
21:00:00	Laptop,Monitor,Modem,Speakers,Fridge,Router,Laptop2,Server,Server_hdd,Kettle,**Dish Washer**
21:30:00	Laptop,Monitor,Modem,Speakers,Fridge,Router,Server,Laptop2,Server_hdd,Kettle,**Dish Washer**
22:00:00	Modem,Monitor,Laptop,Fridge,Speakers,Router,Server,Server_hdd,Laptop2,**Dish Washer**

Fig. 2. Recommendations for House 2

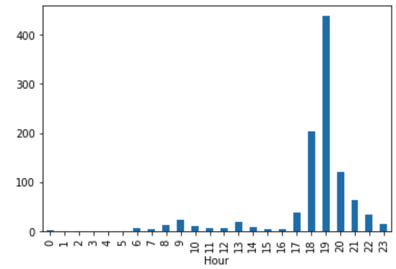

Fig. 3. Avg. power/hour for Dishwasher in House 2.

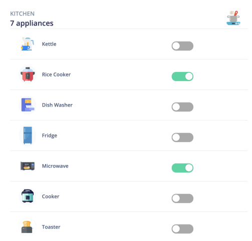

Fig. 4. Appliance control.

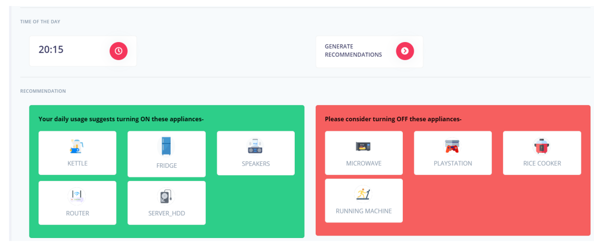

Fig. 5. Energy Saving Recommendations

We empirically observed that the generated recommendations align with routine activities of the household user and the actual appliance power consumption, as observed in the raw data. For example, *Cooker* is recommended to be switched on between 4 and 5:30 pm, immediately followed by *Dishwasher* at 6 pm. This suggests that the user usually cooks their meal around 4 pm and uses the dishwasher after they are done. We also observe, as shown in Figure 3, the average power consumption of dishwasher spikes between 6 and 10 pm, which is the period the system recommends it to be switched on. These observations act as our indirect evaluation for the recommendations. In Section 4, we evaluate the performance of the recommendations using precision, recall and F1-score measures.

System Prototype: In order to simulate a real-life scenario, we developed an application, with a web dashboard for depicting actual consumption per device and for the whole household, an appliance control tab for switching appliances on and off (Figure 4) and a tab for time-specific energy saving recommendations (Figure 5). This intuitive UI allows users to monitor, get recommendations and react. The user can also opt for setting energy goals and filtering out appliances from their recommendations (e.g. appliances that are always on, like a router or a fridge). The prototype also supports a voice mode, to provide accessibility.

4 EXPERIMENTAL EVALUATION

In order to evaluate the recommender system, we used data collected from 4 of the UK-DALE dataset houses (houses 2 to 5), to cover a broad range of use cases, with varying sizes of appliances (5 to 25) and size of training data available (40 to 236 days). For all houses' power demand readings, we divided the data into training and testing following a 90:10 ratio. Table 2 summarizes some energy consumption statistics. We preprocessed (by resampling and aggregation) the power demand data in the test set to identify which appliance channels are most often on in each time segment in the data. This served as our ground truth. We then calculated the precision P and recall R for up to 10 channel recommendations for each house, as follows: $P = \frac{|relevant\_rec|}{|all\_rec|}$, $R = \frac{|relevant\_rec|}{|ground\_truth|}$, where $relevant\_rec$ is the number of "true positives", i.e. the appliances recommended "on" that were also on in the ground truth set. Table 1 shows the precision, recall, and F1-score averaged over all the time segments of all days in each house's test set. We observe that the system achieves high recall in the expense of precision, in other words it correctly predicts the energy habits in terms of appliance usage of a household. We should point out, however, that different $conf$ thresholds result in different coverage of the rules (i.e. including less or more appliances). Moreover, in this dataset some house channel readings covered more than one appliances (e.g. in house 3), leading to a more coarse-grained prediction and recommendation.

Table 1. Evaluation of Recommendations

House	Precision	Recall	F1-score
2	0.3	0.97	0.46
3	0.39	0.73	0.51
4	0.48	0.97	0.64
5	0.34	0.98	0.5

Finally, we calculated how much energy each household would save, if the recommendations for turning off appliances are accepted. In particular, we calculated the energy consumed by all the appliances that were turned on in the test set, but were recommended as off by the system, for each time segment. This is energy that is probably wasted. The results are summarized in Table 2, demonstrating that adoption of such a recommender system could lead to anything between 2% to 17% of energy savings.

Table 2. UK-DALE Energy Saving Statistics

House	Total Consumption (KWh)	Avg. Daily Consumption (KWh)	Total Energy Saved (KWh)	Avg. Energy Saved per day (KWh)	% Energy Saved
2	63871.97	2661.33	3225.04	134.37	5.04
3	2011.73	502.93	346.65	86.66	17.23
4	23317.43	1110.35	473.03	22.52	2.03
5	89576.17	6398.29	2690.94	192.21	3

5 CONCLUSIONS

In this work we presented an end-to-end recommender system that generates recommendations on which appliances need to be turned on/off depending on the time of day and the respective power demand readings of a household. We discuss our clustering-based data engineering approach for turning fine-grained readings into household energy consumption profiles that are subsequently used to generate patterns, using association rules and sequential pattern mining. Through experimental evaluation using the UK-DALE dataset collected from 4 very diverse households, we discovered that Apriori, FP-Growth, and TRuleGrowth generated very similar results in terms of recommendations and performance metrics, with the latter allowing for faster processing and better memory scalability. Our preliminary experimental results show that the system demonstrates high recall and can help a household conserve between 2% and 17% of energy. We also implemented, as proof-of-concept, a system prototype that in the form of a dashboard allows the user to set energy goals and review their energy consumption, as well as get real-time recommendations. As part of our ongoing work, we plan to integrate inter-appliance associations and correlations to further improve the recommendations. We also plan to further evaluate how seasonality or time/day-specific profiles (e.g. weekdays vs. weekends) affect the quality of the recommendations and further improve energy savings.

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