"I Want to ... Change": Micro-moment based Recommendations can Change Users' Energy Habits

Christos Sardianos[1], Iraklis Varlamis[1], George Dimitrakopoulos[1], Dimosthenis Anagnostopoulos[1], Abdullah Alsalemi[2], Faycal Bensaali[2] and Abbes Amira[3]

[1]*Department of Informatics and Telematics, Harokopio University of Athens, Athens, Greece*

[2]*Department of Electrical Engineering, Qatar University, Doha, Qatar*

[3]*Department of Computer Science and Engineering, Qatar University, Doha, Qatar*

Keywords: Recommender Systems, Energy Saving Recommendations, Micro-moments, Energy Habits.

Abstract: Since electricity consumption of households in developing countries is dramatically increasing every year, it is now more prudent than ever to utilize technology-based solutions that assist energy end-users to improve energy efficiency without affecting quality of life. User behavior is the most important factor that influences household energy consumption and recommender systems can be the technology enabler for shaping the users' behavior towards energy efficiency. The current literature mostly focuses on energy usage monitoring and home automation and fails to engage and motivate users, who are not as committed and self-motivated. In this work, we present a context-aware recommender system that analyses user activities and understands their habits. Based on the output of this analysis, the system synchronizes with the user activities and presents personalized energy efficiency recommendations at the right moment and place. The recommendation algorithm considers user preferences, energy goals, and availability in order to maximize the acceptance of a recommended action and increase the efficiency of the recommender system. The results from the evaluation on a publicly available dataset comprising energy consumption data from multiple devices shows that micro-moments repeatedly occur within user's timeline (covering more than 35% of user future activities) and can be learned from user logs.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

The rise in the living standards in modern society over the last years has led to a surge in the daily use of technology devices and appliances (Hu et al., 2017), which led to an increase in the consumption of energy resources and gave rise to new environmental and socio-economic problems. As a counterpart, technology plays an assisting role in helping users improving their energy efficiency levels. However, most of smart-home and energy related automation systems focus on increasing user's ease of access in controlling or monitoring household appliances (Jensen et al., 2018; Darby, 2018), but still, the choice of managing the use of these appliances solely relies on the environmental and economical awareness of the user.

Despite the fact that technology provides means for efficient energy consumption, it is the user behavior that plays the most important role in forming the household's energy footprint (Gram-Hanssen, 2013). Hence, it is important to motivate users—who are not committed and self-motivated—and to increase the awareness about contemporary energy issues and its dramatic repercussions. This is a key factor for increasing individual energy efficiency and consequently reducing the energy footprint of a community.

Considering the impact of motivating the user to change their everyday energy consumption, we identify the need for information technology solutions that address the problem of engaging users in adopting more sustainable energy usage tactics (Coutaz et al., 2018). Everyday energy-related behavior is definitely driven by the user needs and desires. However the behavior is synthesized by many small actions, which are influenced by external factors, such as outdoor temperature and humidity (e.g. turning air-conditioning on when it is hot) and by the user's common habits (e.g. switching the water heater on after arriving home to take a bath). In tandem, user needs, user conditions and user habits shape the user's energy consumption profile.

Sardianos, C., Varlamis, I., Dimitrakopoulos, G., Anagnostopoulos, D., Alsalemi, A., Bensaali, F. and Amira, A.
"I Want to ... Change": Micro-moment based Recommendations can Change Users' Energy Habits.
DOI: 10.5220/0007673600300039
In *Proceedings of the 8th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2019)*, pages 30-39
ISBN: 978-989-758-373-5
Copyright © 2019 by SCITEPRESS – Science and Technology Publications, Lda. All rights reserved

Recommender systems aim at providing data-driven recommendations to users. In the case of raising energy awareness and changing users' energy habits, these systems can be used to recommend energy-related actions to the users that could potentially affect their consumption footprint. But first, they must be able to identify users' behavior (Zhou and Yang, 2016) in order to provide recommendations that match user profile and have a high potential of being accepted. Such personalized recommendations are also most likely to be adopted by the user in the long term and gradually transform user behavior towards energy efficiency.

As mentioned earlier, actions that relate to energy consumption may differ among users depending on their habits, but also can be affected by external conditions (e.g. weather and season changes) or individual user needs, which both may change over time. Considering the repetitive nature of user habits and the temporal change in user needs and external conditions, it is necessary that any predictions or recommendations about user near-future actions must combine both types of information in order to improve efficiency. In this direction, we examine user's daily activities in segments, which are called user "*micro-moments*", in adoption of the term introduced by Google (Ramaswamy, 2015) for capturing the temporal nature of smartphone usage for covering information needs.

The proven success of micro-moments in information search and retrieval (Snegirjova and Tuomisto, 2017) can be adopted by personalized assistants that analyze contextual information from various sources (e.g. GPS data, environmental information, user status and mood, etc.), predict user needs and proactively recommend pieces of information or activities to the user that maybe useful at that specific moment (Campos et al., 2014) or place (Bao et al., 2012). Based on this idea, this paper introduces the concept of a recommender system that is based on users' micro-moments to provide action recommendations that would help users eventually reshape their habits towards a more energy efficient profile.

In section 2, we summarize the most important works on micro-moments and micro-moment based recommendations. In section 3 we begin with a motivating example and then provide an overview of the proposed methodology. In section 4 we give the details of our proposed system architecture. Finally, section 5 summarizes our progress so far and the next steps of this work that are expected to lead to a recommender system that delivers the right recommendation at the right moment.

2 RELATED WORK

The concept of mining useful knowledge from usage logs has been discussed several times in the related literature. Although the initial focus back in 2000 was in web browsing and web usage logs (Srivastava et al., 2000), there are several recent works that mine user activity logs, outside of the web browsing environment, including geo-location logs (Sardianos et al., 2018), app usage logs (Cao and Lin, 2017), bio-signal logs (Alhamid et al., 2013), etc. The aim of geo-location log mining works is to discover hidden patterns in the user's daily behavior and either highlight interesting locations and travel sequences (Cao et al., 2010) or create recommendations for Location-Based Social Networks (Bao et al., 2015). Overall log mining approaches, analyze the activity logs of many users in order to detect the common context in which certain activities are preferred among users. Consequently, these patterns and the user's personal context-aware preferences are utilized in order to create personalized and context-aware recommendations (Yu et al., 2012).

The term "micro-moments" has been introduced in the literature with the 'Janus Factor' theory for determining marketing behavior (Stokes and Harris, 2012) and describe the moments where people are positively positioned towards buying something promoted by a campaign and moments where people are skeptical and difficult to persuade. Google coined the concept of micro-moments to the spontaneous interaction with smartphones in order to learn, discover, carry out an activity, or buy a product online (Ramaswamy, 2015), but it soon has been expanded to more fields, introducing new types of micro-moments that span daily life and can be appropriate for the tourism industry (e.g. I want to show (Jørgensen, 2017), I want to remember (Wang et al., 2012; Biloš et al., 2016)).

In order to transform users' energy habits, it is important first to detect them by processing their activity logs and then to provide the appropriate motivations that will help them change. According to the "habit loop" theory (Duhigg, 2013) a typical habitual behavior goes through three stages: i) the *cue*, a trigger that puts the brain to auto-pilot, ii) the *routine* that refers to the actual action performed by the individual following the cue and iii) the *reward*, which is the satisfaction induced from completing the routine and an indicator to the potential to repeat the behavior. Reconstructing a bad habit loop into a better one requires detecting the cue, modifying the routine and demonstrating the reward in order to strengthen the desired habitual behavior.

In this work, we define a new type of micro-moment related to the behavioral change of users towards energy efficiency, which we call the "I want to change" moment. Such moments are used to deliver the correct recommendation to the user to assist him/her to adopt a better behavior. In order to gradually achieve this habitual behavior change towards energy-efficiency, we must first detect the micro-moments by analyzing user contextual logs, associate micro-moments with specific user activities and recommend actions that can assist the user to reduce his/her energy footprint. In the following section we give a motivating example and then describe the proposed methodology.

3 METHODOLOGY

The motivation of this work is to define a framework that seamlessly provides users with the means to improve their energy consumption profile by exploiting different types of real-time information (e.g. user's consumption, environmental conditions, etc.).

This could be better explained considering the following use case as an example described in Figure 1: *"John, our target end-user, usually switches on the air-conditioning and the water heater to take a bath, as soon as he gets back home after work. This happens around 6 o'clock in the afternoon, but the actual start and the duration of this action varies, depending on the traffic that he founds while returning home and also the environmental conditions"*.

The proposed recommendation framework analyzes historical information about the user's daily consumption and correspondingly extracts consumption habits. The habits result from a generalization of user activities in time and external conditions. In our example, the user habit concerning water heater will be as follows: *"the water heater is switched on between 4 and 7 o'clock in the afternoon during weekdays, for 15 minutes during hot periods and for 30 minutes during cold seasons. However, in some cases, John forgets to switch them off in time, resulting in large cumulative expenses over the year"*.

In the example above, the definition of hot and cold seasons is user-dependent but definitely links to the actual weather conditions. The same holds for the exact time when the on and off activities happen (i.e. if it is at 6:00 pm or at 6:05 pm, if it is after 15 or 20 minutes, etc.). Based on the actual weather conditions, the actual user status (e.g. user is already at home, or user is still driving back home, or user is away from home) a recommendation for a repetitive action that has been properly positioned within the

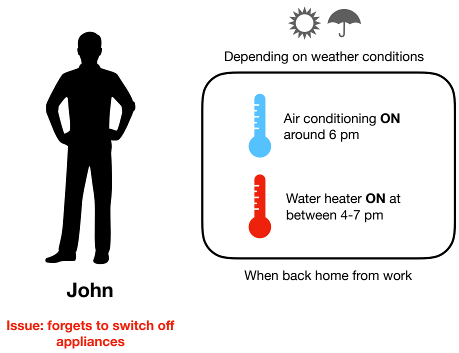

Figure 1: John's Use Case.

user daily schedule and has been smartly shifted a few minutes earlier or later in order to save energy, will be more than welcome for the user. Such a recommendation will increase the user trust to the recommender system and will assist him to not only to benefit in cost of consumption but also to boost the household's sustainability footprint.

As described in the previous example and motivated by behavior change literature (Duhigg, 2013), the aim of the proposed framework is not to completely and abruptly alter users' energy consumption behavior, but rather to incorporate small, gradual changes into users' daily time-lines and assist them to perform minor but influencing actions towards energy efficiency.

The proposed methodology for creating energy efficient recommendations is based on a three-step approach as depicted in Figure 2. The first step of the process refers to the consumption data acquisition and analysis. Based on the analysis of the user's consumption data along with environmental conditions we perform an initial step of analysis to extract meaningful insights. So we process the Consumption Logs and Weather Logs to highlight the user's consumption actions in terms of micro-moments and extract the context of user activities (i.e. when the user tends to switch on and off a specific device). Being able to identify user's energy demands on the spot, in the third step of our approach we can predict user's next energy consumption activities (i.e. in 10 minutes the user will switch on the air-conditioning), which enables our recommender system to recommend energy-related actions to the user beforehand, so as to lead his energy profile in higher levels of efficiency. In the sections that follow we expound each step of the process.

3.1 Data Acquisition and Analysis

In order to collect the user's consumption data we rely on WiFi-enabled smart plugs/outlets equipped in the

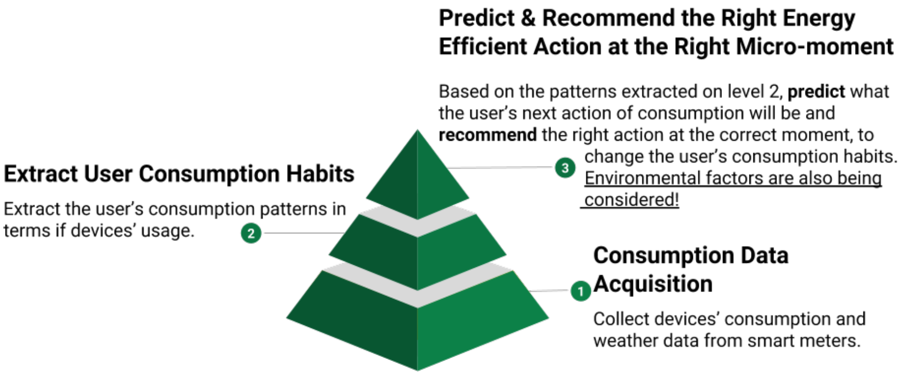

Figure 2: Steps for data analysis and creating energy consumption-related recommendations.

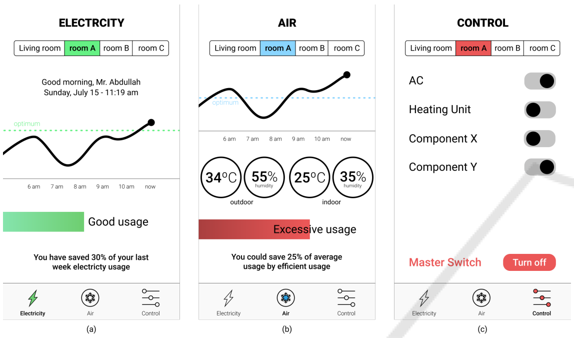

Figure 3: (EM)^3 Energy Tracking Application.

most frequently used appliances (e.g. Sonoff Pow R2) (ITEAD Intelligent Systems, 2016). These smart outlets provide information about the energy consumption of each device, which we collect in a minute window. More specifically, all user’s devices that consume big loads of energy are plugged in a smart plug that measures the consumption in KWh in real time. These measurements are logged in a JavaScript Object Notation (JSON) formatted file (hereafter called *Consumption Logs* for convenience) and stored in a CouchDB no-SQL database (hereafter referred to as the backend)(The Apache Software Foundation, 2018).

In addition, a variety of sensing modules are also installed in the user’s household to record contextual information (e.g. temperature, humidity, and occupancy). Hence, a second JSON file (hereafter called *Weather Logs*) that contains the environmental conditions inside and outside the house is recorded on hourly basis. These two files form the starting input data of the processing pipeline.

This way the system collects and analyses user’s consumption data and weather parameters and provide useful analytics to the user. Information is presented to the user in the EM^3 Energy Tracking Application which we have developed and is shown in Figure 3.

Sensor and smart-plug data are sent to the backend of our framework and stored in the respective log files. The backend also stores user metadata, concerning general information about the user such as full-name and address along with the GPS coordinates, the state and the category of each appliance (e.g. computer, charger, general), like shown in Listing 1.

The user metadata section in the consumption log file, is followed by a section denoted as “*rooms*”. As depicted in Listing 2, this section aggregates the consumption observations made from the pre-installed smart plugs of the household. This block in particular contains the actual consumption measurements recorded from the smart-plugs installed in each room.

Listing 1: Meta-data block in the Consumption Logs file.

```
// Consumption-Logs.json
{   "_id": "data_user_alpha",
   "meta": { "date":"31/10/2018",
       "timezone":"GMT+3",
       "user_info": { "id": "data_user1",
           "name": "James Borg",
           "Address": "Coliseum Way,
                Oakland"
       }, "appliance_info": {
           "app_1": { "longitude": 24.3534,
               "latitude": 23.22222,
               "state": true,
               "category": "computer"
           }, ... }    }    ...
}
```

Each room is identified in the “*room_info*” tag with an ID and a description (referred as name) and a block “*energy_data*” that contains the total consumption of the house in a minute frame for each day. Following, there are two main block tags referred to as “*air_data*” and “*appliance_data*”. The “*air_data*” block contains the consumption values for heating and cooling, while the “*appliance_data*” block contains the consumption measured for each appliance

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

("*app_1*", etc.), all reported in a minute window.

Listing 2: Consumption data block for each room and appliance in the Consumption Logs file.

```
// Consumption-Logs.json
{  ... "rooms": {
        "room1": {
            "room_info": { "id": "room1",
                "name": "Adam's bedroom"},
            "energy_data": { ...},
            "air_data": { "heating": {...},
                "cooling": {...} },
            "appliance_data": {
                "app_1":{...}, ... }
        }...
    } ...
}
```

The Weather Log file contains information regarding the weather conditions that are gathered by the various sensors installed inside and outside the house. In particular, the file is organized into two different block tags, one for the "*outdoor_air_quality*" and one for the "*rooms*" as shown in Listing 3. These two blocks contain respectively the measurements concerning both the outdoor temperature and humidity as well as the indoor temperature and humidity per room per minute.

Listing 3: Format of the Weather Logs file.

```
//Weather-Logs.json
{  "outdoor_air_quality": {
     "outdoor_temperature":{ "00:00": 34,
        "00:10": 34.1, ...},
      "outdoor_humidity":{ "00:00": 0.4,
          "00:10": 0.401, ...}
   },
    "rooms": {
        "room1": {
            "indoor_temperature":{ "00:00":
                34,
                "00:10": 34.1, ...},
            "indoor_humidity":{ "00:00": 0.4,
                "00:10": 0.401, ...}
        }
    }
}
```

3.2 Data Transformation

Data collection is the first step of the process, but in order to exploit the above types of information we need to perform an initial step of analysis that will produce meaningful insights to be used in the next steps of our pipeline. So, we process the Consumption Logs and perform a first level of abstraction that will highlight the user's consumption actions in terms of micro-moments. Then we process the Weather Logs in order to extract the context of user activities.

The processing of the consumption log file will determine whether and when a device is turned on or off with ample accuracy. Subsequently it allows the extraction of the user's actions along with the moment that they took place in terms of micro-moments (e.g. at 10:34:00 AM (GMT) user turned on the microwave and at 11:21:00 AM (GMT) turned on the dishwasher) as shown in Figure 4.

Date	Time	timezone	daytype	room	appliance	action
2006-12-17	10:34:00	5-7am	weekend	kitchen	microwave	on
2006-12-17	10:35:00	5-7am	weekend	kitchen	oven	on
2006-12-17	10:49:00	5-7am	weekend	kitchen	oven	off
2006-12-17	10:49:00	5-7am	weekend	kitchen	microwave	off
2006-12-17	11:21:00	5-7am	weekend	kitchen	dishwasher	on
2006-12-17	11:22:00	5-7am	weekend	kitchen	oven	on
2006-12-17	11:22:00	5-7am	weekend	kitchen	microwave	on
2006-12-17	11:36:00	5-7am	weekend	kitchen	oven	off
2006-12-17	11:36:00	5-7am	weekend	kitchen	dishwasher	off

Figure 4: Micro-moments extracted after the analysis and abstraction of a Consumption Log file.

Micro-moments, as shown in Figure 4, are derived from the Consumption Logs file as a combination of a specific action at a specific moment. This is abstracted after combining and analyzing user's consumption and sensor data and classifying these records per device into actions such as "*turn-on-light*", "*turn-off-ac*", etc. that correspond to the user's energy related micro-moments. We can either assume that the user action information is directly recorded by a smart-plug system, or we can follow an action detection methodology from the time-series data, which will be briefly explained in the experiments section of this work (see subsection 4.2).

The transition from the measurements collected for each sensor every minute to abstracted activities and conditions involves the process of transforming data from one type to another or creating new data from the existing ones. For example, the values for the temperature or humidity had to be transformed from numerical data to categorical (i.e. high, low, medium), whereas based on the temperature difference between two consecutive time-stamps we could create a label for the temperature change such as "temperature has dropped/increased quickly/slowly" to characterize the temperature changes for different time intervals. Furthermore, comparing the temperature recorded at each time interval from the indoor and outdoor sensors we can abstract information whether the indoor/outdoor temperature/humidity difference is big/small, or even in a higher time

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

abstraction level identify the difference of temperature/humidity in the morning/afternoon or even weekdays/weekends. The output of this process is the basis for extracting contextual information behind user actions.

3.3 Extract Context-related Consumption Habits

The result of the Weather Logs processing will be used to identify weather changes, or weather conditions, which can then be associated with the users’ choice for energy consumption. Examples are sharp increase/decrease of the temperature, sudden rains, significant rise of humidity levels, etc. that are frequently associated with the user’s action of switching on the air-conditioning.

The analysis of the user’s energy consumption data and weather conditions’ contextual data as well as the association of user´s actions with abstractions of contextual conditions is followed by the extraction of user’s “consumption habits”. This task refers to the process of identifying frequent consumption patterns (or device usage patterns) in the consumption micro-moments and associating them with weather conditions and other temporal parameters (e.g. time of day, day of the week etc.).

In this step an Association Rule Mining algorithm is employed in order to jointly process user’s micro-moments data (consumption and weather conditions) and find frequent itemsets (condition sets) that are associated with an action in the micro-moments file.

3.4 Recommend User Actions based on Micro-moments

In the final step of the process, which is summarized in Figure 5, real-time data and current environmental conditions are evaluated against frequent associations found in the previous step.

A rule evaluation process is used to detect whether the current context matches any of the frequently occurring energy consumption activities for the user (e.g. the user is back home after work and the indoor temperature is low). Then the recommendation algorithm suggests to the user to perform the action that is associated with this context (e.g. to turn on the heater). However, in order to change the user routine, the system also recommends an energy saving modification to the user, which fits in the current context (e.g. to switch off the heater the earliest possible, based on user’s previously recorded habits).

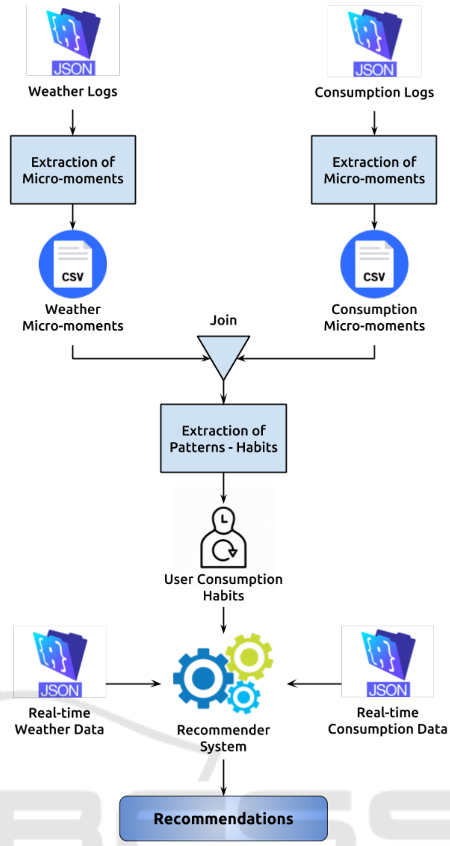

Figure 5: Process of analyzing consumption files and weather data to create energy action recommendations.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

Since the task of extracting frequent occurring energy consumption actions is of great importance for the analysis process, it is appropriate to provide some basic information on the algorithm that was used for the association rule mining. The Apriori association rule extraction algorithm (Agrawal et al., 1994) is used to uncover how items are associated to each other by locating frequently co-occurring items among the users’ transactions.

The typical example for describing association rule discovery algorithms is with the analysis of user shopping carts in an online shop. Let $I = \{i_1, i_2, \dots, i_n\}$ be all the possible itmes that can be found in a cart and $D = \{t_1, t_2, \dots, t_n\}$ be the set of all transactions (shopping carts) in the shop’s database. Each transaction in D contains a subset of the items in I. If $X, \Upsilon \subseteq I$ and $\cap = \emptyset$, then the rule $X \rightarrow \Upsilon$ implies the co-occurrence of X and Υ, meaning that if item X is bought, then item Υ will also be bought together. By definition[1] “*the sets of items (for short itemsets) X and Y are called antecedent (left-hand-side or LHS) and con-*

[1] http://software.ucv.ro/~cmihaescu/ro/teaching/AIR/docs/Lab8-Apriori.pdf

sequent (right-hand-side or RHS) of the rule respectively."

In the energy recommendations scenario the appliance, the space, time and other conditions are the items, that can be found in the LHS part of an association rule and user actions (i.e. switch the appliance on or off) are the consequent (RHS of the rule.).

4 EXPERIMENTAL EVALUATION

4.1 Dataset

It is fundamental for the experimental evaluation of the proposed framework to check whether the transformation and analysis of the consumption data is appropriate for extracting the user's consumption habits, which are consequently fed to the recommender system for creating recommendations based on actual user conditions. For this, we decided to use an online dataset provided by the University of California Irvine through its machine learning dataset repository. The dataset[2] concerns the monitoring of individual household electric power consumption. It is a multivariate time-series dataset with 2,075,259 measurements gathered in a house located in Sceaux (7km of Paris, France) between December 2006 and November 2010 (a time period of 47 months). The dataset contains information about the household global minute-averaged active power (in kilowatt), household global minute-averaged reactive power (in kilowatt) and minute-averaged voltage (in volt). The measurements concern the energy metering (in watt-hour of active energy) of three rooms of the household, the kitchen (which contains mainly a dishwasher, an oven and a microwave), the laundry room (which contains a washing-machine, a tumble-drier, a refrigerator and a light) and a set of energy consuming devices which correspond to an electric water-heater and an air-conditioner.

4.2 Preprocessing

In order to abstract from the original measurements data file to the user activity file as depicted in Figure 4, we followed a time-series analysis methodology on the consumption information data of each room. More specifically, from the actual energy consumption recorded per minute, we computed the changes between consecutive minutes and between consecutive 5-minutes periods. The first feature allowed us to isolate minutes where the power consumption increased or decreased significantly due to powering on or off one or more devices. By applying a k-Means clustering on the different power change values recorded for a room, we obtained a number of clusters of power change values that we mapped to specific actions of operating multiple devices.

Algorithm 1: Characterize device operation action as *on* or *off*.

Require: Series of consumption data of each room recorded per minute.
$CurrentMinute = 0$
loop
  Detect significant power consumption changes.
  if $CurrentMinute = 5$ **then**
    Detect significant power consumption changes in 5minutes periods.
    $CurrentMinute = 0$
  end if
  $CurrentMinute \leftarrow CurrentMinute + 1$
end loop
Apply k-means algo on the power change values.
Find clusters of power change values.
Find the limit values between power changes.
Map changes to actions of operating devices.

In order to map power changes to user actions we assumed that each device has a typical consumption specification. For this purpose, we adopted the values provided by the 'energy calculator' website[3] as depicted in Table 1, which summarizes the devices monitored in each room and an estimation of their power consumption.

Table 1: An estimated consumption for the devices in the dataset.

Room	Device	Power (in W)
kitchen	oven	2400
kitchen	dishwasher	1800
kitchen	microwave	1200
laundry room	clothes washer	500
laundry room	clothes dryer	3000
laundry room	refrigerator	180
laundry room	light	60
central	water-heater	4000
central	air-conditioner	3500

Based on the consumption values of each device, and the devices per room, we map power changes to user actions. For example, the cluster with the largest

[2] https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption

[3] https://www.energyusecalculator.com/calculate_electrical_usage.htm

power consumption changes was mapped to the activity of switching on all the appliances in the room, the one with the second largest changes that switches on all but one device (that with the lowest power), and so on. Applying the same methodology to the 5-minute changes allowed us to detect power-off actions for devices that go to a low power consumption mode before switching off (e.g. a dishwasher).

Since the energy consumption monitoring system is not yet fully deployed and operating, it is not possible to validate the performance of the user action detection method from the publicly available dataset. However, in the full system deployment, smart plugs and smart switches will be places on some rooms and this will allow to validate the method with actual data.

Date	Time	Kitchen	KitchenChange	KitchenPrev	oven	dishwasher	microwave
27/10/2010	13:40:00	0	NaN	NaN	-1	-1	-1
28/10/2010	15:01:00	40	39	1	1	1	1
28/10/2010	15:13:00	9	-30	39	-1	-1	0
28/10/2010	15:14:00	2	-7	9	0	0	-1
28/10/2010	16:18:00	10	9	1	0	0	1
28/10/2010	16:19:00	39	29	10	1	1	0
28/10/2010	16:31:00	34	-5	39	0	0	-1
28/10/2010	16:32:00	0	-34	34	-1	-1	0
29/10/2010	21:49:00	25	24	1	1	0	1

Figure 6: The output of the power consumption log file processing for a single room.

This methodology resulted in series of switch on and off actions for each device (see Figure 6). A second processing of the resulting file was necessary to correct any mistakes, such as detection of two or more consecutive switch-on or switch-off activities. The methodology, allowed us to detect user activities on a group of devices, by simply monitoring the collective consumption of all devices. The complete evaluation of this methodology is ahead of the scope of this paper, since in our final setup, we assume that smart plugs will log all user activities on the devices.

4.3 User Habit Extraction

The next step was to merge the user activity data for all rooms and generate the abstracted user activity file, which allows us to detect frequent user habits. In this step, we process the user activity data file and abstract the timezone and day of the week information for each activity. More specifically, we map each activity to the two-hours time-slot that it occurred (e.g. 1-3 am, 3-5 pm, etc.). The result of this abstraction are similar to those depicted in Figure 4.

Table 2 provides information about the 29,255 on/off actions[4] that have been recorded in the 47 months period for the three devices of the kitchen (i.e. oven, dishwasher and microwave) and the various time-zones they have occurred.

Table 2: The distribution of user on/off actions (that occur more than 4 times per month in average) to the 3 devices located in the kitchen.

Appliance	Timezone	Times per month
oven	7-9 am	5.96
	9-11 am	9.2
	11-1 pm	16.84
	1-3 pm	12.71
	3-5 pm	10.83
	5-7 pm	11.22
	7-9 pm	32.21
	9-11 pm	19.6
	11-1 am	5.33
microwave	7-9 am	6.0
	9-11 am	9.61
	11-1 pm	17.79
	1-3 pm	12.67
	3-5 pm	10.81
	5-7 pm	11.9
	7-9 pm	33.13
	9-11 pm	19.07
	11-1 am	4.64
dishwasher	9-11 am	4.09
	11-1 pm	8.62
	1-3 pm	5.87
	3-5 pm	4.99
	5-7 pm	4.78
	7-9 pm	14.15
	9-11 pm	8.26

Table 3: The association rules extracted for the kitchen devices that have a support bigger that 0.02 (happen more than 12 times per month).

LHS	RHS	Conf	Supp
7-9 pm, microwave, weekday	on	0.51	0.04
7-9 pm, oven, weekday	on	0.51	0.03
7-9 pm, microwave, weekday	off	0.49	0.03
7-9 pm, oven, weekday	off	0.49	0.03
9-11 pm, oven, weekday	off	0.51	0.02
9-11 pm, microwave, weekday	off	0.51	0.02
9-11 pm, oven, weekday	on	0.49	0.02
9-11 pm, microwave, weekday	on	0.49	0.02
7-9 pm, microwave, weekend	off	0.5	0.02
7-9 pm, microwave, weekend	on	0.5	0.02
11-1 pm, microwave, weekend	on	0.5	0.02
11-1 pm, microwave, weekend	off	0.5	0.02
7-9 pm, oven, weekend	off	0.5	0.02
7-9 pm, oven, weekend	on	0.5	0.02
11-1 pm, oven, weekend	on	0.5	0.02
11-1 pm, oven, weekend	off	0.5	0.02
7-9 pm, dishwasher, weekday	on	0.51	0.02

The above information is used as input to the Apriori association rule extraction algorithm (Agrawal et al., 1994). Table 3 presents the top rules extracted from the dataset that have an 'on' or 'off' action at the right hand side, an appliance and an associated

[4]Each on action is followed by an off action, so values in the table count pairs of on/off actions

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

day and timezone at the left hand side, listed in decreasing support order. The frequent actions of Table 2 and the association rules of 3 are used as decision rules for generating recommendations. For example, it is evident from the results of Table 2 that the user utilizes the dishwasher during the day and mostly after dinner. A recommendation for this user would be to postpone the operation of the dishwasher after midnight to take advantage of lower priced power. Similarly, the fact that the user turns on and off the oven on weekdays between 7 and 9 pm makes this time slot ideal for generating micro-moment based recommendations that will help the user to reduce the oven usage or replace it with the microwave.

In addition to this, when the current user status and the actual environmental conditions match a user micro-moment, the exact details of the pattern can be extracted from the usage logs and used to provide better recommendations. For example, when the user turns on the A/C and the action matches a user micro-moment, the system will recommend to the user to switch it off earlier than usual, or put it on power saving mode, in order to reduce energy consumption.

4.4 Micro-moments Recommendation Evaluation

Using the activity data file as input and a frequent pattern extraction algorithm it is possible to extract user micro-moments and consequently to use these micro-moments to address recommendations to users. In order to evaluate the coverage of the generated micro-moment recommendations, we split the activity data set and use the first 80% of the monitoring period for learning user habits and the remaining 20% of the data (last 9.5 months) for evaluating whether a user action matches a user micro-moment.

More than 23,000 user actions on the kitchen appliances have been used for learning user micro-moments, which resulted in 17 micro-moments, all in the evening zone (7 pm - 1 am). These micro-moments match 36.3% of the remaining 5,851 user actions used for validation and partially matches[5] 46.3% of the actions.

[5]This means that the left hand side of the rule matches the time zone and the appliance and does not match weekday or weekend condition.

5 CONCLUSIONS AND NEXT STEPS

Addressing the problem of engaging users in adopting more sustainable energy usage tactics, we identify that the users' everyday energy-related behavior is driven by their needs and desires. However their behavior depends on repetitive small actions that are called micro-moments and are influenced by factors, such as outdoor weather conditions and the user's common energy consumption habits.

Current results show that these micro-moments can be useful for transforming users' energy profile towards efficiency. This article proposed a framework for analyzing user consumption data to identify user consumption habits, extract the micro-moments that are related to power consumption and use these micro-moments to provide recommendations that could help the user on improving his energy consumption footprint.

We are currently in the process of deploying an architecture with smart-plugs and switches, aiming to solve many of the issues of this study (e.g. the detection of user activities from aggregated consumption data) and the main goal of our future work focuses on prototyping the recommendation system and its evaluation in a actual case study, which will verify the usability of the proposed framework.

ACKNOWLEDGEMENTS

This paper was made possible by National Priorities Research Program (NPRP) grant No. 10-0130-170288 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

REFERENCES

Agrawal, R., Srikant, R., et al. (1994). Fast algorithms for mining association rules. In *Proc. 20th int. conf. very large data bases, VLDB*, volume 1215, pages 487–499.

Alhamid, M. F., Rawashdeh, M., Al Osman, H., and El Saddik, A. (2013). Leveraging biosignal and collaborative filtering for context-aware recommendation. In *Proceedings of the 1st ACM international workshop on Multimedia indexing and information retrieval for healthcare*, pages 41–48. ACM.

Bao, J., Zheng, Y., and Mokbel, M. F. (2012). Location-based and preference-aware recommendation using sparse geo-social networking data. In *Proceedings of* *the 20th international conference on advances in geographic information systems*, pages 199–208. ACM.

Bao, J., Zheng, Y., Wilkie, D., and Mokbel, M. (2015). Recommendations in location-based social networks: a survey. *Geoinformatica*, 19(3):525–565.

Biloš, A., Turkalj, D., and Kelić, I. (2016). Micro-moments of user experience: An approach to understanding online user intentions and begavior. *Challenges of big data technology*, page 67.

Campos, P. G., Díez, F., and Cantador, I. (2014). Time-aware recommender systems: a comprehensive survey and analysis of existing evaluation protocols. *User Modeling and User-Adapted Interaction*, 24(1-2):67–119.

Cao, H. and Lin, M. (2017). Mining smartphone data for app usage prediction and recommendations: A survey. *Pervasive and Mobile Computing*, 37:1–22.

Cao, X., Cong, G., and Jensen, C. S. (2010). Mining significant semantic locations from gps data. *Proceedings of the VLDB Endowment*, 3(1-2):1009–1020.

Coutaz, J., Carlesso, A., Bonnefond, N., Balzarini, R., Laurillau, Y., Mandran, N., and Crowley, J. L. (2018). "will the last one out, please turn off the lights": Promoting energy awareness in public areas of office buildings. In *European Conference on Ambient Intelligence*, pages 20–36. Springer.

Darby, S. J. (2018). Smart technology in the home: time for more clarity. *Building Research & Information*, 46(1):140–147.

Duhigg, C. (2013). *The Power of Habit: Why we do what we do and how to change*. Random House.

Gram-Hanssen, K. (2013). Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption? *Energy Efficiency*, 6(3):447–457.

Hu, S., Yan, D., Guo, S., Cui, Y., and Dong, B. (2017). A survey on energy consumption and energy usage behavior of households and residential building in urban china. *Energy and Buildings*, 148:366–378.

ITEAD Intelligent Systems (2016). Sonoff Pow R2.

Jensen, R. H., Strengers, Y., Kjeldskov, J., Nicholls, L., and Skov, M. B. (2018). Designing the desirable smart home: A study of household experiences and energy consumption impacts. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, page 4. ACM.

Jørgensen, L. (2017). I want to show-how user-centered design methods can assist when preparing for micro moments. Master's thesis, NTNU.

Ramaswamy, S. (2015). How micro-moments are changing the rules. *Think with Google*.

Sardianos, C., Varlamis, I., and Bouras, G. (2018). Extracting user habits from google maps history logs. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 690–697. IEEE.

Snegirjova, M. and Tuomisto, F. (2017). Micro-moments: new context in information system success theory. Master's thesis.

Srivastava, J., Cooley, R., Deshpande, M., and Tan, P.-N. (2000). Web usage mining: Discovery and applications of usage patterns from web data. *Acm Sigkdd Explorations Newsletter*, 1(2):12–23.

Stokes, P. and Harris, P. (2012). Micro-moments, choice and responsibility in sustainable organizational change and transformation: the Janus dialectic. *Journal of Organizational Change Management*, 25(4):595–611.

The Apache Software Foundation (2018). Apache CouchDB.

Wang, D., Park, S., and Fesenmaier, D. R. (2012). The role of smartphones in mediating the touristic experience. *Journal of Travel Research*, 51(4):371–387.

Yu, K., Zhang, B., Zhu, H., Cao, H., and Tian, J. (2012). Towards personalized context-aware recommendation by mining context logs through topic models. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 431–443. Springer.

Zhou, K. and Yang, S. (2016). Understanding household energy consumption behavior: The contribution of energy big data analytics. *Renewable and Sustainable Energy Reviews*, 56:810–819.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS