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Achieving Domestic Energy Efficiency Using Micro-Moments and Intelligent Recommendations

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ABSTRACT 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. A large amount of research has been directed towards behavioral change for energy efficiency. Thus, it is prudent to develop an intelligent system 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 AI-based energy efficiency framework for domestic applications and explains how micro-moments can provide an accurate understanding of user behavior and lead to more effective recommendations. Micro-moments are short-term events at which an energy-saving recommendation is presented to the consumer. They are detected using a variety of sensing modules placed at prominent locations in the household. A supervised machine learning classifier is then used to analyze the acquired micro-moments, identify abnormalities, and formulate a list of energy-saving recommendations. Each recommendation is presented through the end-user mobile application. The results so far include a mobile application in the front-end and a set of sensing modules in the backend that comprise, an ensemble bagging-trees micro-moment classifier (achieving up to 99.64% accuracy and 98.8% F-score), and a recommendation engine.

INDEX TERMS Classification, data visualization, domestic energy usage, energy efficiency, micro-moment, mobile application, recommender system.

I. INTRODUCTION

Current energy projections show that heating and cooling energy usage will skyrocket above 80% by 2030 [1]. Despite the rising awareness of global environmental issues, high energy consumption is arguably a colossal constituent of those issues. Namely, in the domestic sector, a vast expanse of research was done in the field of energy efficiency [2]–[5]. Works in the field deduced a number of influencers to the energy consumer's behavior towards (or against) energy-saving behavior [6]–[8]. Conversely, technology can be a strong enabler in raising energy efficiency [9].

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Efforts have been made to utilize cutting edge software and algorithms to transform users' willingness to adopt healthy energy consumption practices [10], [11]. However, as conveyed in [12], [13], intentional behavioral transformation is a step-by-step process in which a user changes from being unaware/unwilling to acknowledge the issue, to being comfortable with making the change and then to sustainably performing the energy efficient action.

Correspondingly, the term habit is defined as a sequence of behaviors triggered by cue-behavior associations not rationalized by situational cues [14]. The more the habit is carried out, the more natural it becomes, utilizing very little forethought [15]. A sequence of habits is referred to as a habitual behavior.

A conventional habitual behavior cycles through three stages referred to as the "habit loop" [16]. Starting with a *cue*, which is a trigger that situates user to auto-pilot and also primes the second stage, the *routine*. The routine is the actual behavior done and the core of the loop. Following, the outcome of the behavior induces a *reward*, the earned self-satisfaction from achieving the routine.

The term "micro-moments" describes the moments of decision making and preference shaping for the consumer in the marketing sector. However, more definitions have been provided. According to [17], for instance, the "I want to change" micro-moment can be employed as an enabler to raise awareness about energy efficiency and as the kindle for behavior change. Comprehensive understanding of domestic energy consumption can be achieved by the collection and analysis of energy micro-moments, which are short, time-based events at which an end-user performs an energy behavior.

In this paper, we present an overview of the micro-moment based energy efficiency framework (also known as $(EM)^3$) that aims to integrate behavior change theories, effective data visualization via the end-user application, and personalized recommenders to build and sustain energy-saving habits for domestic end-users. As a collaboration between Qatar University (QU) and Harokopio University of Athens (HUA), our contribution is based on the unprecedented utilization of micro-moments as means to manifest an accurate energy profile for each end-user and to use that profile to create personalized recommendations that improve their energy-saving behavior.

The remainder of this paper is organized as follows. Sections II, III, IV V, VI depict the data collection, analysis, and visualization components of the proposed framework. Current results are portrayed and discussed in VII followed by a conclusion in VIII.

II. THE $(EM)^3$ ECOSYSTEM

The ultimate aim of the $(EM)^3$ framework is to advance the state-of-the-art of evidence-based, technology-enabled, recommender systems for energy efficiency. The framework is composed of several 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 framework.

Micro-moments are brief events that represent a specific behavior of the end-user,[1,2] [18]–[20]. Examples are switching the lights on, turning on air conditioning, entering a room, and operating an appliance. Each micro-moment is coupled with the current energy profile of the current room of the household, the environmental parameters (e.g. indoor and outdoor temperature and humidity), and consumer's 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 installed and connected to the backend to collect data.

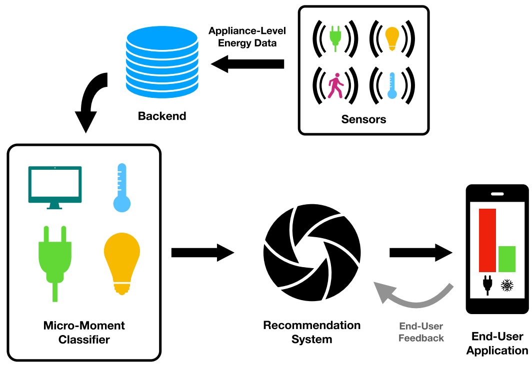

FIGURE 1. Overview of the $(EM)^3$ framework.

III. DATA COLLECTION

The $(EM)^3$ ecosystem is designed to be built upon the cutting edge of energy efficiency recommendation systems for higher domestic energy efficiency that relies on both evidence and technology [17], [21]. The framework includes sub-systems that work together building on the habit loop. Sensing devices capture data, which are securely stored in the framework database. Collected data are classified into their corresponding energy micro-moments, which in turn, are fed to a rule-based recommender system that produces a set of personalized recommendations.

Sensor data is collected and wirelessly uploaded to the backend, a Raspberry Pi server located at the household. Also, the backend stores contextual information, the extracted micro-moments, and energy-saving recommendations in a No-SQL CouchDB server. All files stored in the database use the JavaScript Object Notation (JSON), a widely adopted text format for data exchange that maintains data structure without adding notation overhead.

Currently located at an embedded systems research laboratory at QU, the micro-moment laboratory currently houses two cubicles equipped with appliances. The collected data is 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 an upcoming pilot to be deployed at both institutions. The pilot aims at validating the framework's base assumptions with a relatively large audience. Fig. 2 and 3 illustrate a sample setup with all the used sensing modules used at QU and HUA respectively.

In this paper, we use two datasets that follow the above structure. First, a simulated dataset is employed for

[1]The Basics of Micro-Moments. At https://www.thinkwithgoogle.com/marketing-resources/micro-moments/micro-moments-understand-new-consumer-behavior/ by Think with Google.

[2]How Micro-Moments Are Changing the Rules. At https://www.thinkwithgoogle.com/marketing-resources/micro-moments/how-micromoments-are-changing-rules/ by Think with Google.

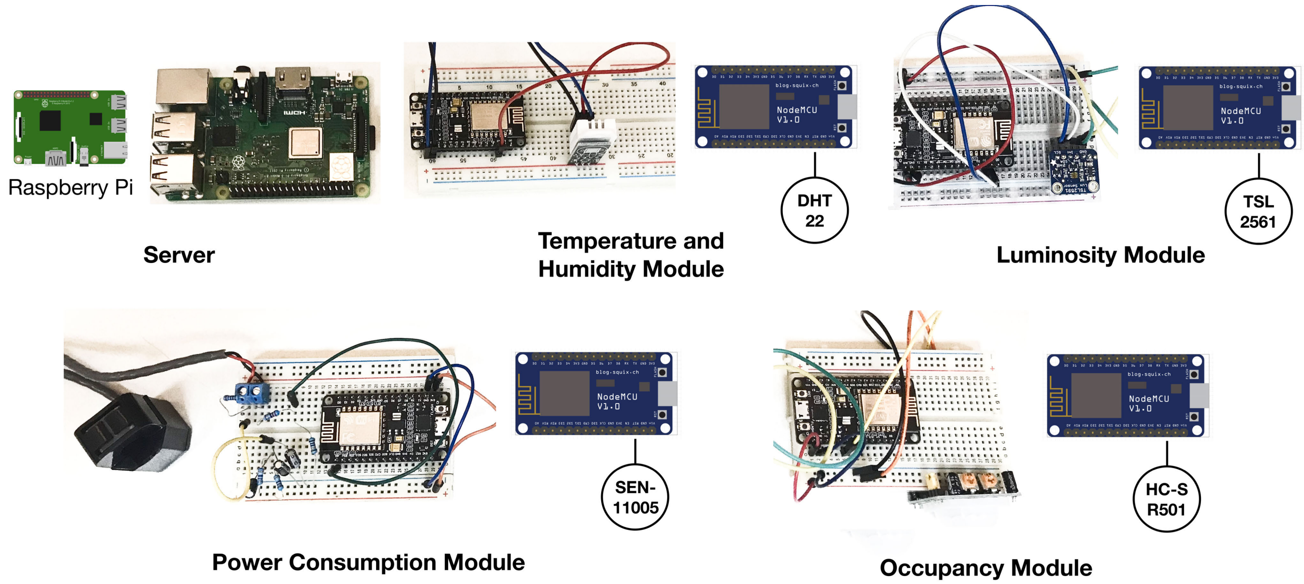

FIGURE 2. The sensor setup employed in the first implementation of the (EM)^3 system at QU.

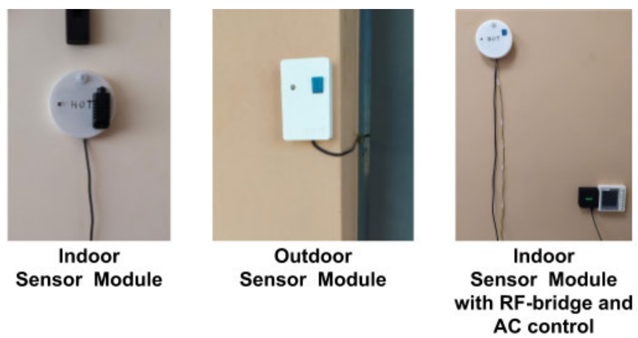

FIGURE 3. The sensor setup employed in the first implementation of the (EM)^3 system at the HUA facilities.

preliminary data analysis based real dis-aggregated smart meter data.[3] Second, using our sensors, real data is collected for a period of two months with variable sending frequency, forming the Qatar University Dataset (QUD) [22].

A. THE POWER 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. Hence, a module that measures current using a non-invasive current transformer has been developed, which measures current values up to 30A. The module is connected to the line wire of the appliance and then calibrated accordingly, whereas the transformer is connected to an NodeMCU-based ESP8266 micro-controller that processes data and transfers measurements to the backend.

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 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 lighting circuits' 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 microcontroller that sends luminosity data to the backend at regular intervals.

IV. DATA CLASSIFICATION

In this section, classification of collected data is discussed along with the topics of data imbalance and measuring

[3] Individual household electric power consumption data set. At https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption

the efficiency of the classified micro-moments. Due to the structured nature of the collected data (i.e. comprising five micro-moment classes as in Fig. 4), decision trees have been employed as the classification algorithm, as described next.

A. ENSEMBLE BAGGED TREES

As discussed in [23], [24], single decision trees show the limit of being unstable when they confront the natural random variability in various systems. To handle this problem, we design ensemble bagging trees that combine an ensemble of pattern tree frameworks into a unique prediction architecture employing bagging or bootstrap aggregation scheme [24].

In practice, ensemble techniques employ numerous learning approaches to complete superior predictive results in comparison to those that can be attained via each of the constituting training techniques separately. Further, ensemble bagging or Bootstrap technique is a parallel integrated training scheme that can be used for both multi-class classification and regression questions [23]. An ensemble bagging trees based classifier can be designed via the following stages:

- If we have a database including N observations, N random observations will be placed back in order to procure the sampling group that will incorporate N variables.
- The decision tree will be the used tree as the primary learner to train each ensemble of variables and draw N basic models.
- Finally, a voting technique will be applied to aggregate all the basic models.

After analyzing and exploring the energy consumption databases used in the validation process, the primary issue that might exist is micro-moment class imbalance [25]. Class imbalance commonly reveals an inequitable partition of variables over classes within the database. For example, in our case, most of the energy patterns pertain to ‹class 0: Good usage› and ‹class 4: consumption when outside› and only small percentage of micro-moment samples belong to the other classes that are ‹class 1: turn on device›, ‹class 2: turn off device› and ‹class 3: excessive consumption›. This leaves us with a ratio of 59:3 between class 0 and both class 1 and class 2 for the case of QUD. Also, a ratio of 51:4 is obtained between the class 0 and both class 1 and class 2 when the simulated dataset is considered. Fig. 4 presents how energy consumption footprints are distributed through the different classes for both QUD and simulated datasets.

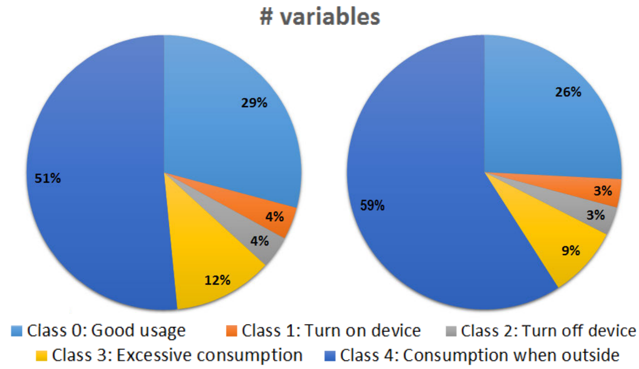

FIGURE 4. Energy profiles distribution over the different classes for the simulated dataset and QUD (left to right).

B. MANAGING AN IMBALANCED DATASET

Traditionally, an intuitive solution to handle imbalanced datasets is undersampling or oversampling, which are solely the processes of deleting some of the variables from majority classes randomly or adding some samples to minority classes in order to balance the number of the observations through all classes. However, this can affect the authenticity of the data. In addition, this is not suitable when analyzing end-user energy consumption fingerprints given that this can lead to an incorrect investigation of consumption behavior and thereby it can affect the results of the developed energy efficiency system. For that reason, we introduce a novel alternative to deal with imbalanced energy consumption datasets without impacting their authenticity throughout applying normalization and quantification of the power consumption data.

If P is considered as the vector of energy consumption patterns that includes N patterns collected for a period of time τ, then P_N reveals the normalized power consumption vector, and thus, each energy consumption profile at time t, $P_N(t)$, can be estimated as described in eq. 1:

$$P_N(t) = \frac{P(t) - mean(P)}{\max(P) - \min(P)} \tag{1}$$

Furthermore, as mentioned above, energy consumption quantification $P_Q(t)$ is the second criteria that should be investigated when managing an imbalanced energy consumption database. In our case, this kind of data is relevant for detecting ‹turn on›, and ‹turn off› classes; hence, it can highly improve the performance of the classification model. It can be computed using Eq. 2

$$P_Q(t) = \begin{cases} 1 & P(t) - P(t+1) > 0 \\ -1 & P(t) - P(t+1) < 0 \end{cases} \tag{2}$$

C. MICRO-MOMENT USAGE EFFICIENCY (MMUE)

To better illustrate and quantify the use of micro-moments in studying energy efficiency, the authors devised a metric named micro-moment usage efficiency (MMUE). It is a simple means to calculate the ratio between excessive usage micro-moments and overall usage for each appliance. Similar to electrical efficiency ranging from 0% to 100%, a higher percentage indicates higher appliance usage efficiency, according to the collected data.

As an example, we will calculate MMUE, as shown at the bottom of the next page, for our dataset for a computer setup appliance.

Hence, the calculated MMUE indicates a reasonably good usage efficiency with space for improvement regarding switching off the appliance (i.e. the computer setup) while not in use and operating at low-power modes when applicable.

V. BEHAVIOR CHANGE THROUGH RECOMMENDATIONS

Following successful classification, micro-moments are fed into a recommender system. 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 - end-user life in a flat in an urban city. Typically, the day-time temperature ranges between 30-35°C along with an average relative humidity around 65%. The user turns on air conditioning early afternoon, but turns it off in the evening, when the temperature falls below 25°C and the humidity below 50%. The $(EM)^3$ framework learns from past user actions using the micro-moment classifier, which can distinguish between different usage patterns [26]. So, the system may suggest extending air conditioning usage at relatively hotter times, but can also recommend switching off and opening the window to allow a cool evening breeze. The recommendation is viewed via a push notification and through the $(EM)^3$ mobile application.

To develop the recommender system, we exploit the micro-moments identified over the user consumption data, and 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. To identify associations among user activities and environmental conditions, we apply the Apriori association rule mining algorithm and frequently locate co-occurring patterns [27]. Fig. 5 illustrates the process of creating recommendations.

The proposed recommender system 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 [26].

After identifying user, frequent energy consumption habits our system takes advantage of this information to create personalized energy-saving action recommendations that shape their consumption habits and potentially impact their total energy consumption profile. Since the objective of our recommender system is to alter user energy-related habits to improve their energy footprint, the user habits are prioritized, and a habit change plan has to be applied in order not to change user's habits completely, but slightly alter them and consequently increase the recommendation acceptance by the user. Also, the recommendations provided to the user have to be evaluated based on the possibility to be accepted by the user and on their effect on the user's total consumption.

So, on a daily basis, a large set of recommendations is being created, so the system has to rank them in order of effectiveness on reaching a higher energy awareness profile. In addition, the order of acceptance based on the knowledge part of the system that learns from the previous behavior of the user in terms of accepting or rejecting a recommendation and adjusts the results of the recommendations presented to the user. This means the system may identify an action having a lower effect on the user's consumption to be more preferable compared to another one is more preferable to be selected. This is achieved through a mechanism that logs the user's answer when a notification is sent to him and quantifies the acceptance ratio of their recommendations.

The above approach for context-aware rule-based recommendations is applied on a single-user setup. When a multi-user setup is applied, our system exploits a Collaborative Filtering (CF) scenario, and a CF algorithm is fed with the acceptance scores of the recommendations provided to all of the available users. In this scenario, the equivalent to a rating that is used by the CF algorithm is calculated based on the times of which the each user accepts each recommended action presented stored in a user-actions-context matrix. In these terms, the CF algorithm uses the user-actions-context matrix in order to recommend actions that are more likely to be of interest to each user based on similar users' preferences.

VI. ASSISTING BEHAVIOR CHANGE WITH DATA VISUALIZATION

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 [28]. For each room in the household, the end-user can view energy consumption data per device, air condition statistics (humidity, temperature, etc.), and statistics on the efficiency of energy usage. Data and recommendations are downloaded from the backend in real-time via a No-SQL based CouchDB server. The CouchDB database management system enables real-time data transfer using representative state transfer application program interfaces (REST APIs) making data transfer to micro-controllers and single-board computers quite feasible. The backend will be a highly-secure, high-performance computer installed at each household independently to ensure privacy. Fig. 6 shows a screenshot of the end-user application.

VII. RESULTS AND DISCUSSION

The system has been developed in multiple stages from proof-of-concept to fully working prototypes of different

$$
\begin{aligned}
MMUE &= 1 - \frac{\sum \text{excessive usage MM} + \sum \text{consumption while outside MM}}{\sum \text{any MM} - \sum \text{switch on/off MM}} \\
&= 1 - \frac{848 + 5934}{9382} \\
&= 72.3\%
\end{aligned}
$$

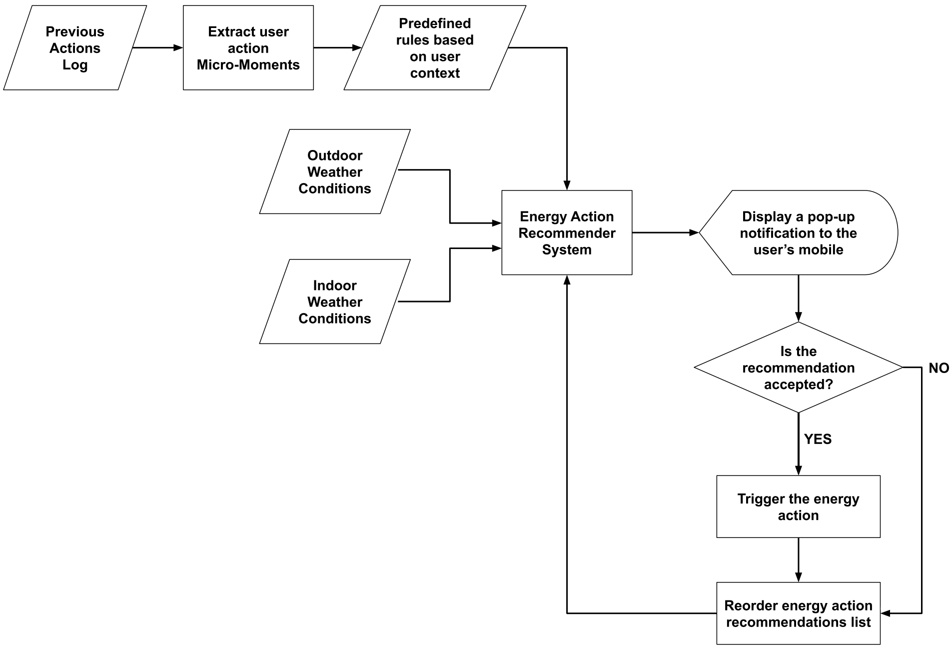

FIGURE 5. The process for creating energy related action recommendations.

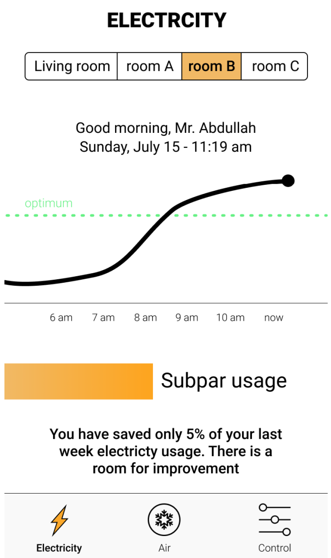

FIGURE 6. The $(EM)^3$ end-user application.

components of the $(EM)^3$ framework. This section summarizes the current progress of the micro-moment classifier, recommender system, end-user application, and the backend.

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 simulated 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.

In this section, the classification performance of the proposed system based on ensemble bagging-trees, together with power normalization/quantification is evaluated. Experimental results on the collected data confirm that the proposed approach can effectively detect anomalous patterns, where 99.64% accuracy and 98.8% F-score are achieved using the ensemble bagging trees on the QUD. Additionally, 94.66% accuracy and 90.17% F-score are obtained when the simulated database is inspected. Fig. 7 depicts the confusion matrices for the classification of QUD and the simulated dataset respectively. In the latter case, we notice that the performance has dropped despite that the results remain respectable. Table 1 depicts classifiers' performance on real and simulated data in terms of accuracy and F-score for each micro-moment.

Evidently, the ensemble bagging trees perform better on real data than on the simulated database. This can be explained by the randomness of simulated data that cannot be readily captured by the proposed approach and even other machine learning algorithms. Moreover, 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.

Moreover, after further tests, the collected data is planned to be published as a publicly available dataset online. The open database will allow the research community to extend the work taking advantage of the first micro-moment based energy consumption dataset in various applications, such as classification, recommender systems, data visualization, etc.

TABLE 1. Performance comparison using different measurement criteria using QUD.

Dataset	Micro-moment class	Accuracy	F-score	Precision	Recall
QUD	Class 0: Good usage	98.71	99.37	100	98.74
	Class 1: Turn on device	100	100	100	100
	Class 2: Turn off device	99.18	95.44	91.22	100
	Class 3: Excessive consumption	100	100	100	100
	Class 4: Consumption when outside	99.99	100	100	100
Mean		**99.64**	**98.81**	**98.26**	**99.75**
Simulated database	Class 0: Good usage	97.58	96.22	95.08	97.38
	Class 1: Turn on device	85.06	77.18	84.47	71.12
	Class 2: Turn off device	93.95	82.91	87.25	78.72
	Class 3: Excessive consumption	97.71	96.27	94.87	97.72
	Class 4: Consumption when outside	99.02	98.28	97.55	99.02
Mean		**94.66**	**90.17**	**91.84**	**88.79**

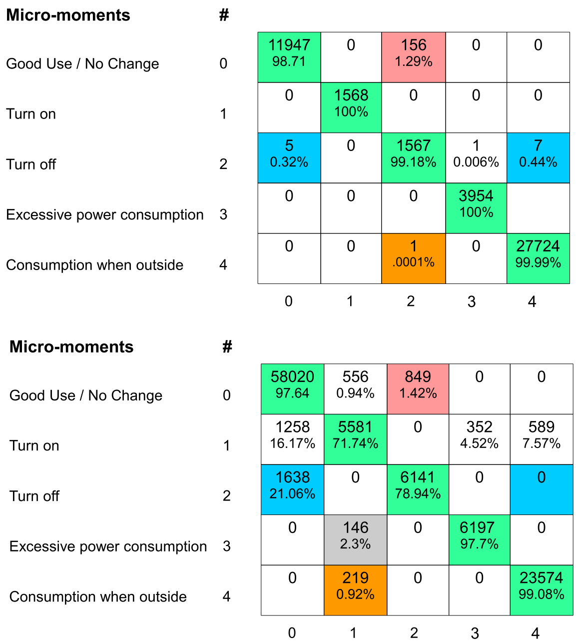

FIGURE 7. Confusion matrix obtained using the proposed scheme under QUD (up) and simulated dataset (down).

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

For this purpose, we have already implemented a real case scenario using a set of sensors and actuators that have been deployed in two main areas: the office and the balcony in front of the office in order to capture not only indoor but outdoor conditions as well. For the indoor conditions, we are interested in capturing user presence, temperature, humidity, luminosity, and power consumption, whereas the outdoor conditions monitored outside are temperature, humidity, and luminosity. To test the efficiency of our proposed method, we use two different sets of sensors/actuators: (*i*) commercial IoT devices from Sonoff (e.g. POW meters, Smart Switches, etc.) and (*ii*) custom type of devices based on the widely used EPS8266 chip. We intend to be able to identify user habits along with user consumption based on our real-time data analysis and test the effectiveness of our proposed system by enhancing the recommendation engine in our pipeline.

VIII. CONCLUSION

This article expounded upon the elements of the $(EM)^3$ framework for improving domestic energy efficiency. The framework 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 efficient the energy usage is 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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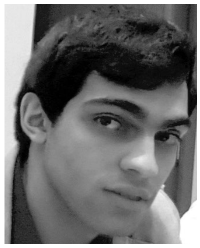

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