Abstract

Energy consumption in the world has increased significantly in the last decades, becoming an important issue nowadays. The eco-aware everyday things were devised to prevent the waste of energy resources in common areas where people often elude their responsibility about the energy consumption when using appliances of collective use, like printers, coffee makers, beamers and so on. These eco-appliances are able to improve their energy efficiency dynamically adapting their operation according to their usage patterns. This work proposes a further step, also aligned with devices’ automation, where everyday consumer devices are transformed into collaborative eco-aware everyday things. Taking advantage of the evolution of the Internet towards the Internet of Things and the Web as a universal communication mechanism both among humans-to-things and things-to-things, it is proposed to use Twitter as a communication channel for eco-aware appliances to share their usage patterns. Thus, other newly deployed similar devices in comparable environments can alleviate the cold-start problem, which is common in scenarios where usage learning is needed. To assess the effectiveness of this approach, a collaboration between three of these eco-aware devices has been simulated, giving place, encouragingly, to a higher energy reduction efficiency when compared with non-collaborative objects.

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Keywords: Collaborative Eco-aware Everyday Things, Eco-aware Everyday Things, Social Devices, Energy-efficiency, Coffee Machines, Predictive Models

1. Introduction

Over the past few years we are witnessing an exponential growth of information technologies in the form of consumer devices. Most of them are smart everyday objects. These, together with the new capabilities to link Internet with everyday devices and the new forms of identification and communication among people, are defining the so-called Cyber-Physical Systems. Such a substantial increase of electrical devices must be absolutely followed by government guidelines and policies to restrain the ecological footprint that these appliances will cause in their overall life-cycle (from design to disposal). Our society should also take a pivotal action-role in such a major concern. Thus, we have to become more aware of energy waste in all its forms and everywhere.

Common area settings, such as workplaces, have remained rather unexplored despite its great potential for energy savings. The workplace is a very relevant case of study inasmuch as our society spends at work more than half of the day, and this sector is now responsible for roughly the 10% of the overall energy demand in the world [1]. A good example is the United States where commercial buildings account for 36% of all U.S. electricity consumption [2]. Focusing in the office environment, the energy consumed by work-appliances of common use (coffee-makers, printers,
screens, kettles and so on) represents more than 15% of the total, and it is expected to rise above 20% in 2020 [3]. In this article we devise means to face up to such energy consumptions.

In a previous research [4] we proposed to reduce the energy consumption of devices of shared use within common areas through the eco-aware everyday things concept. These eco-appliances were able to improve their energy efficiency adapting their operation according to their usage pattern. To perform accurate usage predictions, these devices required a learning period (30 days in [4]). In that work, it was demonstrated that the energy saving potential of learning the usage pattern and making usage predictions upon them was about 15%. In the reported experiment [4], the first week energy consumption was 928 Wh. After the learning phase, the coffee-maker saved 15% per week, that were around 140 Wh per week. This amount of energy, according to carbon.to\(^1\), is equivalent to completing the charge process of 140 mobile phones. This means that any reduction of the aforementioned period, will lead to a reduction of energy consumption.

This paper presents a new iteration in our quest for eco-aware everyday things. Now, eco-aware everyday things collaborate with similar eco-aware devices by sharing their usage patterns through Twitter. This similarity among appliances is reflected in the profile of each eco-aware everyday thing, which encompass information, such as the device type, its location, the users that share it, the activity developed in its deployment setting, the schedule, etc. Eco-aware devices' usage patterns are collected and shared through the social network, so that other similar newly deployed eco-aware devices can acquire them alleviating their cold-start problem. That means to reduce the learning time (30 days in previous work [4]), as much as possible and therefore, to start saving energy earlier.

To test the effectiveness of our approach, we performed a one month trial with three augmented capsule based coffee machines. Two of them, placed in two research laboratories, were collecting usage-data during two weeks. After that, a new coffee-maker was installed in the remaining laboratory. The three devices continued collecting usage-data along the next week (the third week). At this point, the new device could acquire two different behaviours: continue operating alone or accept collaboration. To observe the difference in energy terms between the two approaches during the fourth week of the process, we proceeded to perform two consumption simulations with the collected data, obtaining promising results.

The remaining of the article is organized as follows. In Section 2, different strategies to save energy, middleware solutions for Internet of Things, the relation of social networks with Internet of Things and the methods to identify profiles’ similarity are reviewed. Section 3 describes the eco-aware everyday things challenges. Section 4 illustrates, by mean of a scenario, how collaborative eco-aware devices interact with each other, unlike the ordinary ones, that they operate alone. In Section 5 the trial performed to compare the energy consumption of eco-aware everyday things, both by means of collaborative and individual operation, is explained. In Section 6, the results are shown and analysed. Finally, Section 7 summarises these paper’s contributions and open future perspectives.

2. Background

2.1. Eco-devices

Regarding the commercial deployment of eco-awareness systems, there are several physical gadgets in the market designed to visualize the energy consumption in real-time. For example, Wattio Solar\(^2\), the Energy Orb\(^3\) or Wattio\(^4\). Other commercial eco-awareness system is Nest\(^5\), an intelligent thermostat which learns what temperatures user likes and builds a personalized schedule in his/her home. Aligned with this solution, but not commercialised, there is TherML [5]. This is an occupancy prediction algorithm that uses GPS data from a user’s smartphone to automatically control the indoor temperature of a home.

\(^1\)\text{http://www.carbon.to/}
\(^2\)\text{http://www.diykoto.com/}
\(^3\)\text{http://www.orbenergy.com}
\(^4\)\text{http://www.wattio.com/}
\(^5\)\text{http://nest.com/thermostat/saving-energy/}
Most of these devices are designed for people’s personal settings. That is, individual or by a very small family group use. The solutions presented represent stand-alone meters, devices or applications. There are solutions which are designed to operate autonomously without any kind of interaction nor cooperation with distant Internet-connected devices. Indeed, most of them are focused on household settings. Furthermore, most of the reviewed solutions are mainly aligned with promoting human behaviour change and people awareness, while our approach is focused on optimising electrical everyday things’ performance towards energy-efficiency. We propose a dynamic and automatic collaboration among similar smart eco-aware things deployed in comparable environments, i.e. similar group size and type of work, which would explain that they can import intelligence from each other.

2.2. IoT middlewares

Recently, some architectures for Internet of Things have been proposed by ITU6, EPCGlobal7, The CASAGRAS initiative8, the uID research group9 or Xively10. Analysing them, we conclude that their emerging priorities are:

- Enable full connectivity of things to the Internet.
- Provide middleware and application functionality and protocols to ease the exploitation of things-related services.

One of the main features of the eco-aware everyday things which we promote is that they should collaborate, not only with others devices, but also with people who use them. Hence, we oriented the solution to the social networks, instead of developing a new architecture to connect things between each other and with people by means of Internet.

Twitter is one of the most influential and less intrusive of the reviewed networks. Indeed, with more than 200 million users and roughly 400 million11 tweets per day, Twitter is the most prominent micro-blogging service available today on the Web. The research community is exploiting Twitter for several purposes, such as trends predictions [6], incidents detection [7] or influential users [8]. Studying its functionalities, we reckon that Twitter platform can successfully adapt to our needs. These are: a) to have an identity with an associated profile; b) to find similar devices; and c) to send private messages to other devices. Other social networks, such as Facebook, could also cover all the requirements, but Twitter is more open than them and fits better with our system priorities.

There are many libraries to communicate with Twitter12. Bearing in mind a Django13 application deployed in a server, we advocate using Tweepy14. It is an open-sourced library which enables Python to communicate with Twitter platform and use its API15.

2.3. Introducing social networks

There is scientific evidence that a large number of individuals connected in a social network can provide far more accurate answers to complex problems than a single individual [9]. The exploitation of this principle has been widely investigated in Internet-related research [10, 11, 12, 13, 14].

A first mention of socialization between objects was introduced by Holmquist et al. [10]. In that paper, the focus was on solutions that enable smart wireless devices, to establish temporary relationships. It was also analysed how the owners of the devices should control all the process. That work is dated 2001 and both the concepts of the Internet of Things and social networks were very incipient.

More recent research introduces a new generation of objects. These influence human beings’ daily activities. They are smart objects with a capacity for interaction with each other, which was previously inconceivable. In [11]

6http://www.itu.int/es/Pages/default.aspx
7http://www.gs1.org/epcglobal
8http://www.iot-casagras.org/
9http://groups.csail.mit.edu/uid/
10https://xively.com/
11http://cnet.co/KHlg8q
12https://dev.twitter.com/docs/twitter-libraries
13https://www.djangoproject.com/
14https://github.com/tweepy/tweepy
15https://dev.twitter.com/docs/api/1.1
the Internet, truly connected things are clearly differentiated from the things participating within the Internet of social networks, which are named with the neologism Blogject, that is, objects that blog. Nazzi et al. [12] introduced the theoretical concept of Embodied Microblogging (EM), which challenges the current vision of IoT. Rather than focusing on thing-to-thing or human-to-thing interactions, it proposes two new roles that the augmented everyday objects will play: (i) mediate the human-to-human communication and (ii) support additional ways for noticing activities in everyday life.

In [15], Vázquez and López-de-Ipiña transformed everyday objects into autonomous artifacts that communicate with other objects, services or people, even forming communities of devices that mimic social behaviour.

Guanard et al. investigated in [13] the exploitation of social networks in the context of Internet of Things. They proposed a solution to allow sharing of things, and for that they built it upon social networks (e.g. Facebook, LinkedIn, Twitter, etc.) and their APIs. Using social networks enabled users to share Internet connected things with people they knew and trusted, without the necessity of creating yet another social network on a new online service.

Also Kranz et al. in [14] showed how to empower physical objects to share pictures, comments and sensor data via social networks. They also discussed about the implications of the “socio-technical networks” in the context of the Internet of Things. The Open.Sen.se platform is close to the idea of a social network of objects, allowing developers to connect sensor data to the Web to build applications. However, this platform does not allow objects to autonomously create social groups since it is mandatory the intervention of human beings.

2.4. Social Internet of Things

The authors of [16], in line with the notion of IoT devices with social connections introduced in [14], proposed an innovative paradigm of interaction among objects. The main idea was the definition of a social network of intelligent objects, named Social Internet of Things (SIoT). They analysed the types of social relationships in which things could be engaged. The first form of socialization among objects that they envisaged was a parental object relationship, defined among similar objects, built in the same period by the same manufacturer. Moreover, objects could establish co-location object relationship and co-work object relationship, like humans do when they share personal (cohabitation) or public (work) experiences. These relations were determined whenever objects, such as sensors, actuators or RFID tags, constantly resided in the same place (for instance, to offer home/industrial automation services) or periodically cooperated to provide a common IoT application, such as emergency response. A further type of relationships was defined for objects owned by the same user (mobile phones, tablets, etc.). They named this owner object relationship. The last relationship defined was established for objects that came into contact for reasons strictly related to relations among their owners (e.g. devices belonging to friends). They named this social object relationships. Similarly to people exchanging their contacts, the device, if properly authorized, autonomously exchanges its social profile. The driving idea is that devices with similar characteristics and profiles can share best practices to solve problems already faced by “friends”. In our approach, we could categorize objects’ relationships as profile-based relationships, because they are defined by objects’ profile.

Perez de Almeida et al. presented in [17] the Thing Broker, a core platform for Web of Things that provides RESTful interfaces to things using a Twitter-based set of abstractions and communication model. In this platform, the main abstractions provided are “things” and “events”. Relationships among things are represented using a model similar to what is observed in Twitter, as a following/followed connection.

Recently, the Social Web of Things (SWoT) appeared at the convergence of the Web of People and the Web of Things. Ciortea et al. [18] proposed to extend and transform social networks by integrating autonomous and proactive things.

As previously mentioned, we have opted for not creating a new platform as well as in [17] and [18], but using a very extended social network, namely Twitter.

2.5. Similarity methods

In the literature, there are numerous methods for calculating similarity, dissimilarity and distance matrix between individuals in a population [19]. However, the more appropriate similarity method could be different in each case, basically considering the variety of data types (binary, qualitative or quantitative). For instance, if all the variables’ type
is binary, there are many similarity coefficient [20], such as Jaccard index, which could give good results depending of the number of variables. While if all the variables’ type is qualitative, an alternative method would be chosen. For instance, Everitt [19] recommends an explicit conversion of the identified variables to binary variables.

Nevertheless, when we have to deal with all the data types (binaries, nominal and ordinal), there are other methods, such as the proposed by Gordon [21], who suggests converting all the variables to the same data type or scale (for instance, to binary data type). At present, Gower’s General Similarity Coefficient [22] is one of the most popular measures of proximity for mixed data types. In [23], Lim et al. argue that Gower’s method for assessing the similarity between each pair of items in a population is one of the analysis’ methods with greater potential because of its properties. In 2014, Fontecha [24] applied similarity algorithms based on Gower’s coefficient to evaluate the similarity between elders. In order to do these calculations, the influential variables for the assessment of the fragility were used. Those were qualitative, quantitative and binary variables. Therefore, we consider that Gower’s coefficient makes it also possible to determine the degree of similarity between two devices represented by binary, qualitative and quantitative data attributes within their profiles.

3. The features of collaborative eco-aware everyday things

The eco-aware everyday things were devised to prevent the waste of energy resources in common areas where people often elude their responsibility about the energy consumption of appliances of collective use, like printers, coffee makers, beamers and so on [25]. Our research adds the collaborative feature to eco-aware everyday things in order to earlier start saving energy. To summarise, the features that this eco-devices should have are explained in the following lines.

3.1. Intelligent Devices

The eco-aware appliances incorporate some intelligence to infer how they should operate. They know when they should shift from ON mode to OFF mode or from ON mode to Standby mode in order to save the most of energy.

The usage predictions are done by applying time series forecasting techniques [26]. The time series assume that past patterns will similarly occur in the future, and therefore are predictable. The patterns correspond with the changes of a variable (coffees prepared in a workplace) in a time period (every time slot a work day is divided into). In [4] we demonstrated that intelligent shifting between appliance’s operating modes reduces more energy consumption than to steadily apply one or another mode as traditional methods propose [27].

3.2. Social networks

These networks are now experimenting a exponential growth. Twitter has officially become the next big thing in terms of Internet social phenomena gaining worldwide popularity, with over 400 million users per day [28]. Hence, reaching thousands of users (humans or things) to share information is now much easier with just one ‘tweet’.

The main contribution of social networks to our proposal is that they enable a social infrastructure for eco-aware everyday things, promoting the collaboration among them. Each device has its profile (see Table 1) mapped to a profile in Twitter (see Code 1) and it will have relationships with other devices, as Twitter followers.

<table>
<thead>
<tr>
<th>Device category</th>
<th>Country</th>
<th>Province</th>
<th>City</th>
<th>Developed activity</th>
<th>Field of the activity</th>
<th>Number of users</th>
<th>Start of the activity</th>
<th>End of the activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coffee-maker</td>
<td>Spain</td>
<td>Bizkaia</td>
<td>Bilbao</td>
<td>Research</td>
<td>Internet</td>
<td>12</td>
<td>8AM</td>
<td>6PM</td>
</tr>
</tbody>
</table>

Table 1: Model of an eco-aware everyday thing’s profile.
3.3. Collaborative things

Eco-aware everyday things collaborate with similar devices by sharing their usage patterns through Twitter direct messages, as is presented in Figure 1. This similarity is reflected in their social network profiles (see Code 1), which encompass information related to eco-aware everyday things and the environment where they are deployed. These usage patterns are used to alleviate the cold-start problem, acquiring other usage patterns as their own. That is, to reduce the learning time (30 days in previous work [4]), as much as possible and therefore, to reduce the energy consumption.

Code 1 An eco-aware everyday thing’s profile mapped to Twitter profile in JSON

```json
{
    "name": "MORElab CoffeeMaker",
    "screen_name": "morelabcoffee",
    "location": "Bilbao, Bizkaia, Spain",
    "description": "{
        "ecoawth": {
            "cat": "coffeeM",
            "sp": {
                "devact": "Research",
                "fdact": "IoT",
                "nusers": 12,
                "actsch": {
                    "start": 8,
                    "end": 18
                }
            }
        }
    }
}
```
4. Scenario

The following scenario clarifies how eco-aware everyday things collaborate in order to reduce the energy consumption. It illustrates the potential benefits, in terms of energy, of the collaborative eco-aware everyday things over the ordinary everyday things and eco-aware everyday things.

Aitor is the head of a research group with 12 researches in Bilbao, Spain. The group’s coffee-maker has broken down. Aitor is aware that its group’s computing researchers need several cups of coffee throughout the day in order to perform better. He goes to a specialized shop in order to purchase a new coffee maker. He notices that there are three categories of capsule-based coffee-makers: the normal ones, those labelled as Eco-aware everyday thing and those labelled as Collaborative eco-aware everyday thing. Table 2 shows the three categories’ coffee-makers feature in terms of money and energy efficiency.

<table>
<thead>
<tr>
<th></th>
<th>Price</th>
<th>Energy efficiency class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal coffee-maker</td>
<td>60 €</td>
<td>C</td>
</tr>
<tr>
<td>Eco-aware coffee-maker</td>
<td>100 €</td>
<td>B</td>
</tr>
<tr>
<td>Collaborative eco-aware coffee-maker</td>
<td>120 €</td>
<td>A</td>
</tr>
</tbody>
</table>

Table 2: Features of everyday things’ categories.

What happens in each situation depending on Aitor’s coffee-machine choice is explained below.
**Decision A. Buying the normal coffee machine:**

After having asked the shopkeeper and being informed that the first type are the cheapest, he buys a normal coffee-maker. Once at the research centre, Aitor connects the new device to the mains, leaving it ready for preparing coffees for the researches.

Two months after the purchase, Aitor observes that the coffee-maker’s total consumption for this period, has been 5.20kWh, which corresponds to a normal operation of the device (Energy consumption measured in a coffee-maker at explained conditions).

**Decision B. Buying the coffee machine labelled as Eco-aware everyday thing:**

After having asked the shopkeeper and being informed that the eco-aware ones are not that expensive after all since they save more energy than the first ones, he buys an eco-aware coffee-maker. Aitor reads the device’s instructions guide and figures out that, apart from the obvious connection to the means, it is necessary to configure Wi-Fi Internet access for the machine. After that, the coffee machine is ready to operate normally.

Internally, the coffee machine starts collecting its own usage data and forwards them to a remote Cloud-based server. This process prolongs for one month. After this period, making use of the collected data, the server generates a coffee-maker’s usage prediction model and sends it to the device. At that moment, the coffee machine is able to operate differently as a function of its usage pattern, i.e. keeping itself in standby mode or switching itself off according to the prediction performed. Since there is a bidirectional communication, the server communicates a new prediction model every week taking into account the actual usage reported data every week. Therefore, the coffee-maker always operates according to the latest updated usage prediction model.

Two months after the device’s acquisition, Aitor notices that the coffee-maker’s total consumption, is 4.81kWh, which corresponds to a 1 month working as a normal device and another operating in eco-aware mode (This data has been calculated using the measured energy consumption and the process showed in [4] at the conditions explained above).

**Decision C. Buying the coffee machine labelled as Collaborative eco-aware everyday thing:**

After having asked the shopkeeper and being informed that the latter device consumes the least, he buys a collaborative eco-aware coffee-maker. Reading the instructions manual at the research centre, Aitor realises that the device needs to be initially configured by a human being. Guided by the manual, he connects it to the mains and to the Internet, and then he proceeds with the registration of the coffee machine in a very common social network, introducing all the required data (see Table 1) in a web site exclusively developed for this purpose. Automatically, a web service registers the coffee-machine into Twitter mapping the introduced profile into Twitter profile model.

One the registration has been completed, the coffee machine automatically starts performing actions, being already ready to operate in an eco-aware intelligent manner only one week later, instead of four weeks afterwards, to operate differently as a function of its usage pattern. The process carried out by the coffee machine and represented in Figure 1 is the following:

1. The new coffee machine looks for other eco-aware coffee-makers (e.g. some of those geographically distributed in the Figure 2) which have a similar profile in Twitter.
2. Once similar coffee-makers are identified, the new coffee machine asks them for their usage patterns.
3. During the first week the coffee machine starts collecting its own usage data and sends it to a server.
4. After a 7 day period, the new coffee machine usage pattern is compared in the server with the patterns acquired in the second step, adopting the most similar as new coffee-maker’s pattern.
5. The server runs the process to predict the coffee-maker’s usage. It is done making use of new coffee machine’s collected usage data and in fourth step chosen usage pattern.
6. Then, the server sends the prediction to the coffee-maker and it starts operating according to the prediction made.

![Map of several collaborative eco-aware everyday things distributed by the geography.](image)

Two months after purchase, Aitor notices that the coffee-maker’s total consumption for these two months, is 4.52kWh, which corresponds to a one week working in normal mode and seven weeks running in eco-aware mode (This data has been calculated using the measured energy consumption and the process showed in [4] at the conditions explained above).

5. Comparative study

In order to observe and evaluate the difference in energy terms between taking the Decision B or Decision C in the previously described scenario in Section 4, we have conducted a comparative study at a workplace with three capsule based coffee-makers. To this end, the three appliances were augmented with pervasive technology to be able to collect and log energy data.

**Participants and field of application** The participants that took part in the study were 20 members of three different laboratories within a large technological institute inside a university. Although the laboratories belong to the same institute, each has its own working-room. From now on, we call these laboratories by their name for the sake of simplicity: S3Lab, ProtoLab and SmartLab. The 20 participants belonging to these laboratories are: 8 people, 4 people and 8 people, respectively. The three laboratories had a lounge-corner at the back of their working-room where the coffee-maker was located. The aim of this research was hidden to those laboratories’ users in order not to influence them when making use of the coffee-maker.
The process shown in Figure 3 was designed to compare whether individual or cooperative learning perform better in terms of energy saving. Two shared electrical appliances (capsule-based coffee machines), placed in two research laboratories (SmartLab and S3Lab), were collecting usage-data during two weeks. After that, a new coffee-maker was installed in ProtoLab laboratory. The three devices continued collecting usage-data along the next week (the third week). At this point, before to start the last week of the process, there were two behaviours to acquire by the new device:

1. to predict the next week usage using its collected usage-data the week before (highlighted in red in Figure 3).
2. to predict the next week usage using a combination of its collected usage-data and the usage-data collected by other coffee-maker placed in a similar environment, located in the same country, the users develop technological research activities, they have similar schedule, etc. (highlighted in green in Figure 3).

Figure 3: Process performed to compare the energy consumed by the ProtoLab coffee-maker using its own usage pattern and using a combination of other’s usage pattern and its own.

To observe the difference in energy terms between the two approaches during the last week of the process, (the fourth week), we proceeded to perform two consumption simulations with the obtained data.

1. According to [4] and using the first week usage-data of the ProtoLab appliance as a training-set, and applying ARIMA, a one week prediction of coffees that would be prepared was made. ARIMA (Auto-Regressive Integrated Moving Average) is a time-series forecasting model. There exist others, such as Winters ARMA or ARIMAX. ARIMA models are, in theory, the most general class of models for forecasting a time series which can be stationarized by transformations such as differencing and logging. These transformations are pivotal since one of the necessary conditions for applying Bob-Jenkins method ARMA [26], the underlying model of ARIMA, is the stationary of the time-series, which in practice, is very rarely met. The obtained prediction
model specified the time slots when was worthwhile to leave the coffee-maker on or switched it off. Having this prediction model, we performed a simulation of ProtoLab coffee-maker energy consumption along its second week of operation, which was the fourth week of the process.

2. For the second simulation, a similar procedure was performed. Nevertheless, the prediction was made using as training-dataset the first week usage-data of the ProtoLab coffee-maker and the first three weeks usage-data of the SmartLab coffee-maker. In order to choose what laboratory’s usage-data fitted better, coffee-makers’ profiles were compared applying Gower’s Similarity Coefficient \( S_{ij} \), which compares two cases \( i \) and \( j \), and is defined as follows:

\[
S_{ij} = \frac{\sum_k w_{ijk} * s_{ijk}}{\sum_k w_{ijk}} \tag{1}
\]

where \( s_{ijk} \) denotes the contribution provided by the \( k \)'th variable, and \( w_{ijk} \) is usually 1 or 0 depending upon whether or not the comparison is valid for the \( k \)'th variable; if differential variable weights are specified it is the weight of the \( k \)'th variable or 0 if the comparison is not valid.

It should be noted that the effect of the denominator \( \sum_k w_{ijk} \) is to divide the sum of the similarity scores by the number of variables; or if variable weights have been specified, by the sum of their weights.

Gower defines the value of \( s_{ijk} \) for ordinal and continuous variables as follows:

\[
s_{ijk} = 1 - \frac{|x_{ik} - x_{jk}|}{R_k} \tag{2}
\]

where: \( R_k \) is the range of values for the \( k \)'th variable.

For continuous variables \( s_{ijk} \) ranges between 1, for identical values \( x_{ik} = x_{ij} \), and 0, for the two extreme values \( x_{max} - x_{min} \).

The value of \( s_{ijk} \) for nominal and binary variables is 1 if \( x_{ik} = x_{ij} \), or 0 if \( x_{ik}, x_{ij} \).

<table>
<thead>
<tr>
<th>Device category</th>
<th>Weight</th>
<th>S3Lab</th>
<th>ProtoLab</th>
<th>SmartLab</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country</td>
<td>1</td>
<td>Coffee-maker</td>
<td>Coffee-maker</td>
<td>Coffee-maker</td>
</tr>
<tr>
<td>Province</td>
<td>0.5</td>
<td>Spain</td>
<td>Spain</td>
<td>Spain</td>
</tr>
<tr>
<td>City</td>
<td>0.1</td>
<td>Bizkaia</td>
<td>Bizkaia</td>
<td>Bizkaia</td>
</tr>
<tr>
<td>Developed activity</td>
<td>0.05</td>
<td>Bilbao</td>
<td>Bilbao</td>
<td>Bilbao</td>
</tr>
<tr>
<td>Field of the activity</td>
<td>0.6</td>
<td>Research</td>
<td>Research</td>
<td>Research</td>
</tr>
<tr>
<td>Number of users</td>
<td>0.7</td>
<td>8</td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td>Start of the activity</td>
<td>0.8</td>
<td>7AM</td>
<td>8AM</td>
<td>8AM</td>
</tr>
<tr>
<td>End of the activity</td>
<td>0.8</td>
<td>5PM</td>
<td>6PM</td>
<td>7PM</td>
</tr>
</tbody>
</table>

Table 3: Profiles of devices used in the study.

To calculate the Gower’s Similarity Coefficient between coffee-makers, we assigned different weights to the profiles’ variables (see Table 3) due to the fact that attributes are not all similarly relevant to compare profiles. Making use of all these variables, both nominal and ordinal ones, we obtained the following results:

\[
S_{S3-Pr} = \frac{1 + 0.5 + 0.1 + 0.05 + 0.6 + 0 + 0.7 * (1 - \frac{8 - 4}{4}) + 0.8 * (1 - \frac{8 - 7}{1}) + 0.8 * (1 - \frac{18 - 17}{2})}{1 + 0.5 + 0.1 + 0.05 + 0.6 + 0.1 + 0.7 + 0.8 + 0.8} = 0.57
\tag{3}

\]
Considering these calculations, SmartLab coffee machine’s profile is more similar to ProtoLab coffee machine than the ones located in S3Lab ($S_{Sm-Pr} = 0.76$ is nearer to 1 than $S_{S3-Pr} = 0.57$). Hence, usage-data of the SmartLab device were used for the simulation. Furthermore, looking at the prepared coffees’ distributions of each of the laboratories (see Figure 4), it can be deduced that the more similar usage-pattern to the Protolab was the SmartLab pattern. In a glimpse, it can be observed that the prepared coffees’ distributions of both laboratories exhibited similar patterns, either in the morning and in the afternoon. In contrast, the S3Lab distribution was very sparse and no pattern was recognized during the first two weeks of device’s usage.

**Figure 4: Coffees distribution along the day in SmartLab, S3Lab and ProtoLab respectively.**

### 6. Analysis of results

Quantitative analysis of the simulation’s data will allowed us to know what decision, B or C in the scenario described in Section 4, were better in energy saving terms. Figure 5 shows the energy consumed by the ProtoLab coffee machine along its second week of operation. The top line refers to the energy consumption computed in the first simulation, this is, the coffee-maker was operating in eco-aware mode grounding its operation in the prediction made utilizing the usage-data collected by itself during the previous week. The total energy consumption amounted to 0.68 kWh.
The bottom line indicates the energy consumed by the same coffee-maker in the second simulation. In this case, the prediction was made using the usage-data collected by itself during the previous week and the usage-data collected until that moment (during the first three weeks of the process) by a coffee-maker placed in a different, but somehow similar, laboratory. The total energy consumption was 0.64 kWh.

It can be observed that in the latter case, the energy consumption is smaller in 0.04 kWh. This quantity of energy saving is equivalent to maintaining the coffee-maker operating during 120 seconds, which is the time needed to prepare about four coffees. This is approximately the number of coffees prepared per day in ProtoLab. With that amount of energy, it is also possible to complete the charge process of 40 mobile phones\textsuperscript{17}. Therefore, the energy saving is significant, especially taking into account that ProtoLab coffee-maker had only four users and the average coffees prepared per day is less than five. In a place where the coffee machine would have more activity, the energy saving would be greater.

Figure 5: Energy consumed by the ProtoLab coffee-maker using its own usage pattern and using a combination of SmartLab coffee-maker usage pattern and its own.

7. Conclusions

Experience has shown that humans use electrical devices in common areas less efficiently, in terms of energy, than they should. Thus, automation seems to be a great option to save energy. Authors’ previous work presented a proposal where these devices were able to improve their energy consumption efficiency by operating differently as a function of their usage pattern. This work presents an approach towards an ecosystem of collaborative eco-aware everyday things where they cooperate with each other by sharing their usage patterns. These patterns are used by them to decrease the learning time in order to perform more accurate predictions of devices’ usage. As has been shown, despite having only three small groups of users, two similar patterns have been found and the energy saving is significant. The increase of eco-aware everyday things participating in this devised ecosystem would increase the probability of finding more similar devices and, in turn, the accuracy of the prediction would also increase. This would imply a raise of the amount of energy saved.

Future work will be focused on making progress in the infrastructure which allows eco-aware everyday things to communicate and share their usage pattern with others that have a similar profile. Twitter, one of the most extended social network, is set to become this infrastructure. The eco-aware devices profile will be modelled within Twitter

\textsuperscript{17}http://www.carbon.to/
profile. For this, we will develop a web platform where registration of the eco-aware everyday things can take place, introducing all the information related their profile. Automatically, a web service will register the eco-aware devices into Twitter mapping the introduced profiles into ‘Twitter profiles’ model. It will also seek to add a larger amount of devices to the ecosystem, both of the same type (coffee-makers) and other kinds (beamers, printers, screens, etc.), for a further evaluation and improvement of our approach.

8. Acknowledgements

The authors are very grateful to the University of Deusto for the financial support to their PhD. studies.

References


