2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation

Boosting Domestic Energy Efficiency Through Accurate Consumption Data Collection

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***Abstract*—Domestic user behavior shapes overall power consumption, necessitating the development of systems that analyze and help foster energy efficient behavior. The most important step in the process is the collection and management of comprehensive data on end-user power consumption behavior. This paper presents an appliance-based energy data collection system for domestic households. It revolves around the concept of micro-moments, which are short-timed and energy-based events that form the overall energy behavior of the end-user. The system comprises sensing modules for recording energy consumption, occupancy, temperature, humidity, and luminosity storing recordings on a database server. Sensing parameters were tested in terms of connection stability and measurement accuracy. High stability and accuracy benchmarks have been reached with future work focused on deploying the system for multi-users in addition to enhancing overall data security and integrity.**

***Index Terms*—domestic energy usage, sensing system, energy efficiency, micro-moment, big data.**

I. Introduction

The core of domestic energy usage is human behavior, factoring to the ever increasing need to monitor consumption behavior, understand it, and methodically attempt to better shape it. In the following decades, domestic electricity consumption is expected to surge in developing countries. With the advent of high living standards and the reliance on electric appliances [1], it is instrumental to gather granular energy consumption data in domestic households, understanding behavior patterns, and develop technology-based solutions to boost energy efficiency.

End-user behavior is a crucial factor influencing household energy consumption, and in this context, technology can be a strong enabler in raising energy efficiency [2]. Efforts have been put to employ technology to change end-users' willingness to adopt healthy energy consumption practices [3], [4]. However, as signified in [5], intentional behavior change is a gradual process in which someone moves from being unaware or unwilling to acknowledge the problem, to being ready to make the change and then to performing and maintaining energy efficient action.

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In this context, the concept of "habit" is defined as a phenomenon where learned cue-behavior associations trigger self-directing behavior not justified by situational cues [6]. The repetition of behavior makes performing a habit almost natural, expending minimal forethought [7]. Consequently, a sequence of habits is defined as a "habitual behavior".

According to [8], a typical habitual behavior goes through three stages, known as the "habit loop". The loop starts with a *cue*, a trigger that puts the brain on auto-pilot. This primes the end-user to carry out the second step: *routine*, which refers to the actual action performed by the individual. In the third stage, the result of the action creates an internal *reward*, which is referred to as the satisfaction attained from completing the routine. Also, the reward is considered an indicator to the repeatability of the behavior, i.e. the more the habit is repeated, the stronger the loop becomes, thus reinforcing the habitual behavior.

To transform a particular habitual behavior (e.g. from a "bad" energy habit to a "healthy" one), the habit loop must be carefully studied [8]. The end-user must then gradually change the routine, while sustaining both the cue and the reward. Hence, the golden rule of habit change states that "unhealthy" habits cannot be removed entirely, but can be changed from one form to another.

It is argued that the key to a granular understanding of domestic energy behavior is the proper utilization of micro-moments [9]. Popularized by Google [10], [11], micro-moments are short events at which an energy-related behavior is carried out by the end-user (e.g. switching the lights off, turning on heating, operating an appliance, etc.) We propose that micro-moments are detected using a variety of sensing units located at prominent locations at the building [12].

Therefore, we present a novel data collection system that relies on the concept of micro-moments to obtain a very detailed understanding of domestic consumption and its underlying context and circumstances. We aim to collect appliance-based energy consumption data coupled with room occupancy, temperature, humidity, and luminosity information, which will in turn aid in formulating effective habit change plans for domestic end-users. The proposed data collection system is deployed at Qatar University (QU) in collaboration with Harokopio University of Athens (HUA).

The rest of the paper is organized as follows. Section II depicts an overview of the larger *Consumer Engagement Towards Energy Saving Behavior by means of Exploiting Micro Moments and Mobile Recommendations* (EM)^3 ecosystem and its components. Section III discusses the underlying design

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DOI 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00265

of the appliance-level data collection systems followed by a discussion of the results of the implementation in Section IV. The paper is concluded with a blueprint of the future work in Section V.

II. Overview of the EM3 Platform

The aim of the $(EM)^3$ platform is to advance the state-of-the-art of evidence-based, technology-enabled energy efficiency recommendation systems for higher domestic energy efficiency. The $(EM)^3$ platform comprises a number of subsystems that cooperate to realize this vision based on the three elements of the habit loop with respective components: i) the micro-moment classifier that is responsible for identifying the cue; ii) the recommendation engine that identifies the routine and recommends actions that gradually change it; and iii) the end-user application that demonstrates the results of the habit change as a reward to the end-user [9]. A variety of sensing tools (e.g. smart switches with current sensing capabilities, temperature and humidity sensors, power usage meters, cameras, motion sensors, smartphones, etc.) are put into use to capture various data, which are then transmitted wirelessly to the system's backend as described in the next subsection. There, the data are processed and classified into a set of micro-moments, which are considered by the recommendation engine in order to create the right recommendation within the right context (i.e. at the right moment and place).

A. The Backend

The system backend mainly aggregates data from the various sensors, but also holds processed information about users' energy profiles, micro-moments, and recommendations. Everything is recorded in a No-SQL based CouchDB server [13]. The CouchDB database management system enables real-time data transfer and offers wireless access to a variety of remote devices through REpresentative State Transfer Application Program Interfaces (REST APIs) while facilitating data transfer to micro-controllers and computers. Fig. 1 depicts an overview of the backend. All files stored in the database use the JavaScript Object Notation (JSON), a widely accepted text format for data exchange that maintains data structure without adding notation overhead. To ensure end-user privacy and scalability of the solution, in the final system deployment, the database server will run on a server computer located at the household.

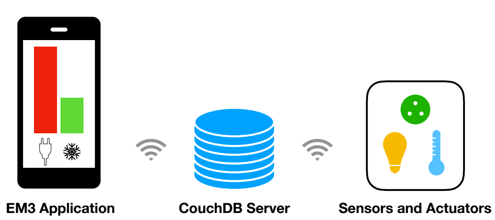


Fig. 1. Overview of $(EM)^3$ backend

B. The Micro-Moment Classifier

The task of analysing power consumption profiles and extracting the corresponding micro-moments, is performed by training multiple classifiers on synthetic data and then using them to assign micro-moment labels on unseen data. An innovative way to understand domestic energy usage patterns based on a micro-moment classifier is developed for this process. The classifier was tested on a synthetic dataset, which has been automatically generated to simulate household energy usage, based on usage patterns extracted from real studies[1]. This has enabled us to obtain a highly-detailed profile of domestic energy consumption, which will therefore aid in improving overall energy efficiency. The classifiers were trained to learn the underlying patterns of power consumption and classify them into one of the five possible micro-moment labels. Parametric classification algorithms such as Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM), along with non-parametric algorithms such as K-Nearest Neighbors (KNN) and decision trees have been employed, with different parameters, to classify the data. Finally, an ensemble bagged tree classifier has been evaluated. The ensemble classifier combines (i.e. weighted average class probability) the predictions of 30 decision trees, trained on different randomly selected subsets of the training dataset, to output a stronger classifier. The ensemble bagged trees classifier achieved the highest overall classification accuracy to 88%.

C. The Recommendation System

To provide evidence-based advice to each end-user that matches the end-user's unique energy consumption profile, a machine learning engine is fed with a set of sensor data that corresponds to many micro-moments (e.g. the user enters/leaves a given room, turns on air conditioning, operates an appliance, etc.). The engine employs the micro-moment classifier and then feeds the classified data into a recommendation system that produces a list of personalized recommendations to the end-user [14].

More specifically, this context-aware recommendation system analyzes user activities and perceives frequently repeated patterns of context conditions and user actions as user habits. The context-related patterns that are extracted from this analysis are used by the recommendation system to synchronize suggested energy saving actions with the user activities and thus deliver personalized energy efficiency recommendations at the right context. The recommendation algorithm considers user preferences, energy goals, and availability to maximize the acceptance of a recommended action and increase the efficiency of the recommendation system. The results from the evaluation on a publicly available dataset that comprises energy consumption data from multiple devices show that micro-moments repeatedly occur within the user's timeline. For example, in a hot summer evening, the system may

[1] In a process, which is not part of this work, we processed the "Individual household electric power consumption Data Set" available from the University of California Irvine at https://bit.ly/2t8sptc and extracted repetitive user activities (switch on/off actions) for multiple home appliances. Then the data generator is fed with these patterns in order to simulate different household energy usage scenarios.

prolong air conditioning usage in order to meet user's desired settings, but can also recommend an early switch-off action, when the conditions allow it (e.g. when a cold afternoon breeze causes a drop in the external temperature, so windows can be opened). The recommendations are viewed via the $(EM)^3$ mobile application, which is presented in the next subsection.

D. The $(EM)^3$ Mobile Application

Proper data visualization of energy usage is instrumental for understanding consumer behavior and for indicating areas of improvement. The $(EM)^3$ application recieves data and recommendations from the backend and correspondingly displays simplified energy consumption statistics and environmental conditions analytics [15]. It also presents the recommendations generated by the system and enables basic appliance control for home automation. The energy and air sections present room-based visualization of appliance and heating/cooling devices, respectively, along with simple recommendations. The basic appliance control panel allows the user to control appliances wirelessly through the application.

III. The Data Collection System

In order to compensate the scarcity of appliance-based energy datasets, a micro-moment lab has been developed as depicted in Fig. 2. First of its kind, the lab enables collecting accurate energy consumption data for various installed appliances (e.g. light bulb, air conditioning, heater, computer) along with contextual information including indoor temperature and humidity, room luminosity, and occupancy. Data is collected using wireless sensing modules communicating to the backend in real-time.

Currently located at a research lab at QU, the micro-moment lab currently houses one cubicle equipped with computers, displays, table lamps, etc. After conducting an evaluation test, the lab will be expanded to a larger area for more end-users, and thus collecting a broader dataset with a more extensive variety of appliances and user habits.

As a real data source, the collected data will be employed in the micro-moment classification algorithm and the recommender system. By employing real data, the developed algorithm can be validated against our simulated data to ensure higher effectiveness during the upcoming pilot. Fig. 3 shows all the used sensing modules described in Table I. Sensors where selected based on their respective accuracy, cost, and compatibility with Arduino-based boards (e.g. NodeMCU).

A. The energy monitoring module

To determine the power consumption for a given appliance, a proper sensing device must be used. For power consumption, the measured parameters are voltage and current. However, voltage is conventionally set to a fixed value (e.g. 240 V at 50 Hz in Qatar), while the current varies from appliance to another [16]. Hence, a module that measures current using a non-invasive current transformer has been developed (Table I), which measures current values up to 30A [17]. The module is connected to the line wire of the appliance and then calibrated accordingly, whereas the transformer is connected to a NodeMCU micro-controller that processes data and transfers measurements to the backend.

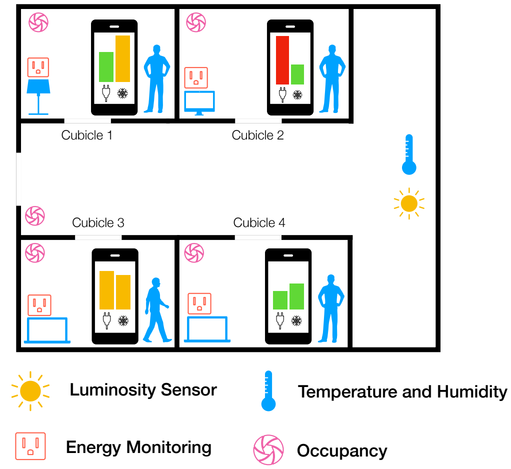
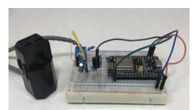
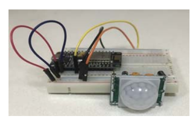
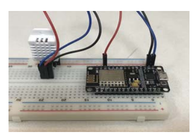
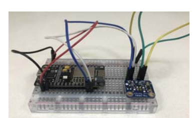


Fig. 2. Block diagram of the appliance-level data collection system with the various sensors used to collect micro-moment based data

TABLE I
List of Lab Modules

Module Photo	Name	Description	Components Used
	Energy monitoring	Measures appliances power consumption in Watts	NodeMCU and SEN-11005 current transformer
	Occupancy	Detects whether room is occupied	NodeMCU and HC-SR501 motion sensor
	Temperature and humidity	Measures indoor ambient temperature and relative humidity	NodeMCU and DHT22
	Luminosity	Measures room's luminosity in Lux	NodeMCU and Adafruit TSL2561
	Server	Stores modules' data and creates local WiFi network	Raspberry Pi 3 Model B+ with CouchDB

B. The occupancy module

A crucial aspect of power consumption monitoring, is to determine whether the end-user is currently occupying the room. This information will aid in identifying the habits of the end-user and in turn, support more informed recommendations. To achieve this, a motion sensor is used to

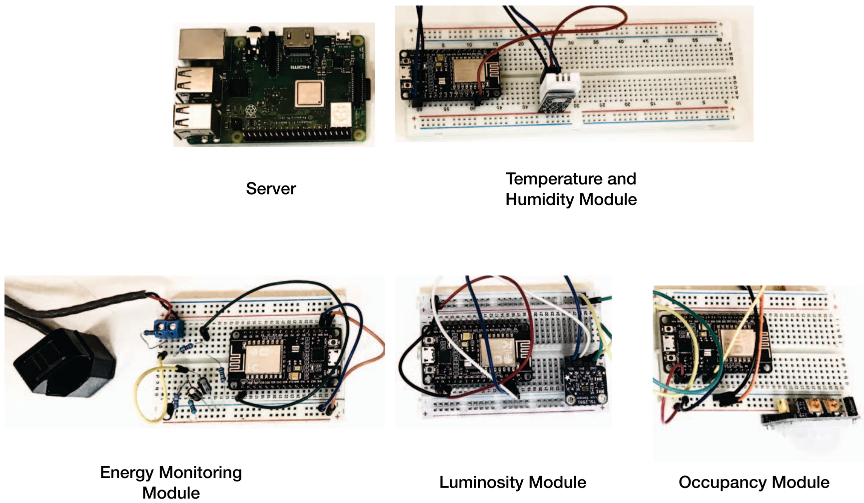


Fig. 3. The sensor setup employed in the first implementation of the $(EM)^3$ lab at QU

determine room occupancy. With proper calibration, the HC-SR501 is connected to a NodeMCU unit to collect and transmit occupancy data.

C. The temperature and humidity module

Contextual information, such as indoor temperature and humidity, aids in providing richer data on the behavior of the end-users (e.g. turning on air-conditioning in an already cool enough room). Accordingly, the DHT-22 temperature and humidity sensor was employed with an operating range of -40-80°C and 0-100% for ambient temperature and relative humidity respectively.

D. The luminosity module

Another piece of contextual information that can be used to make more meaningful recommendations, concerning light bulb energy usage, are the lighting conditions of a room. The TSL2561 light sensor, which can detect light in the range of 0.1-40,000 Lux, connected to a NodeMCU micro-controller that sends luminosity data to the backend at regular intervals.

IV. Preliminary Results and Discussion

This section depicts the results of setting up and collecting extensive data from the aforementioned sensing modules inside one cubicle. The setup will be expanded to span multiple cubicles and collect data from more appliances.

To evaluate our preliminary setup, the modules have been operated for two weeks collecting time-series data on power consumption, cubicle occupancy, indoor temperature, indoor humidity, and luminosity. First, connection stability was checked to ensure no data loss in transmission in addition to saving the data in its corresponding location in the database. For example, temperature data should be stored in the node that corresponds to the correct date, time, and room. This has been done by monitoring the connection logs of each module and verifying the data on the backend side. It is also worthy to mention that the modules are designed to be as energy efficient as possible.

The second evaluation was focused on the respective accuracy of each module compared to a reference measurement apparatus. Testbeds for temperature, humidity, electric current, and occupancy were developed. Note that luminosity was not evaluated due to unavailability of reference measurements. Fig. 4 shows the testbed of electric current for the energy consumption module. Occupancy, on the other hand, was evaluated by comparing sensor values with manually recorded data (i.e. the end-user writes in an Excel sheet the times they are inside the cubicle). Table II depicts the references used and accuracy values for each of the four modules.

On average, the temperature sensor achieved the highest accuracy of 98.3% compared to 93.5%, 85.9%, and 73.3% for humidity, electric current, and occupancy respectively. Standard deviation was also calculated as shown in Table II.

The current implementation has several limitations. First, the collected data is stored solely on the Raspberry Pi server and is not backed up, which is a crucial step to ensure that no records are lost. Second, the connection to the server is not secure (i.e. uses HTTP requests rather than HTTPS), which significantly limits the security of the recorded data. Third, the current setup is only deployed at one room (i.e. research cubicle) and thus the system has not been tested and evaluated for multiple end-users. However, it is on the roadmap of the work to include multi-user implementation in addition to addressing the current limitations. As the results show, the modules' connection stability along with the measured accuracy indicates that the current configuration is quite promising and can be extended to support more end-users and devices, but also to collect richer data.

Moreover, after further tests, the collected data is planned to be published as a publicly available dataset online. The open database will allow researchers around the world to extend

TABLE II
MODULE ACCURACY

Sensing Parameter	Reference Measurement Device	Accuracy ± Standard Deviation
Temperature	Type K Thermocouple	98.3% ± 0.0516 °C
Humidity	BK Precision 720	93.5% ± 0.00337%
Electric Current	Metrix PX 110	85.9% ± 0.0306 A
Occupancy	Manual assignment	73.3% ± 0.774

Fig. 4. The validation testbed for electric current

the work, taking advantage of the first micro-moment based energy consumption dataset in various applications such as classification, recommender systems, data visualization, etc.

V. CONCLUSIONS

This paper presented a novel micro-moment based energy data collection system for domestic households to accommodate the scarcity of available appliance-level datasets. The system comprises four sensing modules: energy consumption, occupancy, temperature and humidity, and luminosity which are connected to a database server. Sensing parameters were evaluated in terms of connection stability and accuracy with reference to high-accuracy measurement apparatuses. High stability and accuracy have been achieved with future work focused on deploying the system for multi-users in addition to enhancing overall data security and integrity.

ACKNOWLEDGMENTS

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.

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