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TOWARDS DOMESTIC ENERGY EFFICIENCY: USING MICRO-MOMENTS FOR PERSONALIZED BEHAVIOR CHANGE RECOMMENDATIONS

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ABSTRACT
Owing to global energy demands and overwhelming environmental dilemmas, excessive domestic energy usage is an impediment towards energy efficiency. Developing countries are expected to witness an unprecedented rise in domestic electricity in the forthcoming decades. On that account, a large amount of research has been directed towards methods for behavioral change for energy efficiency. However, the efforts that focus on technology-enabled solutions are quite scarce. Thus, it is prudent to develop a framework that combines the proper use of technology with behavior change research, in order to sustainably transform end-user behavior at a large scale. This paper presents an overview of our Exploiting Micro-Moments and Mobile Recommendation Systems (EM)^3 platform and how the utilization of micro-moments can enable an accurate understanding of the end-user's behavior, and consequently, more effective interventions. Micro-moments are short-term events at which an energy saving recommendation is presented to the end-user. Each micro-moment is bundled with the energy profile of the household and contextual information. Micro-moments are detected using a variety of sensing modules placed at prominent locations in the end-user's household. A supervised machine learning classifier is then used to analyze the acquired micro-moments, identify abnormalities in usage, and formulate a list of energy-saving recommendations. Each recommendation, along with simplified usage analytics, is presented through the (EM)^3 mobile application. Current results include a fully developed smart mobile application and a backend database together with a set of sensing modules, a micro-moment classifier, and a recommendation engine.

Keywords: Domestic Energy Usage, Energy Efficiency, Data Visualization, Mobile Applications, Micro-Moment, Classification, Recommender System**.**

1. INTRODUCTION

Current energy projections show that heating and cooling energy usage will skyrocket above 80% by 2030 (Ürge-Vorsatz, Cabeza, Serrano, Barreneche, & Petrichenko, 2015). Despite the rising awareness of global environmental issues, high energy consumption is arguably a colossal constituent of those issues (Ouyang & Hokao, 2009). Namely, in the domestic sector, a vast expanse of research was done in the field of energy efficiency (Almeida, Fonseca, Schlomann, & al, 2011; Pablo-Romero, Pozo-Barajas, & Yñiguez, 2017; Poortinga, Steg, Vlek, & Wiersma, 2003). The literature deduced a number of factors that influence the behavior of a domestic end-user towards (or against) energy-saving behavior (e.g., age, gender, income level, household structure, self-identity, etc.) (Thøgersen, 2018; Yue, Long, & Chen, 2013). The repetition of a given energy behavior is habit-forming, and so many research studies attempted to find techniques, strategies, and models that attempt to transform energy excessive habits into energy saving ones (Huebner, Cooper, & Jones, 2013). Examples of the methodologies are the transtheoretical model (He, Greenberg, & Huang, 2010), the reasoned action approach (Fishbein, Ajzen, & Ajzen, 2011), motivational interviewing ("Motivational Interviewing," n.d.), and reinforcement learning (Decker, Otto, Daw, & Hartley, 2016; He et al., 2010; US20140099614A1, 2014; "Motivational Interviewing," n.d.).

The analog and abstract nature of the current literature has scarcely employed modern technology. For example, in (Jahn et al., 2010), an "energy aware" smart home was proposed, where energy-efficiency features such as wireless power metering and energy data visualization were used. In a similar context, the Nest Thermostat, a commercial product, promises to adjust the heating and cooling settings based on user behavior and preferences (Nest, n.d.). Those two examples, in spite of recording and making use of end-user energy profiles, fail to apply the habit change research to endorse energy-saving behavior. Based on the above, it is evident that there is a growing need to revisit our conceptualization of how energy-saving behavior is created and sustained.

In this paper, we present an overview of the consumer engagement towards energy saving behavior by means of Exploiting Micro Moments and Mobile Recommendation Systems (EM)^3 platform that aims to combine behavior change models, proper data visualization, and personalized recommender systems in a cohesive system that effectively sustains energy-saving habits for domestic end-users. Our contribution is based on the novel use of micro-moments as means to manifest an accurate energy profile for each end-user and use that profile to recommend better behavior.

The remainder of this paper is organized as follows. Section 2 lays out the Methods of the various components of the (EM)^3 platform. Section 3 summarizes the implementation progress and discusses current limitations. The paper is concluded in Section 4.

2. METHODS

The overarching goal of the (EM)^3 platform is to advance the state-of-the-art of evidence-based, technology-enabled, recommender systems for energy efficiency. The platform is composed of a number of components that holistically work together: the micro-moment classifier, the recommender system, the end-user application. Fig. 1 illustrates those components. We first expound upon the concept of micro-moment and then describe the core components of the platform.

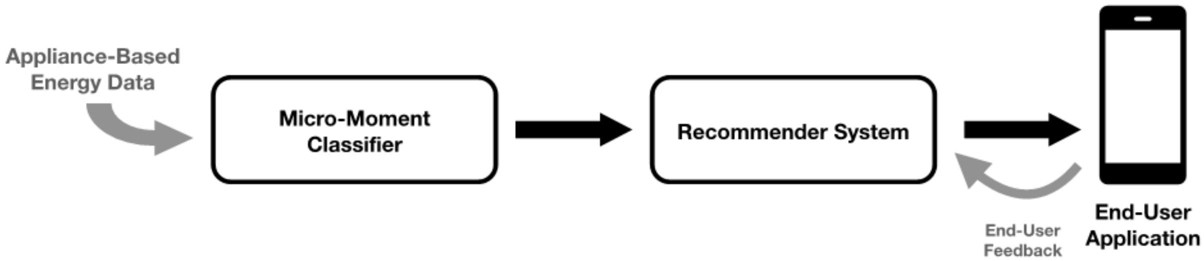

Fig. 1. Overview of the (EM)^3 energy efficiency platform.

2.1. Micro-Moments and the (EM)^3 Laboratory

Micro-moments, a term publicized by Google ("How Micro-Moments Are Changing the Rules," n.d.; "The Basics of Micro-Moments," n.d.), are short events that represent a specific behavior of the end-user. Examples are switching the lights on, turning on air conditioning, entering a room, and operating an appliance. Each micro-moment is bundled with the current energy profile of the current room of the household, the environmental conditions, and end-users' habits profile. The collection of those micro-moments defines the context of an energy-saving recommendation.

In order to capture a given end-user's micro-moments correctly, a rich energy profile must be recorded in real-time. A variety of sensors are put into use to collect various types of data. Examples are smart switches with power metering functionality, temperature and humidity sensors, occupancy sensors, and smartphones.

2.2. Micro-Moment Classifier

Machine learning has been previously used in the context of power consumption and energy saving. However, most of the previous work focuses on power forecasting and prediction of abnormal consumption (Amin-Naseri & Soroush, 2008; Amjady, 2001; Li, Bowers, & Schnier, 2010). In our work, a supervised, decision-tree based classifier is trained on the collected data to recognize the patterns in the data in a supervised learning setting. The trained classifier is then used to classify unlabeled data records online into their corresponding micro-moments labels. The labels are chosen to reflect relevant micro-moments for different appliances in different rooms instead of assigning different micro-moment labels to different appliances. For example, switching the light and the heater on both have a micro-moment label of "switch on."

2.3 Energy Efficiency Recommender System

Following successful classification, micro-moments are fed into a recommender system that produces a list of potential recommendations along with respective confidence levels. The recommendations must be personalized to the individual end-user and take advantage of the habit change research to transform the end-user's behavior for sustainable energy-saving behavior gradually.

To illustrate the concept further, a sample scenario is presented. An end-user lives in an apartment in a city. Usually, the day-time temperature ranges between 40-45 °C with an average relative humidity of 75%. The end-user turns on air conditioning around early afternoon, but switches it off in the evening, when the temperature falls below 38°C and the humidity below 75%. Instead of developing a knowledge-based with rules that strictly decide when to switch off the air-conditioning, the system learns from past user activities using the micro-moment classifier, which can distinguish between different usage patterns. In an overly hot summer evening, the system may suggest extending air conditioning usage, but can also recommend a switch-off action and opening the window to allow a cool evening breeze. The recommendation is viewed via the (EM)^3 mobile application.

To develop the recommender system, a rule evaluation workflow is employed that matches the user's current context with any of the frequently occurring energy consumption activities for the end-user. The Apriori association rule extraction algorithm is used to understand how activities and user or environmental conditions are associated to each other by locating frequently co-occurring patterns among them (Agarwal, Srikant, & others, 1994).

Fig. 2 illustrates the process of creating recommendations.

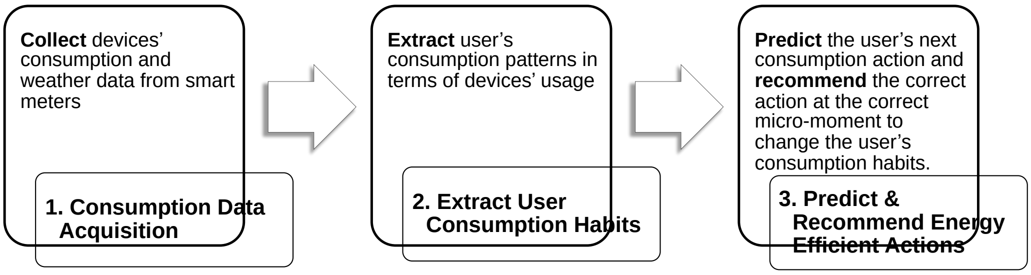

Fig. 2. The process of producing energy-saving recommendations.

2.4 The End-User Mobile Application and Backend

In addition to presenting recommendations, the end-user application provides intuitive and meaningful visualizations of energy consumption in addition to a basic appliance control functionality. For each room in the household, the end-user can view energy consumption data per device, air condition statistics (humidity, temperature, etc.) and proofs of the current efficiency of energy usage. Fig. 3 shows the three sections of the application. Data and recommendations are downloaded from the backend in real-time via a No-SQL based CouchDB server (The Apache Software Foundation, 2018). The CouchDB database management system enables real-time data transfer using representative state transfer application program interfaces (REST APIs) that makes data transfer to microcontrollers and single-board computers quite feasible. Database files are stored as JavaScript Object Notation (JSON) files, which are widely adopted in programming languages such as Python, C, and MATLAB. The backend will be a highly-secure, high-performance computer installed at each household independently to ensure privacy.

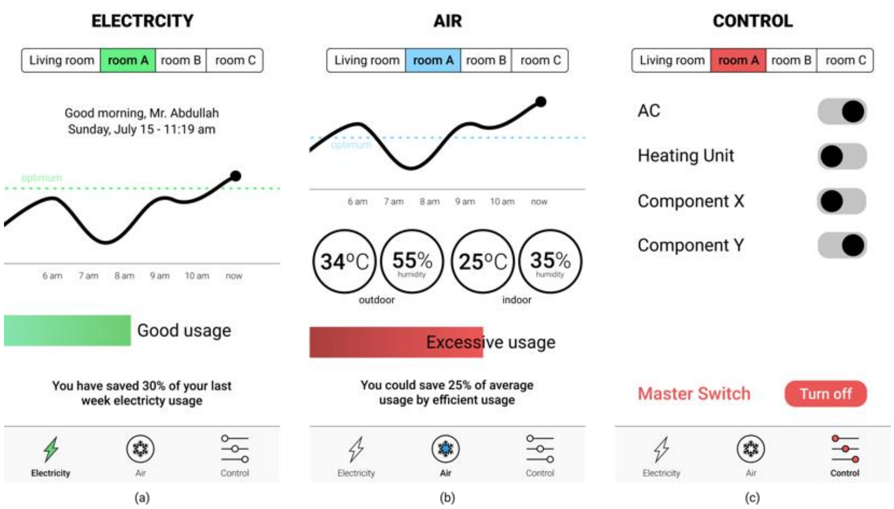

Fig. 3. The (a) electricity data, (b) air data, and (c) appliance control sections of the end-user application.

3. RESULTS AND DISCUSSION

The system has been developed in multiple stages. From proof-of-concept to fully working prototypes of the different components of the $(EM)^3$ platform. This section summarizes the current progress of the micro-moment classifier, recommender system, end-user application, and the backend.

Starting with the micro-moment classifier, where a supervised learning classification model is trained to assign the correct micro-moment label to the collected data, the labels are then fed to the recommender system that will provide the user with relevant energy saving recommendations. A range of supervised learners (both parametric and non-parametric) was used to classify the data and the performance of each classifier was assessed based on 10-folds cross-validation on the training data. Learners such as linear discriminant analysis, support vector machines, K-nearest neighbors, and decision trees were trained with different settings. Ensemble learning was further employed to combine multiple learners to strengthen the proposed classifier. The ensembled bagged decision trees have yielded the best performance on the training data, achieving a cross-validation accuracy of 87.9%.

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 show that micro-moments repeatedly occur within user's timeline (covering more than 35% of future user activities) and can be learned from user logs.

To evaluate $(EM)^3$ application along with the backend, tests have been conducted against real energy data. We have obtained data from a combination of AusGrid solar home electricity data and a publicly available dataset comprising heating/cooling data and daily power consumption data for 47 months (Ausgrid, n.d.; Georges HÃ©brail & Alice BÃ©rard, 2012). Results show that the application can display the data with an average latency of 33.39 msec for energy data and 77.7 msec for air quality monitoring. Table 1 summarizes latency results for simulated and real data respectively.

Table 1. Summary of end-user application latency test results.

Metric	Simulated Data	Real Data	Combined
Average latency (msec)	48.33	55.80	52.06

Overall, the current prototypes are working separately with relatively good performance. However, the system needs to be integrated to be deployed as a whole. Moreover, real-time energy data will be incorporated into the $(EM)^3$ lab. Following successful evaluation of a mature prototype used on real data, a comprehensive pilot study will be conducted at QU and HUA to measure the effectiveness of the $(EM)^3$ platform in improving domestic energy efficiency.

4. CONCLUSIONS

This article expounded upon the elements of the $(EM)^3$ platform for improving domestic energy efficiency. The platform encompasses a sensor-equipped environment that collects rich behavioral data. Data is classified into their corresponding micro-moments, which act as a benchmark of how much efficient is energy usage for a given end-user in a given room of the building. To improve the behavior, a recommender system processes the end-user profile and produces actionable recommendations through a mobile application. Current results include working prototypes of the micro-moment classifier, recommender system, end-user application along with laboratory and backend. Future work includes refinements to the algorithms, full system integration, and a comprehensive pilot study in both Qatar and Greece.

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