Improving Energy Efficiency in Tertiary Buildings Through User-Driven Recommendations Delivered on Optimal Micro-moments

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Abstract. Sustainable energy is hands down one of the biggest challenges of our times. As the EU sets its focus to reach its 2030 and 2050 goals, the importance of energy efficiency for energy consumers/prosumers becomes prevalent. Over the years, a lot of different approaches have been followed to engage end-users and affect energy-related occupant behaviour towards improving energy efficiency results and long term behaviour changes. This work presents the SIT4Energy user-centered approach for tertiary buildings that delivers an end-to-end solution that takes into consideration a set of tools and models for successfully engaging and affecting the end-user's energy-related behaviour. Starting from appropriate user profiling models for energy-related behaviour models and an explainable recommendation engine, to on the fly human activity tracking and micro-moments detection on mobile devices, a set of recommendations are delivered to the end-users through a mobile device, presenting valuable information with user-tailored context and on the optimal timing. The overall solution is clearly documented, whereas real-life results are presented from the deployment in offices in a university building. From the evaluation performed it is clearly depicted that a positive impact has been achieved both in terms of energy efficiency as well as energy-related behaviour.

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Keywords: Energy Efficiency · Recommender Systems · Micro-moments · Energy-related Behaviour.

1 Introduction

The impact of building user behaviour on energy consumption is usually not considered during the design phase or the post-occupancy optimization phase although changes in human behaviour can increase the efficiency of the energy used in the building [1]. Lasting changes in behaviour are difficult to achieve, but new ways to foster energy efficiency have emerged over the past few years. In fact, following the Fogg's [2] and Oinas-Kukkonen's Frameworks [8], various ICT-based solutions have been introduced, able to act as persuasion mechanisms for sustainability, health preservation or marketing. New technologies to measure, store, and display energy information (e.g., smart meters, dashboards, mobile phone applications) are available and provide data that allow consumers to make informed choices. While significant investments have already been made in sensing infrastructures that can provide relevant data, less attention has gone toward making energy information comprehensible, attractive, and relevant.

In general, studies of the impact of behaviour in public buildings are sparse or controversial and the impact of user behaviour is difficult to quantify for methodological reasons [7]. In principal, lighting, thermal and air quality comfort are considered as the three major factors that affect occupants' quality of living/working in a building environment and also building energy management. Occupancy status also plays a central role in energy behaviour inside a building and, as authors in [12] [14] support, significant energy savings are possible, by effectively utilizing occupancy measurements.

However, data by themselves are not enough to accurately capture the state of a building's performance. The amount of energy consumed depends not only on the criteria set for the indoor environment and applied technology but also on the behaviour of occupants. This may create a conflict between strategies that focus on the reduction of energy consumption and those to maintain a healthy and comfortable indoor environment. To achieve a balance between comfort and efficiency, synergies between building design, building climate control and occupant needs have to be established. Developing optimal strategies to control HVAC and lighting systems which also comply with occupant needs require a) a detailed modelling of the air quality requirements, as well as the respective thermal and comfort levels that the occupants desire and b) correct estimation of the current comfort conditions, based on environmental measurements (air temperature, humidity, illumination etc.) building energy management (BEM) methodology.

An eco-feedback system was found to lead to significant reductions in energy consumption [4][9]. This system provides to occupants with information regarding their historical and current energy consumption. Such knowledge greatly helps occupants to acknowledge energy saving and waste and to increase awareness of energy consumption and was found to be a big motivator to encourage energy efficient practices. A large-scale study of 2000 households has concluded that users respond well to eco-feedback with reported energy savings of 15% [15]. Combining the system with recommendations and tips has been reported to be an effective way to further improve the impact of eco-feedback and provide greater energy savings [16], [3]. In fact, tailored information can cause a significant shift in occupant behaviours, as presented in [5] (and the studies therein).

The SIT4energy project [4], addresses the challenge of effective user engagement by delivering an end-to-end solution that not only incorporates state-of-the-art behavioural models and real-time rule-based systems, but also delivers AI-driven lightweight edge computing algorithms that are executed on the user's mobile device. In addition, in contrast to most practices, it introduces the use of redefined micro-moments [10] for effectively identifying the most appropriate timing for delivering user-aware recommendations with enriched incentivisation messages. To evaluate the proposed framework a real-world pilot has been deployed, with some very promising preliminary results in both energy efficiency and user engagement.

The remainder of this paper is structured as follows: Section 2 presents the proposed solution in detail, Section 3.1 describes the experimental setup and evaluation metrics, whereas Section 3 introduces results from the real-life deployment in Athens, Greece. Finally, Section 4 concludes this paper and proposes future improvements.

2 The SIT4Energy solution

The overall architecture of the SIT4Energy framework for tertiary end-users is presented in Figure 1. Starting from the infrastructure layer, data generated by various sensors, smart meters, or other IoT devices, are pushed to the Service layer, through the Data Retrieval & Profiling tool. After a very simple pre-processing (e.g. outliers removal, filling missing values, etc.) the data are stored in a database. In the same database, an extensive list of recommendations (both generic and personalised, trigger-based) is available. As will be shown in the following paragraphs, beyond a simple tip, the presented framework also introduces an additional incentivisation message that takes into account two key user profiling aspects. By directly accessing all available information stored in the database, a rule-based recommendation engine is able to identify the most appropriate context per user, taking into account not only the current state of the consumption of the building, but also the type of the user and their energy-related behaviour. This enriched recommendation is pushed to the mobile app through an intermediate security layer (i.e. Google Firebase [5]), based on the preferences configured by the user through the app. After receiving the recommendation, the mobile app introduces an AI-driven time-dependent tool for identifying on the fly the best timing (in the form of micro-moments) for actu-

[4] `https://sit4energy.eu`
[5] `https://console.firebase.google.com/`

ally delivering the notification to the user. Each of the individual components, is presented in more detail in the following sections.

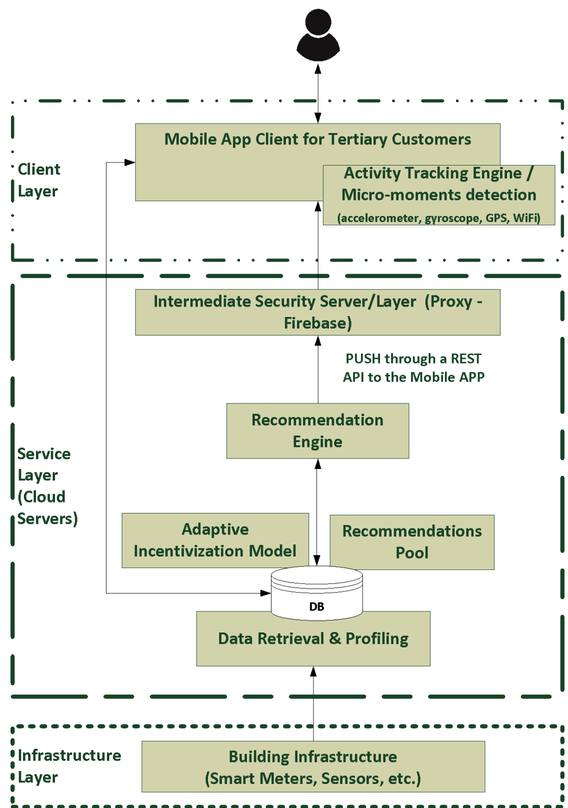

Fig. 1. The SIT4Energy framework architecture for tertiary end-users

2.1 Data Retrieval & Profiling

The SIT4Energy recommender back-end is built on Laravel[6], an open-source PHP web framework using MVC architectural pattern. MVC architecture is used to separate the model which represents the part of the software where the data are stored or created, the view which represents the part that is displayed for the user or sent via a web service and the controller which is the part that changes the view upon request. Although Laravel is designed mainly as an MVC framework, it can be used to create APIs as well. It provides easy to setup user authorization and authentication (OAuth2), along with other modules that are

[6] `https://laravel.com/`

needed for various operations (such as RESTful web services), using up to a point OOP PHP.

For data retrieval the HomeAssistant [7] tool has been employed for efficiently communicating with both smart meters and sensors deployed within the offices of the tertiary building. Installed locally on a raspberry pi, this module covers a range of measurements, such as temperature, humidity, luminance, occupancy, and energy consumption.

2.2 Adaptive Incentivisation Model

In order to be able to more accurately profile end-users, and thus introduce more user-driven recommendations with higher success rates, two concepts have been introduced and modelled: i) the user type, and ii) the change stage. The former reflects the user behavioural values, which following the norm activation theory, conceptualize into three main orientations in regards to behavioural change: a) egoistic (concerned for the self-relation), b) altruistic (concerned for other people) and c) biospheric (concerned for the non-human, e.g., environment) [13]. The later, follows the modified trans-theoretical model of behavioural change introduced in [6], to describe the distinct stages of behavioural change: a) pre-contemplentation (people unaware or having no intention to change), b) contemplation (people aware of the need for change and are ready to act, but do not do so for certain reasons), and c) action stage (people aware of the need for change and taking actions towards it).

Both the user type and the change stage are extracted through a survey that is given to the users when first installing the app. The answers are then evaluated through specific rules to define this dual user profiling. As a result, for each set of user type and change state (e.g. altruistic in pre-contemplation) a specific incentivisation message is selected (from a predefined list) to support the recommendation generated by the recommendation engine.

The adaptiveness of the model relies on the two aspects. First, the back-end periodically queries the user's latest app login frequency, and based on that alters the users' contemplation state, whereas every two months of app usage, a repetition of the survey is offered to the end-user, which potentially redefines both user type and contemplation state.

2.3 Recommendation Engine

Based on the data collected from the energy meters and smart sensors, the initial recommendation engine implementation is built on a rule-based system with predefined conditions that trigger a recommendation to be sent to the mobile app when these prerequisite conditions are met. In addition, the users must give their consent for receiving recommendations as well as select a preferable timeframe in which they wish to receive the notifications. Both can be defined in the Settings section of the mobile app provided to the user.

[7] https://www.home-assistant.io/

If the rules are only partially satisfied, the engine selects among eligible generic recommendations to be sent to the app, that are still relative to the collected energy consumption type. (i.e. If there is adequate sunlight and light energy consumption then suggest to the user *to switch off the lights*, else if there is only light energy consumption provide a recommendation related to energy saving of type Lights: *"replace light bulbs with led ones to save energy"*). The prioritization of the generic recommendations is based on their overall score collected from the users' feedback.

The precision and validity of the recommendations is further strengthened by combining the user's feedback (for every recommendation sent to the user, a request to rate it is also provided) with comparison of related changes in their energy consumption compared with their historical consumption data.

These rules used in this study are:

1. If no movement is detected in the room for the last 20 minutes and the lights of the room are switched on, then the user is alerted to turn off the room lights.
2. If outside luminosity is over a predefined threshold and the lights of the room are switched on, then the user is alerted to turn off the room lights.
3. If outside temperature is deemed within a comfortable zone (18-27 Celsius) and the A/C is switched on, then the user is alerted to turn off the A/C.
4. If inside temperature is over the hot threshold (27 Celsius), the A/C is switched on and outside temperature is lower than the hot threshold, the user is alerted to turn off the A/C and open the windows to balance the room's temperature with the external conditions.
5. If inside temperature is lower than the cold threshold (18 Celsius), the air-condition is working and outside temperature is over than this threshold the user is alerted to turn off the A/C and open the windows to balance room's temperature with the external conditions.
6. If inside humidity is above the comfortable threshold (55%) and outside humidity is lower than this threshold, the user is alerted to open the windows to balance room's humidity with the external conditions.
7. If inside humidity is lower than the minimum comfortable threshold (45%) and outside humidity is above this threshold, the user is alerted to open the windows to balance room's humidity with the external conditions.

The recommendation pool, out of which the recommender selects, includes a range of tips that are divided per device type (e.g. lighting, HVAC, office appliances, etc.), customer type (consumer vs prosumer), but also with two added value metrics: the difficulty to apply the recommendation, and the consumption gain, which refers to the importance of the tip towards energy efficiency (higher values lead to higher energy savings). Both these metrics participate in the decision making process.

2.4 Mobile App

The SIT4Energy front-end is a top notch rich HTML5, CSS3 and JavaScript application. It can be wrapped with Apache Cordova, an open source mobile application development framework, enabling programmers to develop a platform-independent application without losing native smartphone functionality such as Geolocation and Notifications. The front-end application has one single responsive code basis and therefore can be easily built for desktop environments as well as various mobile operating systems.

Beyond basic functionalities such as secure login and profile configuration, the users have access to various visualisations, such as consumption graphs, with detail defined by the available level of asset monitoring (e.g. entire office or per device) (Figure 2). The user is also able to define some target values (daily, monthly, etc.) based on which, if achieved, he/she can gain points and calculate savings (Figure 3).

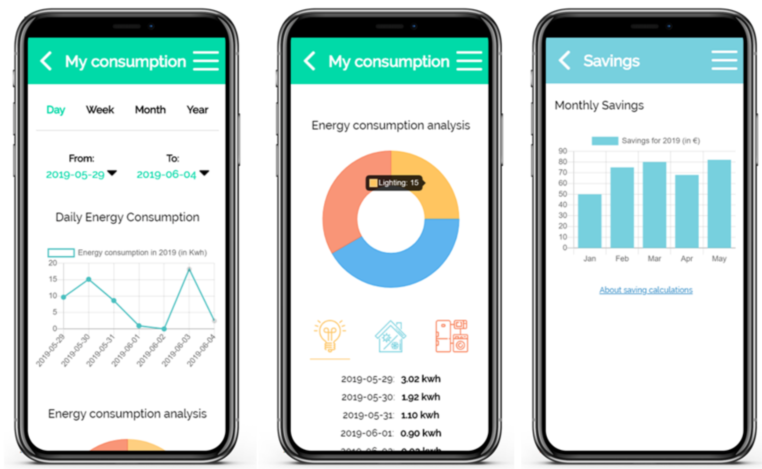

Fig. 2. Consumption analysis and energy savings visualisation.

Activity Tracking and Micro-moment detection tool One of the core innovations of the presented framework, that was evaluated in real-life conditions in this study, is the use of a lightweight human activity recognition (HAR) algorithm, fully described in a previous work of the authors [11]. It consists of a novel deep neural network model, which combines feature extraction and convolutional layers, able to recognize in real-time human physical activity based on tri-axial accelerometer data when run on a mobile device.

Based on the results of the HAR model which is executed on the fly, as well as additional information from the mobile device (e.g. the screen is on, home screen enabled, etc.) another decision layer is included for identifying the appropriate micro-moments (as redefined in [10]) for actually delivering incoming

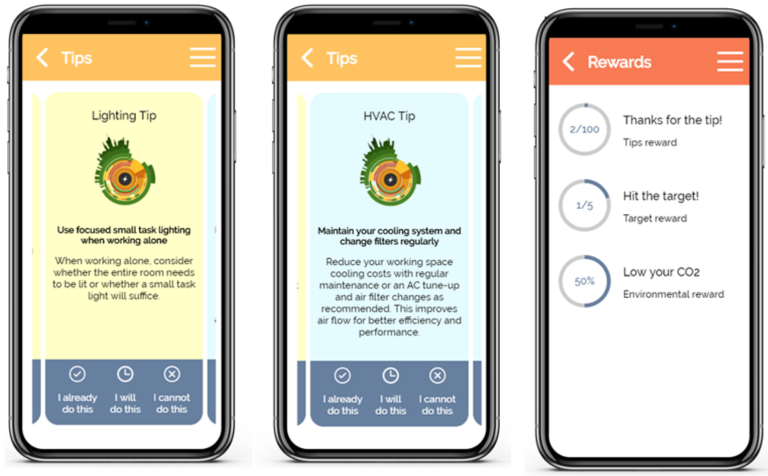

Fig. 3. Recommendations with Incentivisation messages and Rewards Representation

recommendations. Hence, an incoming message from the recommendation engine is not directly pushed to the user, but is filtered towards delivering it in the optimal moment during which the user would be more susceptible to a nudge. By doing so, not only it is possible to increase the percentage of recommendations becoming actual actions, but also increasing overall engagement as the user is more likely to pay attention to the incoming message, than disregarding due to other reasons. As micro-moments can be highly unpredictable and user-specific, such an edge computing tool creates the necessary conditions for customised experience for every user.

3 Experimental Results

3.1 Deployment Setup

The introduced framework was deployed at two working offices (Figure 4) at the premises of the Informatics and Telematics Faculty of the Harokopio University of Athens. Targeting the academic staff and students of the university the mobile app was distributed to 11 users, providing access to information from the two offices (consumption, temperature, humidity, luminance, and occupancy.

The deployment started on May 2019, when the sensors and meters were installed, and data retrieval has been initiated, for establishing a baseline, as well as to support the implementation of the various tools. A first complete version of the framework was deployed on June-July 2020 for testing purposes, whereas the complete pilot was initiated on September 2020 and will continue until June 2021. Preliminary results extracted, showcase some very interesting and promising aspects.

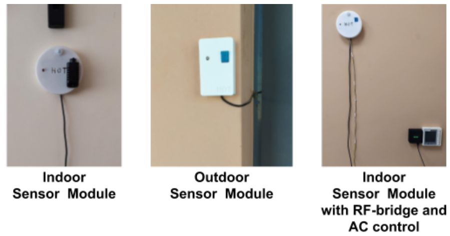

Fig. 4. Sensors deployed at offices in HUA.

3.2 Results

In general, since users have the capability to customise their preferences for receiving recommendations, a different amount of tips is delivered per user, as depicted in Figure 5.

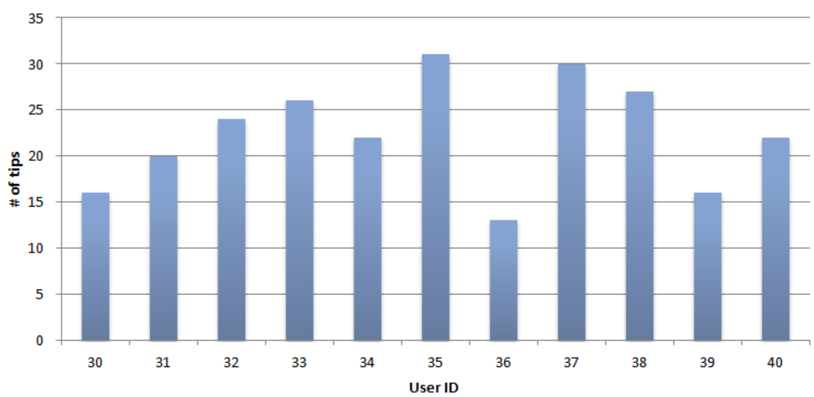

Fig. 5. Amount of tips delivered to the HUA end-users during the deployment.

In terms of energy consumption, and taking into account that from 10th of March to the 4th of May 2020 and from November 2020 to March 2021, Athens was/is under lockdown due to the pandemic, consumption patterns in Q1 and Q4 cannot be taken into account. However, as can been seen in Figure 6, a slight improvement is observed in the consumption of HVAC units, mainly in Q2, whereas a more evident decrease is observed in the consumption of PCs for both Q2 and Q3 periods.

As external weather conditions may affect these results, a baseline is to be created towards more accurately comparing the two periods. To expand the evaluation, it is also suggested to include the lockdown periods as well, with a proper annotation and a different baseline model.

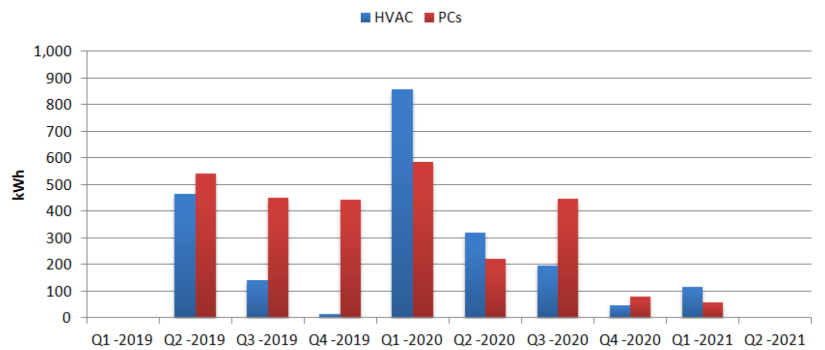

Fig. 6. Energy Consumption at pilot offices in HUA.

In terms of users' behaviour evaluation, as the pilot activities are still on-going, the feedback provided for each recommendation sent is analysed. As can be seen in Figure 7, during the first three months (Q3) quite a lot of recommendations have been provided to the users with the most being things already performed by them, followed by the ones they never do. The same situation was observed in the fourth trimester as well, but with less recommendations sent to the users. However, in the last trimester included in this study, an interesting change has been observed. The system improved from the previous knowledge and delivered more recommendations that the users are keen to do, and are not already doing. This is quite interesting, as additional actions have been identified and recommended, whereas from all the recommendations delivered, a smaller percentage (compared to the two previous periods) is attributed to actions that the users will not follow. This leads to the assumption that more accurate recommendations were delivered, avoiding things that the users already do or will not do even if recommendations are to be provided. Hence, the system is actively raising awareness, offering to the users more targeted information towards a more energy efficient behaviour.

4 Conclusions

In this paper, the real-life deployment of an end-to-end ICT-based recommender system for tertiary buildings is presented. The framework introduced, covers holistically the challenge addressed, by taking into account real-time data from the building, user behavioural models, asset-based and generic recommendations, fed to a rule based decision making engine for identifying the proper context per user, whereas on the client side, a user friendly mobile app is enriched with a lightweight AI HAR model that supports the identification of the optimal micro-moment, for delivering and engaging the user. The framework has been deployed to real-life infrastructure in a university building, covering two offices, with multiple devices (such as HVAC and PCs) and users (academic staff and

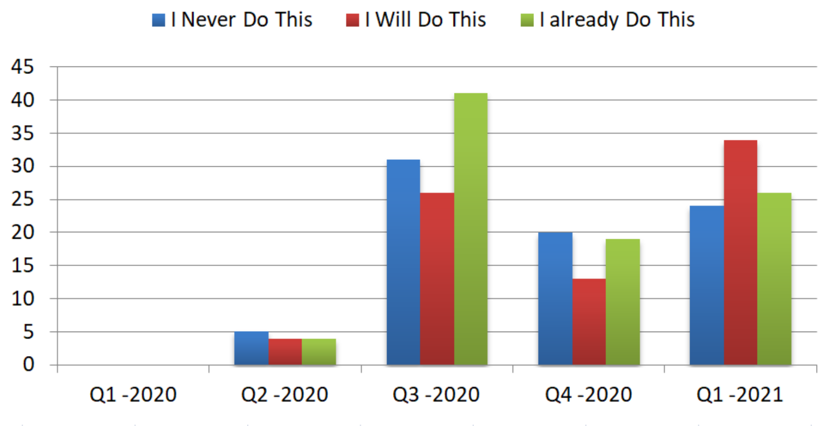

Fig. 7. Users' Feedback on recommendations provided

students). Preliminary results after six months of deployment have introduced some interesting results, mainly in terms of end-users' behaviour.

In order to be able to assess more accurately energy savings, the need of introducing a more properly defined baseline model is imperative. It is also important to take into account the impact enforced due to the corona virus situation, and evaluate in more detail the periods before and after the intervention. In terms of user behavior, besides the feedback provided upon receiving a notification, the users will fill in once more a survey that will cover both the user type and change stage for the 11 users. Hence, it will be possible to evaluate whether both aspects have been improved or not. Finally, as the number of users is quite limited for the deployment examined, which however seems to deliver the necessary proof-of-concept, to properly validate the framework proposed a larger deployment is required.

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