Saving Energy Through Collaborative Eco-aware Everyday Things

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Abstract—The reduction of energy waste in any of its forms and everywhere is a major challenge of our society. An important proportion of such waste is due to the misuse of consumer appliances of shared use in public areas (computers, printers, coffee makers, etc.). To face this issue, we have transformed everyday consumer devices into collaborative Eco-aware everyday things. The presented work contributes with a first approach to reduce the learning time of Eco-aware objects to perform accurate predictions. The general idea is to enable a platform where Eco-aware appliances interchange their collected usage pattern in a cooperative manner to reduce energy wasting in order to alleviate the cold-start problem for new coming Eco-aware appliances. To this end, we have simulated a collaboration between two of these appliances, leading to an energy reduction regarding non-collaborative objects.

Keywords—Eco-aware Everyday Things; Social Devices; Eco-awareness; Energy-efficiency; Coffee Machines; Predictive Models;

I. INTRODUCTION

In recent years we are witnessing an exponential growth of information technologies in the form of consumer devices. Most of them are everyday objects with the addition of the ‘smart’ prefix (e.g. smart-phones, smart-appliances, smart-meters, and so forth). 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 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. However, appliances’ designers and researchers have forgotten the latter statement. That is, they have mainly focused their efforts towards energy efficiency and energy-waste awareness within households - where motivational approaches towards sustainability have aimed to individuals rather than groups. Surprisingly, the public areas, like workplaces, have remained rather unexplored despite its great potential for energy savings.

Our research is motivated to cope with the waste of energy resources that we unconsciously do in our everyday life, and by the assumption that people do inappropriate and inefficient use of power consumption devices during their operation. In a previous authors’ work [16] we overviewed how Internet-connected objects can lead to a social change towards energy-efficiency in public areas. To such end, we proposed the use of social networks, such as Twitter, as an appropriate Eco-awareness platform which enables a channel for the interaction and communication between smart objects and human beings. In that paper we discussed the promising potential of combining people and future smart everyday objects teaming up to promote a more sustainable behaviour on the planet’s behalf.

The work that we present now is based on a series of research-experiments aiming to reduce the energy consumption of devices of collective use within public areas through the Eco-aware everyday things concept [16], [3], [17]. However, this article opens a new path to reduce energy consumption. The strategy is not anymore centered in a human behavior change, but focused in the dynamic and automatic collaboration among similar smart Eco-aware things towards energy efficiency. Being the main idea enabling Eco-aware appliances to interchange their collected usage pattern with newcomers, the goal is to let the latter ones to accelerate their learning time in order to perform, as soon as possible, accurate usage predictions to save energy. Hence, to tackle the cold-start problem.

The remaining of the article is organized as follows. In Section II the background of different strategies to save energy and the challenges to identify user similarity in social networks are reviewed. Section III formalizes the problem statement, assumptions and presents the hypothesis. Section IV describes the process performed to validate the hypothesis. In Section V, the results are shown and analyzed, while Section VI summarises this paper contributions and open future perspectives.

II. BACKGROUND

In the field of commercial Eco-awareness systems, there are several physical gadgets which are designed to make visible the energy consumption in real-time (electricity feedback systems). For example, Wattson Solar\(^1\) the Energy Orb\(^2\), TED detective\(^3\) or Onzo\(^4\). ‘Current cost’ is a more powerful meter with embedded Internet connection to send

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1http://www.diakyoto.com/
2http://www.orbenergy.com
3http://www.theenergydetective.com/
4http://onzo.com/
data to its associated web-site\(^5\). These commercial devices are designed for people’s settings (i.e. individual use) while our work advocates for collaborative Eco-aware objects to tackle energy saving in public spaces. In the research field, we find two important revisions of Eco-feedback technologies [6], [20]. All the reviewed approaches are stand-alone meters, devices or applications -i.e. solutions which are designed to operate autonomously without any kind of interaction nor cooperation with distant devices. Indeed, most of them target, as well as commercial devices, to households. Furthermore, the reviewed solutions are mainly aligned with promoting human behavior change and people-awareness, while our approach is focused in the dynamic and automatic collaboration among similar smart Eco-aware things.

In [16] we proposed the use of social networks as appropriate platforms to bridge the communication between people and Eco-aware objects. Twitter was selected since it was the most influential and least intrusive of the reviewed networks. Indeed, with more than 200 million users and roughly 400 million\(^6\) tweets per day, Twitter is the most prominent micro-blogging service available today on the Web. The research community is exploiting this service for several purposes (trends predictions [11], incidents detection[13], influential users [4], and so forth). We consider that Twitter is also the best platform to make Eco-aware objects communicate and cooperate between each other.

Analogous investigations to ours aimed to find similarities among Twitter users [10], [12], [5] to recommend information or similar users to them. The user similarity problem to make user’s recommendation is not new. There exist two approaches: i) Content-based, which was a well know method on P2P networks -i.e. people with similar content to share is prone to be similar; ii) Collaborative filtering -i.e. it is the process of filtering using techniques involving collaboration among multiple agents. Its basic idea is aligned to ‘homophily’ whose more commonly known phrase is ‘birds of a feather flock together’[7].

In Twitter the typical approach is the latter, collaborative filtering. The features that are most commonly used to group users together are: user profiles (usually constructed by a specific user modelling strategy [21]), Twitter lists, hashtags or retweets [10]. Some recent developments in collaborative filtering have demonstrated the power to integrate rich content from external sources out from the social network itself. For instance the use of research articles’ databases to link researchers with similar interests [5] or Kim et al. [12] proposed a probabilistic model derived from Probabilistic Latent Semantic Analysis (PLSA) for collaborative filtering to recommend potential followers to users in Twitter. The presented work follows this tendency by including not only the user profile, but also implicit information as usage-pattern and geographical data. The works in [14], [15] have also studied the relationship between the geographic location of users and the relationships among them.

In spite of these large research efforts, the user recommendation in social networks is a non-trivial task. Collaborative filtering approaches exhibit a high computation when the population is large [1] and any of the state-of-the-art methods suffers from the same limitations: sparsity and scalability [1] and cold-start problems [19]. Probably the most important one is the latter. New users, in our case newcomer Eco-aware objects, flow into the system continuously and they do not have any information of similar users with whom to share relevant information. Hence the cold-start issue tends to be severe in these social platforms when compared to traditional information systems. In addition, as Hong et al. discussed [9], a tremendous amount of content is rich yet noisy. Simple information retrieval or topical modelling techniques may not be sufficient to capture users’ similarity.

### III. Problem Statement

The behavior patterns in public spaces, despite being aleatory, follow a defined pattern. This vary depending of the location, the culture, the type of the space, etc. The coffee consumption pattern is an adequate example of that. Figure 1 shows the places where coffees are prepared in U.S. during 2008, 2009 and 2010 [18].

![Figure 1. Places where coffees are prepared in U.S. during 2008, 2009 and 2010 [18].](http://cnet.co/KHlg8q)

In a previous work, the authors presented a proposal [17] where Eco-aware everyday things were able to improve their energy efficiency operating differently as a function of their usage pattern. To perform accurate usage predictions, these devices required a usage-data collection period (30 days in [17]). In that work, the energy consumption was measured and it was demonstrated that the energy saving potential of learning the usage pattern and make predictions with these 30 days, was about 15%. The first week energy consumption was 928 Wh, so according to [17], after the learning phase the coffee-maker would save 15% per week, i.e. around

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\(^5\)http://currentcost.com/

\(^6\)http://cnet.co/KHlg8q
140 Wh per week\(^7\). This means that any reduction of the aforementioned period, will lead to a reduction of energy consumption.

This paper presents an approach where Eco-aware everyday things collaborate with similar devices by sharing their usage patterns. This similarity is reflected in the kind of the devices, their location (as shown in Figure 1), the number of users, these user’s habits, etc. These usage patterns are used to alleviate the cold-start problem, acquiring other usage patterns as their own -i.e. to reduce the learning time, in previous work 30 days, as much as possible and therefore, to reduce the energy consumption.

A. Assumptions

In this work, we assume that we have an platform that allows Eco-aware everyday things to communicate and share their usage patterns with others placed in a similar context. Although the initial work in this scope is focused on social networks, specifically Twitter, we do not discard other kind of architectures. In any case, the results of this work are independent of this platform being a social network (Twitter, Facebook, etc.), a middleware based on the paradigm of Triple Spaces\(^8\) or a semantic solution.

B. Hypothesis

The hypothesis of this research is the following:

“It is possible to reduce electrical devices’ energy consumption by automatically commuting its operation mode, based on a collaborative learning with other devices”

IV. A First Step Forward

In order to validate our hypothesis, the process shown in Figure 2 was designed. Two shared electrical appliances (capsule-based coffee machines), placed in two research laboratories (hereinafter SmartLab and S3Lab, both with eight users), were collecting usage-data during two weeks. After that, a new coffee-maker was installed in ProtoLab laboratory, where there were four users. The aim of this research was hidden to those users in order not to influence them when making use of the coffee-maker. The three devices continued collecting usage-data along the next week. At this point, there were two behaviors to acquire by the new device: 1) to predict the next week usage using its collected usage-data the week before; 2) to predict the next week usage using a combination of its collected usage-data and the usage-data collected by other coffee-makers located in a similar context.

To observe the difference between two approaches, we proceeded to perform two simulations.

\(^7\)To comprehend better what these reductions mean, we encourage the readers to search in http://visualization.geblogs.com/visualization/appliances/ what they could do with them

\(^8\)Auto-Regressive Integrated Moving Average (ARIMA) is a time-series forecasting model. There exist others, such as Winters ARMA or ARIMAX. ARIMA are, in theory, the most general class of models for forecasting and predict if 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\(^2\) - the underlying model of ARIMA - , is the stationary of the time-series, which in practice, is very rarely met.

1) According to [17] and using the first week usage-data of the ProtoLab appliance as training-set, we made, applying ARIMA\(^8\), a one week prediction of coffees that would be prepared. This prediction noted the time slots when was worthwhile to leave the coffee-maker on or switched off. Disposing of this prediction, we performed a simulation of ProtoLab coffee-maker energy consumption along the second week of operation.

2) For the second simulation, a similar procedure was performed. However, the prediction was made using as training-set the first week usage-data of the ProtoLab coffee-maker and the first two weeks usage-data of the SmartLab coffee-maker. Note, that the more similar usage-pattern to the Protolab was the SmartLab pattern. In a glimpse, it can be observed in Figure 3 that the prepared coffees distributions of both laboratories exhibit similar patterns, either in the morning and in the afternoon. In contrast, the S3Lab distribution is very sparse and no pattern has been recognized during the first two weeks of device’s usage.
V. Analysis of Results

Quantitative analysis of the simulation’s data will let us validate or reject the hypothesis. Figure 4 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 prediction was made making only use of the usage-data collected by itself during the previous week. The total energy consumption amounts 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 by a coffee-maker placed in a different, but somehow similar, laboratory. In this case the total energy consumption is 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, i.e. to prepare about 4 coffees, that approximately is the number of coffees prepared per day in ProtoLab. Therefore, our hypothesis is validated by this plot.

VI. Conclusions

Experience has shown that humans use electrical devices in public areas less efficiently, in terms of energy, than they should. Previous authors’ works presented a proposal where these devices were able to improve their energy efficiency operating differently as a function of their usage pattern. This work presents a first step forward towards an Eco-aware everyday things ecosystem where they collaborate with each other by sharing their usage patterns. These patterns are used by them to decrease the learning time in order to perform accurate predictions of devices’ usage and therefore, to alleviate the cold-start problem. As has been shown, despite having only three small group of users, two similar patterns have been found and the energy saving is significant. More Eco-aware everyday things participating in this devised ecosystem would increase the probability of finding devices placed in a more similar context and, in turn, the accuracy of the prediction would also increase.

The future of this ongoing research is very promising. Next steps will be focused on making progress in the infrastructure which allows Eco-aware everyday things to communicate and share their usage pattern with others located in similar contexts. It will also seek to add a larger amount of devices to this ecosystem, both of the same type (coffee-maker), and other kinds (printers, copiers ...) for a further evaluation and improvement our belief, i.e. Eco-aware everyday things can enhance and speed-up their energy consumption reduction, providing means to enable their cooperation and knowledge sharing are made available.

Acknowledgement

The authors are very grateful to the University of Deusto for the financial support to their PhD. studies. This paper is also supported by the Basque Government project Future Internet II (IE11-316).

References


