Real-time Energy Consumption Feedback

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Abstract — The goal of an Energy Feedback Device (EFD), also known as In-Home Display, is to make electricity visible by presenting the real-time consumption information and consequently helping occupants to control their energy usage. Nevertheless, most of these devices do not satisfy consumers’ preferences over functionality and design. Thus, there is a need to make them user-friendly, as some householders cannot understand the displayed information. This paper presents the design and test of a cloud-based EFD with differentiating features when compared to those of most commercial products. The proposed EFD aimed to be informative, intuitive and aesthetically pleasing. The goal was to bring energy savings by influencing residential consumers’ behaviour to be more energy efficient. A quantitative analysis of the participants’ energy consumption was conducted. The treatment group’s participants reduced their average energy consumption between 15% and 36%, when comparing it for a period of 30 days before and after the installation of the EFD within their households. These results presented statistical significance when using a paired t-test (95% of confidence level). In opposition, the control group, without the EFD, increased its average consumption by 2% over a similar time frame. A qualitative analysis was also conducted via survey to assess the participants’ opinions, showing that the EFD fulfils the proposed requirements of being informative, intuitive and aesthetically pleasing. Moreover, the participants claimed that all the occupants interacted with the device and that the EFD modified their consumption behaviour.


I. INTRODUCTION

The occupants’ behaviour plays a central role over a household’s energy consumption. However, electricity is invisible for most residential consumers, as they only know the consequences (i.e., cost) of their actions after a long time.

The use of a monthly electrical bill is not an appropriate tool for the management of consumption, making conservation practices for householders both unusual and difficult [1]. This paradox was already identified in the 80s by the following analogy: “think of a store without a price tag on items, that presents the total single bill on the cash register” [2]. However, electricity suppliers still resort to a system with more than 40 years that is economically unbenefficial for both the consumer and supplier, in addition to the harmful effects on the environment due to the excess of electricity usage.

Thus, in this work, we need to further explore the current approaches used to turn the consumption behaviour of electricity consumers into an efficient one, as well as understand their current limitation to come up with innovative solutions to solve the electricity consumers’ problems.

The main objective of this work can be reflected by the following research question: Can an Energy Feedback Device bring energy savings and be simultaneously pleasant and informative to the consumer?

A. Occupants’ behaviour on household’s energy consumption

Summerfield [3] studied the factors affecting a household’s energy consumption as well as their relationships. Fig. 1 illustrates them based on Chiang’s adapted diagram [4].

We can highlight the building characteristics (construction, design, materials, extension, etc.) and their influence in the household’s internal conditions (temperature, humidity, lighting level, etc.). However, we can grasp that occupants’ behaviour plays a central role over the other factors.

Moreover, a study [5] conducted for 10 identical electrical houses with similar appliances showed that the most energy-intensive house consumed 2.6 times more electricity than the least—backing up the occupants’ behaviour impact over energy consumption.

B. Modifying occupants’ behaviour

A previous study [6] showed that most residential consumers are unable to take steps towards a more efficient use of energy. A considerable discrepancy exists between consumers’ self-reported knowledge and their actual behaviour; therefore, a knowledge gap is notorious among consumers towards identifying how their households consume energy.

Abrahamse [7] performed a meta-analysis to 38 peer-reviewed studies on interventions to promote energy conservation among households, concluding that “providing households with feedback, and especially frequent feedback, has proven to be a successful intervention for reducing energy
consumption”. To do so, consumers can install an Energy Monitoring and Feedback System (EMFS) in their houses. The EMFS is comprised of a monitoring and a feedback part.

The monitoring part is usually a smart meter, or an electric meter equipped with a sensor and a transmitter – to read and send the power consumption to the feedback part of the system.

The feedback part is the Energy Feedback Device (EFD), also known as In-Home Display (IHD), which in turn presents the household’s consumption information to its occupants, commonly, through an LCD.

Previous studies [8, 9] claimed that the EFD is one of the best ways to visualize the consumption, as well as to change the householders’ consumption behaviour into an efficient one.

According to these studies, EFDs can bring energy savings ranging from 4%-15% [8] and 5%-15% [9].

Darby [10] categorized the EFDs’ display design into three types: numerical display – the consumption information is presented through numbers (e.g., current power consumption in Watts); analogue display – the information is mostly presented through scales (e.g., charts, graphs, dials, etc.); and ambient display – the information is presented using alternative ways to numbers and scales (e.g., light, colours, movement, sound, etc.).

C. Ambient display design and EFD problems

Upon the literature review, we found a lack of studies towards the design and test of ‘pure’ ambient displays (‘pure’, i.e., not mixing two types of display design, such as ambient and numeric). One of the few studies found was Energy Puppet – “an ambient display device that provides peripheral awareness of energy consumption for individual home appliances” – producing different pet-like behavioural reactions according to the appliance’s current energy consumption pattern [11]. Nevertheless, the Energy Puppet was just a laboratory experiment, not being tested on real energy consumers nor directed to the feedback of the household’s overall energy consumption.

In the literature, references to commercial products using a ‘pure’ ambient display design are almost nonexistent. In [4], we found a reference to Energy Orb, an ambient display that emits light to present colour-coded information through the traffic lights scheme (i.e., green as low, orange as medium and red as high). However, this device presents the current electricity price (e.g., for a bi-hourly tariff) instead of presenting the household’s consumption information.

Chiang’s study [4] backs up the ambient displays’ potential towards energy savings through consumption feedback. In a laboratory experiment, the researcher presented three ‘pure’ display designs to the participants, whereby respondents preferred the numerical display (54%) over the ambient (34%) and analogue (32%). However, in a field experiment, the three types of ‘pure’ displays were placed in the dorm rooms of college students – concluding that, in the ‘real world’, the ambient display “worked better than the other two designs at an arbitrary statistical significance level of 0.95”.

Finally, several studies showed that many householders are not willing to invest time to understand the usage of unintuitive EFDs [4]. According to a study conducted in the United Kingdom [12] consumers consider that most of the EFDs offered in the market do not satisfy their needs towards functionality and design. Furthermore, according to another study [13] the use of EFDs are generally limited to men. These researchers suggested that other approaches must be taken in order to extend the scope of EFDs to women and children, by making these devices more user-friendly [13]. This way, all the occupants can understand the displayed information, and consequently contribute to the efficient consumption of their household.

Next, we will present our market analysis to verify some of the previous findings (e.g., lack of commercial products that use ‘pure’ ambient displays) as well as to collect the commercial EFDs’ features and the potential customers’ opinions.

II. MARKET ANALYSIS AND CUSTOMER SEGMENTS

We surveyed 47 companies providing Energy Monitoring and Feedback Systems (EMFS) to obtain an overview of the market. We also analysed 20 Energy Feedback Devices to identify innovative features for the development of our own. Moreover, we hypothesized and interviewed potential customers for this kind of device, to find the most suitable as well as to collect their opinions.

A. Energy Monitoring and Feedback Systems

From the 47 surveyed companies, most of them provide EMFS for commercial (83%) and/or industrial (77%) clients, while only 45% of them target the residential consumers. We found that most companies provide software-based energy feedback (whereby the consumption information is presented through software platforms, i.e., desktop, web-based or mobile app). On the other hand, as to hardware products, the most commonly offered are electric meter’s sensors. Finally, the hardware-based energy feedback is the least offered product (whereby consumption information is presented through EFDs).

B. Energy Feedback Devices

We analysed 20 EFDs from 12 different companies: Effergy, The Energy Detective, Blueline Innovations, Current Cost, Clogooy, The Owl, Eco-Eye, Green Energy Options, Onzo, WattsClever, Canary Instruments and Watson. We reviewed the devices’ features summarizing them into the following topics:

1) EFD – Information and Display

The majority of the EFDs show the consumption information through LCDs (90%), mainly, on black and white ones (80%). With regards to display design, most of them use numerical (50%) or analogue displays (40%). The only ‘pure’ ambient display that presents colour-coded information through light is the Canary Instruments’ EFD.

2) EFD – Sensor communication

Almost all the devices use Radio Frequency to communicate with the electric meter’s sensor (95%), with
the only exception of Canary Instruments’ EFD, which uses Wi-Fi.

3) **EFD – Access to data**
   The most common way to access further consumption data is through the EFD’s USB port (40%) by connecting it to a computer and using a desktop software to retrieve the data. On the other hand, 35% of the EFDs do not have any mean of access to further consumption data.

4) **EFD – Historical and Forecasting Energy Consumption**
   Most of the EFDs (85%) present historical consumption data, while only 40% of them have energy forecasting features.

5) **EFD – Power supply**
   We found that 45% of the reviewed EFDs are plugged in, i.e., powered using an electrical socket, while 40% run on batteries. The remaining 15% have both power supply options available.

   The 20 EFDs only work with their respective company-specific electric meter’s sensors, i.e., they are not compatible with third-party sensors. Most of the reviewed sensors, from the 12 companies, use current transformer clamps (75%) to read the household’s power consumption. In terms of power supply, most of the sensors use batteries (66%). Finally, we found that 58% of the sensors update the household’s power data reading in intervals smaller than 11 seconds, while the remaining 42% update it in intervals between 12 and 35 seconds.

   As to the gateway – a hardware device responsible for sending consumption data to the cloud – half of the companies do not have this additional equipment. However, we start to verify an increase towards the availability of gateways, as 40% of the companies provide it as an optional equipment and other 10% provide it as a required equipment, i.e., included in the system’s kit.

**C. Customer Segments**

   We hypothesized three customer segments: Small and Medium Businesses, Hospitality Landlords and Residential Consumers.

   As to Small and Medium Businesses we approached bars, pastries and restaurants. However, the businesses owners were not able to follow an EFD’s instructions as “the customer (of the bar or restaurant) dictates the use of the appliances”.

   The Hospitality Landlords – renting their houses for short-term lodging in platforms such as Airbnb – have not shown much interest for the use of an EFD in their rented houses. However, some of them presented interest in acquiring the system for their own home, where they can have control over energy consumption.

   The Residential Consumers considered the EFD as a useful solution for their houses. We interviewed 10 consumers, from which 80% felt no control over their energy expenditures – showing interest in the acquisition of a system that would help them to save energy. Furthermore, they claimed that the system must be “easy to install” – as most of the respondents have “fear” of touching their electric panel. Moreover, the EFD must be “easy to understand” and avoid the use of “technical details” (i.e., units of consumption, such as Watts or Watts-hour). Finally, as to the consumption feedback presentation, most of them preferred an always-on hardware solution (70%) instead of a software-only one (30%).

**D. Conclusions and proposed features**

   According to the previously collected data, we found that most commercially available EFDs are commonly featured by: an LCD presenting consumption information through numbers or scales and using Radio Frequency (i.e., not Wi-Fi) to communicate with a company-specific sensor.

   We proposed the following differentiating features for our EFD: a device that uses light to show the real-time consumption behaviour through colour-coded information, using Wi-Fi to connect to a cloud server, which in turn communicates with a third-party electric meter’s sensor. We used the sensor from EnergyOfThings, which allows remote access to the current consumption data through Wi-Fi.

   Furthermore, we also developed a web-based software solution to provide access to further consumption data (used also as the control panel of our EFD).

   Considering the findings, we proposed the development of a cloud-based Energy Monitoring and Feedback System for Residential Consumers. In the following section, we will further explore the features of our EFD.

**III. PROPOSED ENERGY FEEDBACK DEVICE**

   As previously presented, we proposed a Wi-Fi Energy Feedback Device for residential consumers, resorting to an ambient display design and presenting compatibility with third-party Wi-Fi electric meter’s sensors.

   This decision was based on the literature review (lack of studies towards the development and test of EFDs using ambient display design), on the market analysis (lack of commercial products using Wi-Fi, ambient display design and compatible with third-party sensors) and on the potential customers’ opinions (preference for a hardware-based feedback solution presenting intuitive consumption information).

   We started by considering two important electricity measurements to be displayed: the household’s power and energy consumption.

   Many manufacturers present the household’s power and energy values on their EFDs (in watts and kilowatt-hours), requiring the user’s effort to understand the significance of the information.

   Therefore, we proposed the reformulation of the power and energy measurements’ presentation by using scale-based information – in levels and percentages – instead of using numbers. This way, we can show the household’s current consumption behaviour rather than only presenting values.

   The two proposed consumption information are the Instant Consumption Level (power-related) and the Daily Consumption Percentage (energy-related) – which use colour-coded information presented through light, and consequently follow
The device aimed to be intuitive, informative and aesthetically pleasing. Due to the need of a differentiating design for our EFD, we resorted to Prof. Paulo Parra and his team (Faculdade de Belas-Artes da Universidade de Lisboa).

Fig. 2 presents the EFD’s casing, comprised of two parts – the Tower and the Base – whereby the Instant Consumption Level and the Daily Consumption Percentage are displayed.

A. Instant Consumption Level

The household’s real-time power consumption presented in levels. For the sake of innovation, we experimented the use of 6 levels: very low, low, medium, medium-high, high and very high – to provide further consumption information granularity when compared to the use of only three levels (i.e., low, medium and high). We assigned a colour to each level based on the traffic lights scheme – low levels in green, medium levels in orange and high levels in red. To distinguish between levels using the same colour we resorted to luminous actions – e.g., the medium level is an orange light (no action) while the medium-high level is an orange light fading in and out (action). This luminous action logic was used for the other levels.

Each level is contained within an interval of two power values. As there are six levels, we have seven power limits for this scale: 0, P1, P2, P3, P4, P5, ∞ - i.e., very low level is between 0 and P1, low level is between P1 and P2, and so on. These values are calculated each day by the process named Extractor (presented in section V) – resorting to the user’s power data from the last 7 days.

The householders’ objective is to maintain a low consumption level to the best of their abilities.

B. Daily Consumption Percentage

The household’s energy consumption up to the moment, presented as a percentage of the predicted consumption for the day. Each day at midnight, our proposed forecasting algorithm predicts the energy consumption for the day, through the user-specific process called Forecaster (presented in section V).

We used a luminous circumference (in the EFD’s Base) to show the percentage of consumed energy (in orange) and remaining energy (in green), using the predicted energy consumption for the day as the reference. When this reference is updated, at midnight, the luminous circumference is fully green.

The householders’ objective is to avoid the luminous circumference to become fully orange, i.e., consume less than the predicted energy for the day.

C. Printed Circuit Board and Light Actuation Variables

We developed a Printed Circuit Board (PCB) to connect the device to the cloud and to provide the luminous feedback.

The main component of the PCB is the ESP-12F, a microcontroller and Wi-Fi module, responsible for retrieving the current light actuation variables from the cloud and actuating the two light circuits (Base and Tower), which in turn show the two proposed colour-coded consumption information.

The Base’s light circuit has 22 WS2812B LEDs, to present the Daily Consumption Percentage, and the Tower’s light circuit has 6 WS2812B LEDs, to present the Instant Consumption Level.

Moreover, the PCB has two components accessible to the user: a micro USB input, to supply power to the device through an USB transformer, and a button, to activate the Wi-Fi configuration mode.

Fig. 3 presents the PCB, the population of LEDs associated to the Base (Daily Consumption Percentage) and to the Tower (Instant Consumption Level), as well as the light actuation variables hierarchy.

We defined the three following light actuation variables:

1) Individual variables: LED-related

These variables define each LED’s current colour (using the RGB colour code) and action (static, fade in/out, or blink).

2) Population variables: Base-related and Tower-related

These variables are divided into two groups: one set of population variables for the Base and another for the Tower. They define how each population of LEDs behave, i.e., if the LEDs are actuated all at the same time or if they are actuated sequentially (whereby the next led only performs its action after the previous LED finishes its). Moreover, these variables define the duration of the LEDs’ action within a population.

3) Aggregated variables

These variables control the population variables. They define the order of actuation for each population of LEDs, i.e., if the Tower is actuated before or after the Base, or if both Tower and Base are actuated simultaneously.
D. Final Prototype

Fig. 4 presents the 3D-printed final prototype as well as the placement of the PCB on it.

Fig. 4. Final 3D-printed prototype of the proposed Energy Feedback Device – assembled (left) and disassembled (right)

Besides the previously overviewed features, the EFD has a NFC Tag so that the user can quickly access to the web-based software solution – the Web Panel (presented in section V) – by approaching a NFC-enabled smartphone or tablet to the EFD.

Next, we will present the process for the forecasting algorithm development, used to predict the following day’s energy consumption (in which turn is the reference for the Daily Consumption Percentage).

IV. PROPOSED HOUSEHOLD ENERGY FORECASTING ALGORITHM

Upon the development of the proposed forecasting algorithm, we started by targeting two forecasting methods: Linear Prediction and Decision Trees. We experimented different conditions for the tests (e.g., training period, input variables, etc.) to find the method and parameters that would lead to the best result for our data. The prediction performance of each test was evaluated by the mean absolute error (MAE).

Due to the large number of possible combinations for the parameters in test, we resorted to the greedy algorithm – using the locally optimum solutions to find an approximated global optimal solution. The database contained a year of consumption and temperature data from a family of four people; being divided into a training, validation and test set. The final algorithm and the majority of the tests resorted to Python 2.7 and scikit-learn (open-source machine learning library). However, we used MATLAB R2015a for the first tests, namely, for the Linear Prediction ones.

A. Linear Prediction Forecasting Algorithm

Linear prediction estimates future values using a linear function of previous samples, commonly represented as:

\[ x(n) = \sum_{k=1}^{N} a_k x(n-k) \]  

(1)

In (1), \( x(n) \) is the predicted value, \( x(n-k) \) the previous observed values, \( N \) the number of previous samples and \( a_k \) the predictor coefficients.

We modified (1) to create (2) and (3) – associated to the two linear prediction hypotheses in test. We used \( x = W \) to denote energy consumption in kilowatt-hours (kWh).

\[ W_i(n) = \sum_{k=1}^{N} \frac{1}{N} W(n-k : K') \]  

(2)

\[ W(n) = \sum_{k=1}^{N} a_k W(n-k : K') \]  

(3)

When compared to (1), both (2) and (3) have an additional variable, \( K' \), related to the interval between the previous \( N \) days used as samples. Thus, we aimed to check if the usage of non-consecutive previous days’ energy data (\( K' \neq 1 \)) would lead to better results.

In (2) we replaced the predictor coefficient by \( 1/N \) (i.e., a simple average), and in (3) we computed the predictor coefficients using MATLAB (i.e., a weighted average).

Our objective was to find the equation – (2) or (3) – that would lead to the best results, by comparing their mean absolute error under the same conditions (i.e., using the same \( K' \) and \( N \) values). After that, we intended to find the combination of \( K' \) and \( N \) values that would lead to the smallest MAE.

We found that \( K' = 1 \), i.e., using previous consecutive days, led to smaller MAE results for both (2) and (3), when compared to the use of non-consecutive previous days (\( K' \neq 1 \)).

Using \( K' = 1 \) and varying the \( N \) from 1 to 20, we found that (2) led to MAE results inferior to 3 kWh, which was not achieved by (3). Therefore, we chose (2) as the best hypothesis for Linear Prediction.

Finally, for (2) and \( K' = 1 \), the smallest MAE result was found when using \( N = 7 \). Therefore, in our data, the best result was found when using a simple average of the last 7 days’ energy consumption to predict the following day’s energy consumption, given by:

\[ W(n) = \sum_{k=7}^{N} \frac{1}{7} W(n-k) \]  

(4)

The MAE results of (4) for the training, validation and test set were: 2.80 kWh, 2.59 kWh and 2.67 kWh, respectively. These values were used as a baseline, i.e., as a comparison term, for the MAE results of the Decision Trees’ tests.

B. Decision Trees’ Forecasting Algorithm

Decision Trees, unlike Linear Prediction, allow the use of input variables with a different type from the one to be predicted. Therefore, besides energy, we used power-related and temperature-related variables (see Table I). The Decision Trees’ method uses a dataset with the input variables and their associated target values (in our case, energy consumption) to train a model, creating a tree-like graph. Decision Trees is an umbrella term for several methods using this logic. Thus, we approached three methods to be tested: Regression Tree, Random Forests and Extremely Randomized Trees.
To select the best method and its associated parameters, we followed these steps:

1) **Number of days used as the training period:** We performed two experiments using different sets of 3 input variables—creating two 3-variable’s Regression Trees to be tested under the same conditions. We tested 6 different training periods in multiples of 7, i.e., in weeks (7, 14, 28, 35, 42 and 49 days). The smallest MAE results for both Regression Trees was found for the use of 28 days as the training period (i.e., 4 weeks) with a MAE of 2.91 kWh and 2.92 kWh. The second-best result was found for the use of 14 previous days, with a MAE of 2.95 kWh and 2.96 kWh. This preliminary test was only used to have a reference for the number of previous days, as the rest of the parameters will be tuned according to it.

2) **Forecasting Method:** We performed two experiments also using two different sets of 3 input variables. Furthermore, we used a total of 80 different combinations for the pre-pruning parameters, testing them for the 3 Decision Trees’ methods. We concluded that Extremely Randomized Trees consistently achieved smaller MAE results when compared to Regression Tree and Random Forests under the same conditions (i.e., when using the same set of input variables and pre-pruning parameters). Furthermore, when compared to the Linear Prediction’s baseline (2.80 kWh), Extremely Randomized Trees was the only Decision Trees’ method that achieved better results (the smallest MAE found was 2.71 kWh).

3) **Pre-pruning parameters:** To avoid both overfitting and underfitting, the best case was found when using pre-pruning parameters that would limit (upon the predictor’s method training) a maximum of 4 leaf nodes combined with a minimum of 5 required samples to define a leaf node for each Extremely Randomized Tree. Furthermore, the mean absolute error was used as the criterion to evaluate the quality of the splits. Using these parameters, we reached to the smallest MAE results – 2.49 kWh for the Training Set and 2.55 kWh for the Validation Set. Moreover, these values are smaller than the ones from our baseline (Linear Prediction MAE results – Training Set: 2.80 kWh; Validation Set: 2.59 kWh).

4) **Number and type of input variables:** To select them, we used a combination of greedy algorithm and MAE results analysis. Over the several tests, the smaller MAE results were found, consistently, for the usage of 10 to 13 input variables. Moreover, the use of 11 input variables was either the best or second-best case. When compared to the Linear Prediction’s baseline, Extremely Randomized Trees always performed better for 11 variables, independently from the type of input variables used. In one of the tests for 11 variables, the Extremely Randomized Trees MAE results for the training, validation and test set were: 2.53, 2.52 and 2.59 kWh. These results are smaller than the Linear Prediction’s baseline for these three sets (2.80, 2.59 and 2.67 kWh). The final test was performed by merging the yearly data of two different households (a family of four and a family of two) and using both Training and Validation Set of this mixed database, reaching to the following 11 input variables as the best case: \( P_{\text{med}} \), \( P_{\text{med}}(n - 1) \), \( W_{14}(n) \), \( \text{Day}(n) \), \( \text{CDD}(n - 1) \), \( T_{\text{med}}(n - 1) \), \( W(n - 1) \), \( P_{\text{med}}(n) \), \( W_{28}(n) \), \( T_{\text{min}}(n) \) and \( W_2(n) \).

Table I presents the 24 input variables available for each day as well as their meaning. We found that the use of the 11 previously presented input variables led to the best results for our data.

![Table 1](image-url)  
**Table I**  
**24 INPUT VARIABLES AVAILABLE**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{Day}(n) )</td>
<td>Monday to Sunday represented from 1 to 7</td>
<td>( P_{\text{med}}(n) )</td>
<td>Last 7 days’ maximum power average</td>
</tr>
<tr>
<td>( W(n - 1) )</td>
<td>Yesterday’s energy consumption</td>
<td>( P_{\text{med}}(n - 1) )</td>
<td>Time when ( P_{\text{med}}(n - 1) ) was registered</td>
</tr>
<tr>
<td>( W_2(n) )</td>
<td>Last 7 days’ energy consumption average</td>
<td>( T_{\text{med}}(n) )</td>
<td>Yesterday’s minimum temperature</td>
</tr>
<tr>
<td>( W_{14}(n) )</td>
<td>Last 14 days’ energy consumption average</td>
<td>( T_{\text{med}}(n + 1) )</td>
<td>Last 7 days’ minimum temperature average</td>
</tr>
<tr>
<td>( W_{28}(n) )</td>
<td>Last 28 days’ energy consumption average</td>
<td>( T_{\text{med}}(n - 1) )</td>
<td>Last 7 days’ maximum temperature average</td>
</tr>
<tr>
<td>( W_{14}(n - 1) )</td>
<td>Yesterday’s minimum power value</td>
<td>( T_{\text{min}}(n) )</td>
<td>Yesterday’s maximum temperature</td>
</tr>
<tr>
<td>( W_{28}(n - 1) )</td>
<td>Last 7 days’ minimum power average</td>
<td>( T_{\text{min}}(n - 1) )</td>
<td>Last 7 days’ minimum temperature average</td>
</tr>
<tr>
<td>( P_{\text{med}}(n - 1) )</td>
<td>Time when ( P_{\text{med}}(n - 1) ) was registered</td>
<td>( \text{CDD}(n - 1) )</td>
<td>Last 7 days’ Heating Degree Days</td>
</tr>
<tr>
<td>( P_{\text{med}}(n - 1) )</td>
<td>Yesterday’s mean power</td>
<td>( \text{CDD}(n) )</td>
<td>Last 7 days’ Heating Degree Days average</td>
</tr>
<tr>
<td>( P_{\text{med}}(n - 1) )</td>
<td>Last 7 days’ mean power average</td>
<td>( \text{CDD}(n - 1) )</td>
<td>Last 7 days’ Cooling Degree Days</td>
</tr>
<tr>
<td>( P_{\text{med}}(n) )</td>
<td>Yesterday’s maximum power</td>
<td>( \text{CDD}(n) )</td>
<td>Last 7 days’ Cooling Degree Days average</td>
</tr>
</tbody>
</table>

C. **Final Algorithm**

We developed the final algorithm resorting to *Python 2.7* and *scikit-learn* (open-source machine learning library) – applied to the process called *Forecaster* (presented in section V). We used 28 days as the training period of 10 *Extremely Randomized Trees*. As to the method’s pre-pruning parameters, we defined a maximum of 4 leaf nodes per tree, and a minimum of 5 samples to define a leaf node. Along with it, we used the mean absolute error as the criterion to evaluate the quality of the node splits. Finally, we selected the following 11 input variables, as they led to the best prediction results: \( P_{\text{med}}(n) \), \( P_{\text{med}}(n - 1) \), \( W_{14}(n) \), \( \text{Day}(n) \), \( \text{CDD}(n - 1) \), \( T_{\text{med}}(n - 1) \), \( W(n - 1) \), \( P_{\text{med}}(n) \), \( W_{28}(n) \), \( T_{\text{min}}(n) \) and \( W_2(n) \) (see Table I).

V. **PROPOSED SYSTEM ARCHITECTURE (EMFS)**

We also proposed a cloud-based Energy Monitoring and Feedback System for residential consumers.

In terms of hardware, the system is comprised by the Wi-Fi electric meter’s sensor (as the monitoring part) and by our Energy Feedback Device (as the feedback part).

In terms of software, we developed a web-based solution – the Web Panel. Furthermore, the core of the system is the cloud server (*CentOS 6*), responsible for integrating both system’s hardware and software components, running user-specific processes (in *Python 2.7*) and saving users’ data.
Fig. 5 presents the diagram of the system architecture, its components and their interaction. The cyan box represents the cloud server, in which the grey boxes depict user-specific processes.

The **Measuring Device** is the Wi-Fi electric meter’s sensor, responsible for reading and sending the household’s current power consumption to the cloud, namely, to the Measuring Device Web Service. The **Weather Service** provides access to the current temperature in the user’s geographical location through the Weather Web Service.

The **Data Collection System** accesses to the Measuring Device and Weather Web Services to retrieve and save the user’s current power consumption and temperature (in the geographical area), at 35-seconds intervals.

Then, the **Energy Feedback App** retrieves the user’s real-time power consumption to compute the current values for both *Daily Consumption Percentage* and *Instant Consumption Level*. These values are then converted to light actuation variables and sent to the **Feedback Device Web Service**, which acts as a communication bridge between the Energy Feedback Device, the Energy Feedback App and the Web Panel.

The **Energy Feedback Device** retrieves the light actuation variables through the Feedback Device Web Service, to perform the luminous feedback associated to the household’s current consumption.

The **Web Panel** is the web-based software solution. Besides providing further consumption information to the user, it is also the control panel of the Energy Feedback Device.

The **Data Manager and Forecasting Systems** run once a day, at midnight, to organize and treat the previous day’s user data and to compute the daily reference values for both the *Instant Consumption Levels* and *Daily Consumption Percentage*.

Fig. 6 depicts the three data systems, their user-specific processes and associated data files.

---

### A. Data Collection System

This system is constituted by the **Scheduler** (a general process), **Temperature Updater** and **Gatherer** (both user-specific processes).

The **Scheduler** is responsible for running the **Temperature Updater** and **Gatherer** associated to each user of the cloud server, at 35-seconds intervals.

The **Temperature Updater** retrieves the temperature in the user’s geographical location from the Weather Web Service.

The **Gatherer** retrieves the user’s real-time power consumption, from the Measuring Device Web Service, and the current temperature, provided by the Temperature Updater. Then, this pair of samples is saved into the user’s *Daily Data File*, a comma-separated values file named after the date of the current day, i.e., *year-month-day.csv*.

### B. Data Manager System

This system is comprised by the **Master Gatherer** and **Filter**. These user-specific processes run once a day, at midnight, to handle the previous day’s data.

The **Master Gatherer** accesses to the previous day’s *Daily Data File* (containing all the power and temperature samples from the previous day), computes its 14 daily variables and saves them into the *Historical Data File*. Table II presents the 14 variables and their meaning.

**Table II**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Date</strong>&lt;sub&gt;(n)&lt;/sub&gt;</td>
<td>Date in <code>day–month–year</code> format</td>
</tr>
<tr>
<td><strong>Day</strong>&lt;sub&gt;(n)&lt;/sub&gt;</td>
<td>Day of the week (Monday to Sunday)</td>
</tr>
<tr>
<td><strong>W</strong>&lt;sub&gt;(n)&lt;/sub&gt;</td>
<td>Energy consumption, in Watts/h</td>
</tr>
<tr>
<td><strong>P&lt;sub&gt;min&lt;/sub&gt;(n)</strong></td>
<td>Minimum power, in Watts</td>
</tr>
<tr>
<td><strong>P&lt;sub&gt;mean&lt;/sub&gt;(n)</strong></td>
<td>Mean power, in Watts</td>
</tr>
<tr>
<td><strong>T&lt;sub&gt;min&lt;/sub&gt;(n)</strong></td>
<td>Minimum temperature, in Celsius</td>
</tr>
<tr>
<td><strong>T&lt;sub&gt;mean&lt;/sub&gt;(n)</strong></td>
<td>Mean temperature, in Celsius</td>
</tr>
<tr>
<td><strong>HDD</strong>&lt;sub&gt;(n)&lt;/sub&gt;</td>
<td>Heating Degree Days</td>
</tr>
<tr>
<td><strong>CDD</strong>&lt;sub&gt;(n)&lt;/sub&gt;</td>
<td>Cooling Degree Days</td>
</tr>
<tr>
<td><strong>Daylog</strong>&lt;sub&gt;(n)&lt;/sub&gt;</td>
<td>Day’s data quality [-1 or ‘0’: partial or total invalid; ‘1’: valid]</td>
</tr>
</tbody>
</table>

For clarification purposes, we will further explore some of the previously presented variables. **Day**(n) ranges from 1 to 7, to represent each day of the week, from Monday to Sunday.

**HDD**(n) reflects the amount of energy needed to heat a building, while **CDD**(n) reflects the amount of energy needed to cool a building. Both are temperature-related variables, relative to a base temperature – the outside temperature which a building needs no heating or cooling, respectively.

**Daylog**(n) classifies the day’s power data monitoring quality, using one of the following metrics: *valid* – when more than 90% of the day was successfully monitored; *partially invalid* – when 50% to 90% of the day was monitored; or *totally invalid* – when less than 50% of the day was monitored.

The **Filter** identifies the invalid monitored days and replaces their electricity variables (i.e., related to energy and power) by the ones on a previous valid day with the same day of the week. The filter’s replacement process was required to have available data for the **Data Forecasting System** when the electric meter’s sensor fails to monitor the user’s power data. The output of this process is saved into the *Treated Historical Data File*. 
C. Data Forecasting System

This system is constituted by the Extractor, Forecaster and Error Calculator. These user-specific processes run once a day, at midnight, to compute the power values’ limits of the 6 Instant Consumption Levels and to predict the day’s energy consumption for the Daily Consumption Percentage.

The Extractor starts by merging the last 7 days’ power consumption data and then, calculates the power values associated to its 60, 70, 80, 90 and 95 percentiles, ending up by saving them into the Power Levels Data File. These are the power limits for the 6 levels of the Instant Consumption Level associated to the current day.

Then, the Extractor accesses to the Treated Historical Data File to compute the 24 input variables (presented in Table I).

These 24 variables are computed for the previous 28 days as well as for the current day (to be predicted). The Training Set Data File contains a total of 27 variables for the previous 28 days. Besides the 24 input variables presented in Table I, it contains the target variable $W(n)$ – energy consumption of day $n$, in Watt-hours; Daylog($n$) – to identify if the day’s data is either valid or replaced by the Filter; and Date($n$) – the date of the day as an additional information.

The Predictors Set Data File contains a total of 25 variables related to the current day. It has the 24 input variables presented in Table I and the Date($n$) of the current day.

The Forecaster predicts the current day’s energy consumption, using the 11 input variables selected for the final algorithm (see section IV). The Forecaster accesses to the Training Data Set to retrieve the 11 input variables for each one of the last 28 days, as well as their associated energy consumption, $W(n)$, as the target variable. Then, it trains an Extremely Randomized Trees predictor. Finally, it accesses to the Predictors Set Data File and gets the 11 input variables of the current day, inputting them into the previously trained tree to predict the current day’s energy consumption. The predicted energy consumption is saved into the Forecasting Data File, which contains the historical of energy predictions.

The last process, Error Calculator, retrieves the previous day’s real and predicted energy consumption, and calculates the difference between them. This value is then saved into the Prediction Error Data File, containing the historical of these calculations. The last seven days are shown in the Web Panel, to reflect the user’s behaviour towards energy savings, i.e., if the user complied with the objective of consuming less than the predicted energy – associated to the Daily Consumption Percentage shown by the EFD.

VI. EXPERIMENT AND RESULTS

We resorted to 6 residential electricity consumers as the participants of our experiments. In the first stage of the experiment, we installed the third-party Wi-Fi electric meter’s sensors in the participants’ households, to remotely monitor their energy consumption.

In the second phase of the experiment, we installed our EFD in the households of the treatment group’s participants. Due to the limited number of available EFDs, we randomly assigned 5 participants to the treatment group while the remaining participant was assigned to the control group.

We defined two variables: the dependent variable, associated to the household’s energy consumption; and the independent variable, associated to the installation of the EFD. The hypothesis was to test if the EFD would bring energy savings.

We conducted a quantitative analysis using a methodology similar to [14], by dividing the treatment group’s daily energy consumption data into two periods of 30 days: one before the installation of the EFD and another after. We also defined two periods for the control group (without the EFD) using the same time frame as the treatment group. We also employed a paired t-test to check the statistical significance of the results.

Furthermore, we conducted a qualitative analysis, through a survey, to collect the treatment group’s opinion – in order to assess if the device was informative, intuitive and aesthetically pleasing, as well as to evaluate its impact on modifying the consumption behaviour.

Using both quantitative and qualitative analysis, we aimed to collect the needed data to answer our research question: *Can an Energy Feedback Device bring energy savings and be simultaneously pleasant and informative to the consumer?*

A. Participants households’ characterization

From now on, we will refer to the participants by their Household ID – whereby Households 1 to 5 belong to the treatment group and Household 6 belongs to the control group.

As regards to the participants’ household characterization, we found that the number of occupants varied between 2 and 4, and the number of rooms ranged from 3 to 6. All the participants lived in apartments, except for one (Household 4). Moreover, almost all the participants lived with their families, having a contracted power of 6.9 kVA and a bi-hourly tariff, except for Household 3 (a non-familiar household with a contracted power of 3.45 kVA and a simple tariff).

With regards to appliances, all the participants owned a microwaves, washer and fridge-freezer. Three of them had a water heater – two from the treatment group (Household 1 and 5) and the one from the control group (Household 6) – being this appliance responsible for the higher energy consumption of these households.

B. Quantitative Results and Analysis

We started by dividing each participant’s daily energy consumption data into two periods of 30 days: one before the installation of the EFD and another after. We also assigned a 30-day “before” and “after” period to the control group’s participant (without the EFD) on a similar time frame as the treatment group.

Then, we computed the average energy consumption of each participant for the before ($\bar{W}_{before}$) and after ($\bar{W}_{after}$) period. Afterwards, we computed the percentage change between these two averages, through the following equation:

$$\Delta \bar{W}_{%}(i) = \frac{\bar{W}_{after}(i) - \bar{W}_{before}(i)}{\bar{W}_{before}(i)} * 100$$  (5)
In (5), the index $i$ is the Household’s ID (from 1 to 6). This equation aims to check if there is a reduction or increase of the average energy consumption between the two 30-day periods.

Finally, we resorted to a paired t-test to check if there is a significant difference between the before and after period’s consumption, by defining two hypotheses and a condition to reject the null hypothesis:

1) Null Hypothesis: the before and after period’s energy average are similar. Thus, there is no effect on the energy consumption values, even if the EFD has been installed.

2) Alternative Hypothesis: there is a significant difference in the energy consumption average between the after and before period. Therefore, the energy consumption using the EFD is significantly lower than without it.

3) Rule for rejecting the null hypothesis: If the p-value is smaller than 0.05, i.e., 95% of confidence level, then the difference is significant (otherwise accept the null hypothesis).

Table III presents each participant’s before and after periods energy consumption average, the percentage change using (5), and the p-value from the paired t-test.

### Table III

<table>
<thead>
<tr>
<th>Household</th>
<th>$\bar{W}_{\text{before}}$(*)</th>
<th>$\bar{W}_{\text{after}}$(*)</th>
<th>$\Delta\bar{W}_i$</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(T)</td>
<td>19.75</td>
<td>16.60</td>
<td>-16%</td>
<td>0.0093</td>
</tr>
<tr>
<td>2(T)</td>
<td>10.39</td>
<td>8.79</td>
<td>-15%</td>
<td>0.0258</td>
</tr>
<tr>
<td>3(T)</td>
<td>4.12</td>
<td>2.96</td>
<td>-28%</td>
<td>2.56 x 10^-6</td>
</tr>
<tr>
<td>4(T)</td>
<td>8.82</td>
<td>6.43</td>
<td>-27%</td>
<td>5.027 x 10^-5</td>
</tr>
<tr>
<td>5(T)</td>
<td>12.75</td>
<td>8.15</td>
<td>-36%</td>
<td>1.34 x 10^-6</td>
</tr>
<tr>
<td>6(C)</td>
<td>11.46</td>
<td>11.68</td>
<td>+2%</td>
<td>0.277</td>
</tr>
</tbody>
</table>

(*) Results in kilowatt-hours

(T) – treatment group; (C) – control group

The results show that the treatment group’s participants (Household 1 to 5) **reduced their energy consumption from 15% to 36%**, when comparing the average consumption between the 30 days before and after the EFD installation.

On the other hand, the control group’s participant (without the EFD) increased his average energy consumption by 2%.

It should be noted that Household 5 understood (through the EFD) that his water heater was consuming more energy than needed. Therefore, he reprogrammed it to be more efficient, and along with it all the occupants followed the feedback provided by the EFD – reaching to 36% of energy savings.

With regards to the paired t-test, we confirmed the device’s impact over energy savings as there is a significant difference (i.e., statistical significance) for the treatment group’s energy average between the after and before period – the best p-value found was $1.34 \times 10^{-6}$ and the worst was 0.0258 (below 0.05).

With regards to the control group, without the EFD, we found no statistical significance in the average consumption between the before and after period.

### C. Qualitative Results and Analysis

We surveyed the treatment group’s participants, mainly, using a 5-point Likert scale (very poor, poor, fair, good and very good) as well as open questions.

All the participants gave the best rating to the device’s ability on informing about the real-time and daily consumption. Most of them (80%) also gave the best rating to the ease of understanding the consumption information. Moreover, most of the respondents (60%) gave the best rating to the EFD’s impact on modifying their consumption behaviour, while the rest classified it as ‘good’. As to the overall aesthetically pleasing aspect of the device (i.e., 3D-printed prototype) only one participant classified it as ‘fair’, while the remaining classified it as ‘good’ (40%) or ‘very good’ (40%). All participants placed the device in their living room, claiming that all the other occupants understood and interacted with it.

From a customer’s perspective, 60% of the participants preferred to rent the system by paying an annual fee (between 50-80€) while the rest preferred to buy it (between 125-200€).

All the participants accessed to the Web Panel, but only 40% used the NFC Tag to quickly access to the Web Panel, by approaching a smartphone or tablet with the NFC technology (60% did not use the NFC Tag, as their smartphones do not support this technology – more specifically, the iPhone cannot use this technology the same way as Android smartphones do).

### VII. Conclusion and Future Work

This work presented a process that can be generalized for the development and test of other cloud-based technological products, when focusing in the discovery of innovative features. In our case, we targeted EFDs (and consequently EMFS). We started by reviewing the existing literature to understand their potential over energy savings as well as their current problems. Then, we performed a market analysis to check some of the literature review’s findings as well as to find innovative features for our EFD. We also hypothesized customer segments and interviewed potential clients, to identify the most suitable and to collect their opinions for such devices.

We found that most of the commercially available EFDs have the following features: an LCD presenting consumption information through numbers or scales and resorting to Radio Frequency to communicate with a company-specific sensor.

Considering these features, we defined the following differentiating ones for our EFD: a device that emits light to show the current consumption behaviour through colour-coded information, resorting to Wi-Fi to connect to our cloud server, which in turn communicates with a third-party Wi-Fi electric meter’s sensor.

The proposed EFD aimed to be informative, intuitive and aesthetically pleasing. Therefore, to design an always-on device constantly interacting with the consumer, we resorted to two knowledge areas – design and engineering – to enhance the quality of the human-machine interaction and user-friendliness.

As a cloud-based solution, we also developed a framework for the system architecture of the Energy Monitoring and Feedback System (EMFS), comprised by our cloud server and
by the system’s hardware and software components.

After developing both EFD and EMFS, we needed to test the effectiveness of our solution. To do so, we resorted to 6 residential consumers as the participants of our experiments, acquired through a previously held campaign.

In the first phase of the experiment, we installed a third-party Wi-Fi electric meter’s sensor in the participants’ households, to remotely monitor their energy consumption (for a few months, before the second phase).

In the second phase of the experiment, we installed our EFD in the participant’s households, which brought higher energy savings (ranging from 15% to 36%) when compared to the ones found in the literature (ranging from 5%-15% [9]).

Moreover, according to the surveyed participants, our EFD prototype fulfilled the proposed objectives, as by their opinion our proposed EFD was considered intuitive, easy to understand and aesthetically pleasing. Furthermore, most of the participants claimed that our EFD modified the occupants’ consumption behaviour, as all occupants understood and interacted with the device.

Finally, as regards to our research question: Can an Energy Feedback Device bring energy savings and be simultaneously pleasant and informative to the consumer? – we can answer affirmatively, based on both quantitative and qualitative results.

This work can be complemented with further development and experimentation. The proposed EFD encompasses several areas. Therefore, we will present the following topics as the most important ones to be approached in a future work.

Firstly, use a larger and equal number of subjects for both treatment and control groups (i.e., increase the scope of the experiment). Furthermore, another quantitative analysis could be conducted using a larger period of consumption data.

Secondly, further work can be done on the proposed forecasting algorithm to increase its accuracy towards energy consumption prediction, which in turn is used as a reference for the Daily Consumption Percentage, i.e., the consumed and remaining energy percentage based on the predicted consumption for the day. Also, other methods can be tested for the definition of the power intervals for the six levels of the Instant Consumption Level, i.e., the household’s current power consumption represented in levels.

Thirdly, as to the presentation of these two consumption-related information, we suggest the test of alternative approaches, such as using other predefined light actions and colours (besides the traffic lights scheme), including a “sleep” function (i.e., turning of the device’s lights when the consumption is too low, or when no one is home) and adjusting the light intensity (day vs. night).

Fourthly, as to the Energy Feedback Device, we may consider the use of other materials to improve its aesthetically pleasing aspect, such as epoxy (instead of 3D-printed material). As to the Feedback Device’s Tower, other shapes could also be tested.

Fifthly, the Web Panel may be improved. We suggest the presentation of the historical consumption using larger periods (instead of presenting only the last week), provide predefined themes for the customization of the light’s colours and actions used for luminous feedback, and allow the adjustability of the device’s light intensity.

Lastly, other methods could be tested to replace the invalid monitored days, due to the sensor’s failures. Moreover, other customer segments could be approached, mainly in the Small and Medium Businesses (e.g., co-working and open space offices).

Despite the need of further work, the proposed EFD showed satisfactory results towards energy savings for residential consumers.

REFERENCES


