A Holistic Approach to Energy Efficiency Systems through Consumption Management and Big Data Analytics

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Abstract— **Improving the energy efficiency is one of the most effective ways to increase supply security and reduce Green House Gasses emissions. Furthermore, the increased cost of energy has encouraged the development of new technologies that allow the efficient use of them, such as monitoring the final users energy demand; hence, it is possible to have a more efficient consumption behavior without lowering the threshold of comfort that consumers are used to. The Smart Home Energy project makes a profitable use of these technologies by allowing the final user to manage, control, plan and, in most cases, reduce the electric bill. To facilitate the bidirectional interaction between the customer and the devices integrated in the smart home communication network it is necessary to follow a holistic approach. This proposal aims to go a step further by using the massive consumption datasets to predict future energy behaviors, offering personalized recommendations and developing a customized "consumer energy knowledge" for every home, through heavily processed Machine Learning algorithms.**

Keywords— Digital Home; Energy Efficiency; Smart Metering; Cloud; Big Data Analytics

I. INTRODUCTION

From a technical point of view, a home is an extremely complex system with many uncertain variables, which can be influenced by environmental conditions and human behavior.

In recent years, the appliances that are being incorporated to the households are reaching higher and higher levels of energy efficiency. However, these contributions are still not enough in the current energy scenario, where external energy dependence and indefinite rising prices question the profitability of these devices compared to their useful life-spam and their necessary initial investment.

In addition, these facts cause that energy saving measures and common recommendations (energy-efficient light bulbs, electrical appliances A++, awareness campaigns, etc.) are increasingly ineffective in achieving a significant reduction of the energy costs, stating the need of more advanced strategies.

Therefore, the inclusion of management and control systems can represent an adequate line of action to increase the energy efficiency at household level. It permits the quantification of the home energy demand, recording the consumption values and characterizing personalized profiles of energy patterns. Based on this information, a set of recommendations can be generated, which would modify the consumer behavior and ultimately result in reducing the electric bill. Other complementary visual tools can help also to analyze the consumption and consequently to reduce it.

Due to the amount of data that these systems has to handle is large and expected to keep growing in the future, the architecture work presented at ICSEA 2012 [1] has been revised and extended with the description of an operational system, where the addition of new Big Data based components is the key, in order to give the necessary support to a massive set of Digital Homes.

The paper is organized as follows: in Section II, the State of the Art is described. The proposed solution is explained in Section III. A brief extension of the work focusing on the exploitation of the data obtained by the system is done in Section IV. In the last section, conclusions are drawn and future work is indicated.

II. STATE OF THE ART

The integration of various automation and control technologies in the domestic environment is called "Digital Home" [2]. This term is not only applied on the domestic tasks performed by smart appliances, but also aims to cover specific customer needs of personal assistance, education and/or entertainment as well as security and surveillance.

One of the main objectives of a Digital Home is to design an efficient Energy Management System (EMS). Therefore, an appropriate starting point is to study the features and functionality of Building Management Systems (BMS) [3] such as tasks related to the Heating, Ventilation, and Air

Conditioning control, a correct monitoring of lighting, allowing a control of consumption and its associated costs.

In terms of architecture, BMS has a similar structure and characteristics to those described on the mentioned home environment: hardware components as sensors, computer processing power, user interfaces (smartphones, PCs, tablets, etc.) as well as means of transmission. However, neither control of electrical appliances and service robots, nor the integration of smart metering devices, are covered by BMS.

In the last decades, the integration of Distributed Energy Generation Units (DEG) at the household level constitutes the latest addition to the in-home EMS [4]. There are various types of renewable technologies available to install at homes, but solar and wind power energy sources are the most popular ones. Due to unpredictable weather fluctuations, it is challenging to incorporate this type of energy sources to the home systems and elaborate accurate energy productions, hence reliable prediction models are a main milestone to make these installations profitable. Weather data needed to make the consumption predictions are highly variable in a worldwide approach, because of its different sources (meteorological services and institutions), formats, and protocols. Short time meteorological predictions also change frequently, where an hourly interval is usual to get new predictions for the next 72 hours, meaning that done predictions also could be changing hourly.

After integrating these DEG Units, the more integrated and synchronized the home energy systems are, the more energy savings are achieved due to self-production consumed energy. Additionally, these systems are also acceptable to help energy operators to get easily equilibrium between the energy demand and supply curve. Finally, due to the decentralization of the energy system, the losses inherent to its medium and long distance transportation will be significantly reduced.

From a physical standpoint, the different elements that compose the EMS, e.g., appliances, domotic control elements or renewable energies, may interact with each other, exchange heat and an influence in the in-doors temperature and humidity, changing comfort conditions. For that reason, the accurate quantification and statistical analysis of all variables involved in the heat exchange together with its possible interactions have to be made in order to propose real energy-efficient alternatives within the comfort conditions predefined by the user.

The domain of smart homes develops fast but still many restrictions have to be faced: the high cost of certain systems, storage and processing limitations, etc. Nevertheless, the most important limitation to solve is the lack of true interoperability between systems of different manufacturers, which makes them to work independently. That could result at the end in a duplication of the performed tasks. So, it is essential to communicate those devices with each other in a complementary way, i.e., sharing the services to study what is happening around them and take decisions accordingly.

The use of an open, extensible and modular protocol would resolve that requirement. An open platform to be considered is UniversAAL [5], supported by the European Commission, which has taken promising steps by aiming to design, develop, evaluate, standardize, and maintain a common service platform for Ambient Assisted Living.

Covering a wider field, the standard DHCompliant (DHC) [6] communication protocol at the application level of TCP/IP stack offers a cost-effective solution regarding other protocols, such as technological and brand independence, savings in solution investment and control and simultaneous management of service robots and smart appliances.

Regarding the storage and processing of data, and in contrast to other researches [7][8], all business logic will be in the Cloud. Although it is usual to allow remote control, the exploitation of the data is performed locally [9]. Commercial solutions, which are typically linked to a specific product of smart metering, which allow local monitoring of a home, do not allow relating information of several houses to extract information collaboratively.

An energy consumption metering infrastructure generates large amount of data per home and the quantity increases proportionally with the number of houses sending data simultaneously. It should also be taken into account the large number of users requesting information. In an acceptable time response, the system must be able to acquire, store and process large amount of data, and scale horizontally. In the gap between the very expensive solutions of specific hardware supercomputers and enterprise servers, Big Data techniques are the key for achieving that goal [10].

Moreover, it provides more capabilities to work with this large amount of data. It should be mention the integration with Machine Learning algorithms, generation of statistics, capacity of mixing varied data such as internal data (measurements) and external data (climatology, open data, etc.). Although there are precedents of using machine learning techniques to improve energy efficiency [11], to the best of our knowledge, they are not been applied in a collaborative way, i.e., using the data collected from all houses that are part of a larger network, known as Smart Grid.

III. Proposed Solution

The presented solution is framed within the Smart Home Energy (SHE) project [12]. The architecture of the system was designed following a necessary holistic approach that takes into account all the elements involved in a smart domestic environment, such as electrical appliances, lighting, people or external conditions, in order to model and analyze all contributions and interactions.

As it is graphically shown in Figure 1, the main components of the architecture, which will be explained in the following subsections, can be grouped according their physical situation:

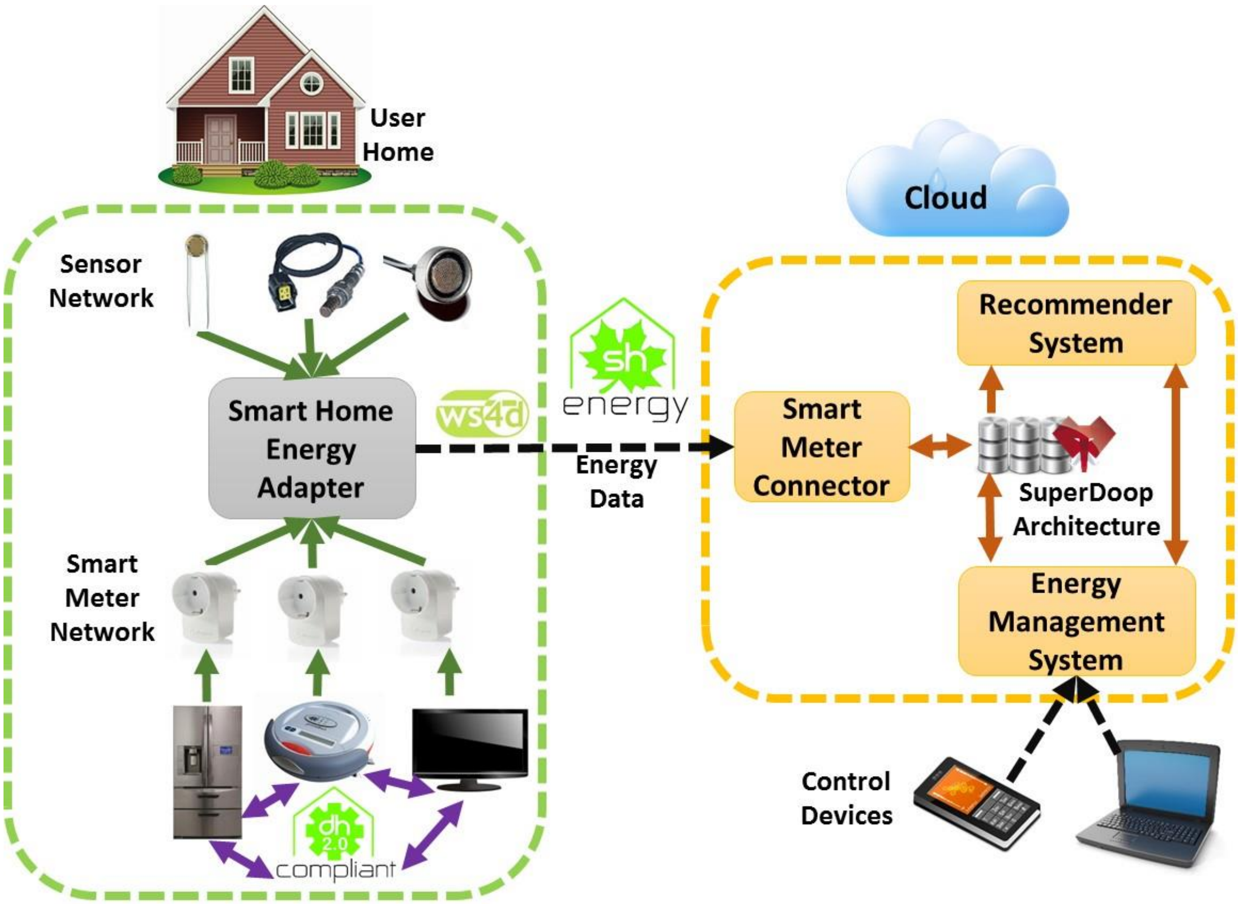

Figure 1: Smart Home Energy architecture schema

- The user home environment, where all the appliances and service robots are able to interoperate among them by means of the DHC communication protocol.
  Specifically, Smart Metering devices and sensors are responsible of acquiring the energy-related home information such as the power consumption, the luminosity or the temperature. Then, the software Smart Home Energy Adapter (SHE Adapter) obtains the energy data from the mentioned devices and sends it to the cloud in a predefined rate.
- The cloud [13] infrastructure is based on SuperDoop technology, developed by Ingenia [14]. It stores large amount of data coming from each home. The recommender system works on the data produced from the monitored homes in order to generate predictions and recommendations through Machine Learning methods. Finally, the user can access by Internet to the EMS interface, to manage and control the operations. For instance, the appliances can be remotely turned on and off

These parts – the user home and the cloud environments – are going to be described in detail in the next subsections.

A. *User Home Environment*

A Smart Meter is an intelligent measuring device capable of measuring, in real time, the power consumption of the appliances connected to them [16]. In addition, the type of meters used in the project allows to turn them on and off remotely.

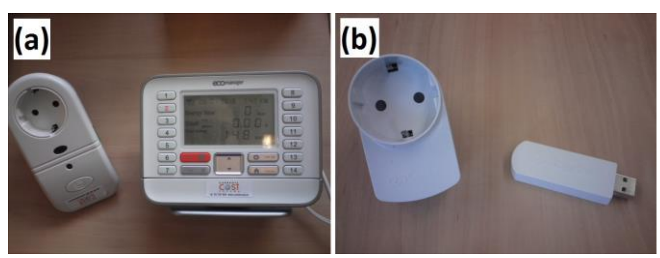

Figure 2: Smart meters (a) EcoManager (Current Cost) and (b) Plugwise

For instance, the plug-based EcoManager by Current Cost [17] and Plugwise [18][19] options shown in Figure 2 (a) and (b) are already integrated in SHE, although the project aims to be independent of the hardware used for obtaining the measures.

Other useful information to define the characteristics of the environment (humidity, number of sunlight hours, rain, wind, etc.) to improve energy efficiency, is collected from the home through a sensor network of different types, such as the ones detailed in Figure 3.

Figure 3: Carbon monoxide (CO), luminosity and temperature sensors

The devices integrating the Digital Home are interconnected through DHC communication protocol. As they come from different manufacturers, it is necessary the implementation of a specific DHC Adapter for each one. A DHC adapter must include the services that are set out below:

- DHC-Security & Privacy service: prevention of fraudulent use, control of the devices, and also, data access by unauthorized agents.
- DHC-Groups service: coordination of collaborative tasks done by different devices belonging to the system.
- DHC-Localization service: Supplying information to locate devices within the home and help them in navigation.
- DHC-Intelligence service: The intelligence is given to the system through the management of rules that control the tasks and the Machine Learning predictions and pattern recognition.
- DHC-Energy service: Incorporation of energy and Smart Grid [20] concepts to the DHC protocol, by means of allowing the user to know the energy consumption data, analyzing the obtained information to improve the energy efficiency of the system and thereby generating savings. Those are the main motivation of SHE project.

In order to clarify the performance role of the DHC-Energy adapter, the main operations are described in detail below.

- Establishment of the charging settings: The types of charging modes (maximum consumption, cost per kWh, etc.) are shown to the customer, which will select the best rate. For instance, the possibility of choosing when a device will have its loading period depending on the tasks that have to be performed, time of the day and the tariffs to be applied. Figure 4 shows a sequence diagram describing the process.

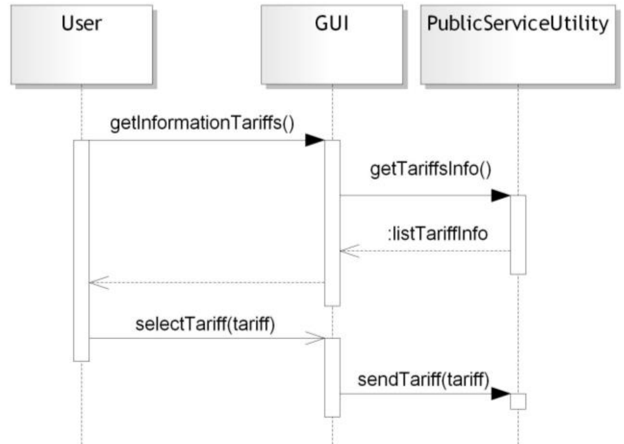

Figure 4: Sequence diagram: Obtain tariff information.

- Device status: It is also important to know the preferences of the user, and compare it with the data that shows the state of the device and the power source (either renewable or normal electrical supply). The process carried out can be seen in Figure 5.

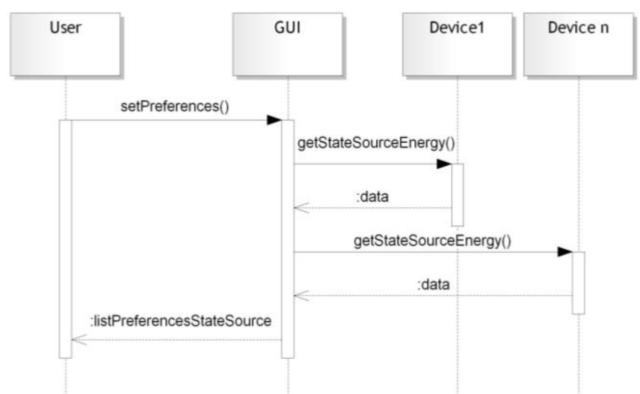

Figure 5: Sequence diagram: Device status

- Energy profiles: The system allows a set of possible energy consumption configurations. When the user does not need the device, the power consumption should be zero ("Off" profile) or minimum in case of awaiting orders ("Stand by" profile). In the operation mode, some devices can be fixed to the highest energy saving rate ("Low" profile) or to lowest energy saving rate, which operates on a full capacity ("High" profile). Some indispensable devices can be set to an especial level without caring the savings ("Emergency" profile).

Moreover, if a device remains in an inactive state, the device must reduce its energy profile to a lower level. The way in which this operation is done is shown in Figure 6.

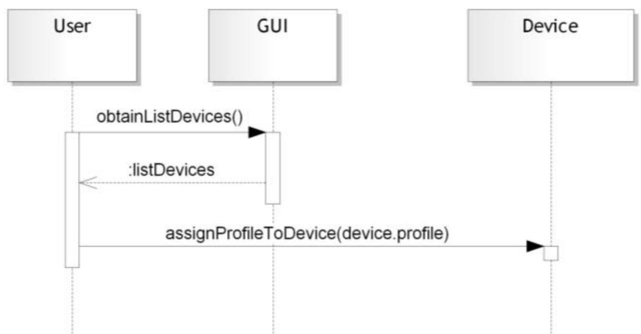

Figure 6: Sequence diagram: Election of an energy profile

For achieving an optimal performance of the system, it is necessary to process the large amount of data generated by the different devices in a fast rate. Therefore, Web Service for Devices (WS4D) technology [21] has been chosen. The main driven behind this selection is that DPWS maintains the philosophy of Service Oriented Architecture (SOA) combined with the convenience of Web Services. This solution means that a Digital Home can transmit the captured information through the DHC adapter to the Cloud.

B. Cloud

It is necessary to store the information from the Digital Home in a centralized way in order to have a database that allows comparative and heuristics analysis. From the user's perspective, the stored information needs to be accessed from any device, anywhere [22].

SHE project uses SuperDoop technology [23], which is a Hadoop [24] and Storm [25] based Open Source Big Data Stack integration, that scales horizontally to solve challenges as acquisition, storage, searching, sharing, analysis and visualization of large data sets on a tolerable response time-frame. This can be used for general-purpose applications, such as communications, banking, security, smart cities, energy efficiency, emergencies, social networks and many others areas.

SuperDoop fits into Lambda Architecture concepts [26]. The designed architecture, which is schematized in Figure 7, has the following main components:

- The energy measurement reception from the environment can be made over different types of networks (wired and wireless). Representational State Transfer Application Programming Interface (REST) API [27] is used for the communication between the Digital Home nodes and the Cloud. It defines an interface among the software components, where an URL represents a resource whose content can be accessed via HTTP protocol via. The use of this technology brings some advantages as portability between different languages, performance and scalability.
- Acquisition Layer is an additional layer to solve the acquisition of the data used by the Speed and Bath layer, described below. This concept has been implemented as a prototype in a flexible way for SHE project using REST and JSON APIs, a temporal storage or cache using MongoDB, and a Redis based system for the speed data layer data insertion.
- The Speed Layer was needed to provide a real time monitoring and control services to users through a Graphical User Interface. This layer needs to aggregate the data, using typical functions as average and summarization for each user, group of devices, and time intervals, in a continuous computing close real time. Finally, this layer provides the information to the Service Layer to make it available to the interface.
- The Batch Layer includes several components to store and process the data, applying data mining and Machine Learning algorithms to acquire a customized knowledge pool for home energy consumption. These algorithms can be executed massively for each home or user, many times a day, to learn and predict the consumption using a large set of data for each execution.
- The Service Layer is the closest to the user, and includes data publishing through a REST API for both layers, the Batch Layer and the Speed Layer, allowing the interface to query, receive and show the data.

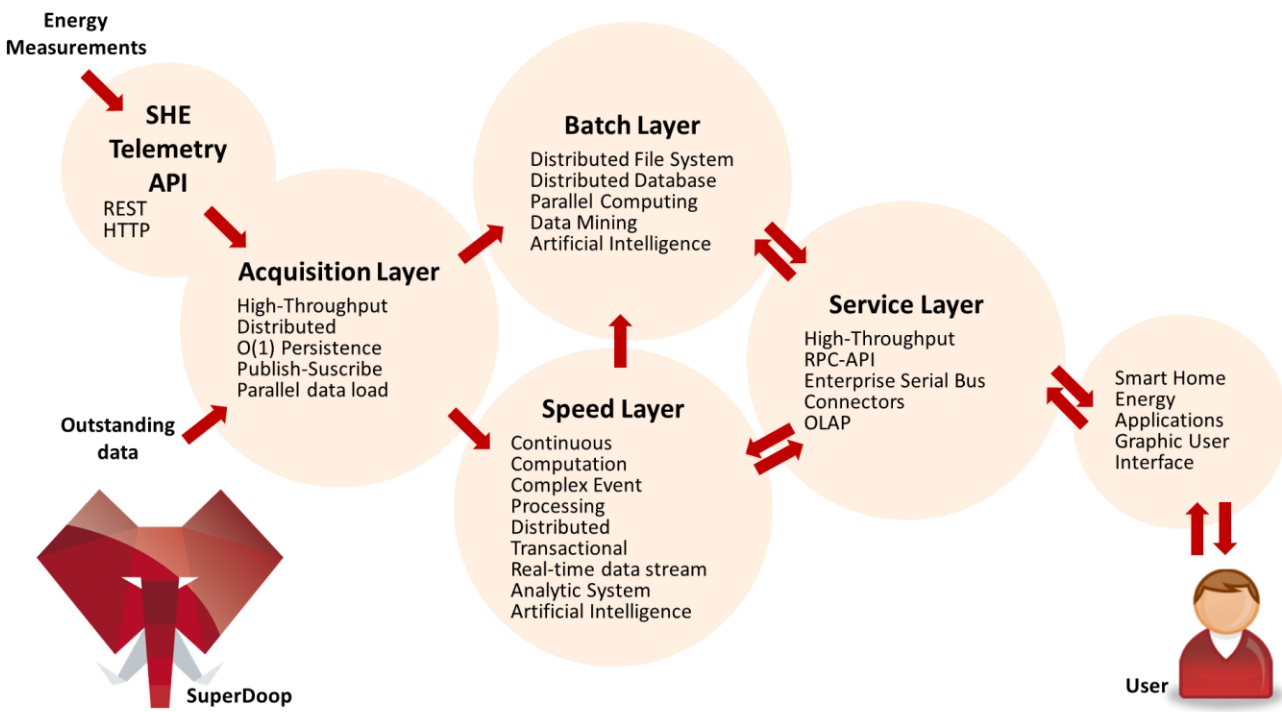

Figure 7: SuperDoop Architecture applied to SHE project

The smart meter connector acts as a middleware between the SHE Adapter, which is in execution in the user home and the SuperDoop platform, in the cloud.

The stored information is used by the system to generate specific recommendations, which will depend on its environmental conditions. This is done through an expert system that, based on its experience, uses rules to model the system. It integrates a knowledge database of the consumption data and a rule editor, which enables the customer to test and simulate the rules. The rule execution is done with an inference engine based on an execution of rules and tree forward.

Going a step further, this element can also generate collaborative recommendations based on actions performed in homes belonging to a similar environment profile. For making this, it would be necessary to define the way in which the distance between two homes or two users is calculated. Taking into account that the users can agree (value 0) or not (value 1) with the completion of an action, the most appropriate algorithms are Tanimoto [28]. The distances between all the users are calculated and stored in a matrix. When a recommendation is required to be given to the user, the algorithm returns the actions that most similar users have done, and that the user has not carried out yet.

It is also possible to extract consumption patterns and thus allow making predictions to anticipate and adapt to other cheaper options.

The user can access remotely and from different devices to the Energy Management System. Through its interface, the consumer is able to manage, control and plan the bill. That is to say, the user has a Smart Billing. Furthermore, in the user home page, the mentioned energy efficient recommendations are offered associated with actions to carry them out.

A complementary useful tool is the incorporation of interactive and customizable graphs to show the information to the user, who is able to manage the energy consumption and consequently improve the energy efficiency.

As it is shown in Figure 8, the consumption insights screen displays the consumption of each day, its distribution in the different hourly periods, the accumulated per month and the distributed consumption among the various days of the week, within the filtering dates, in an interactive and visual way.

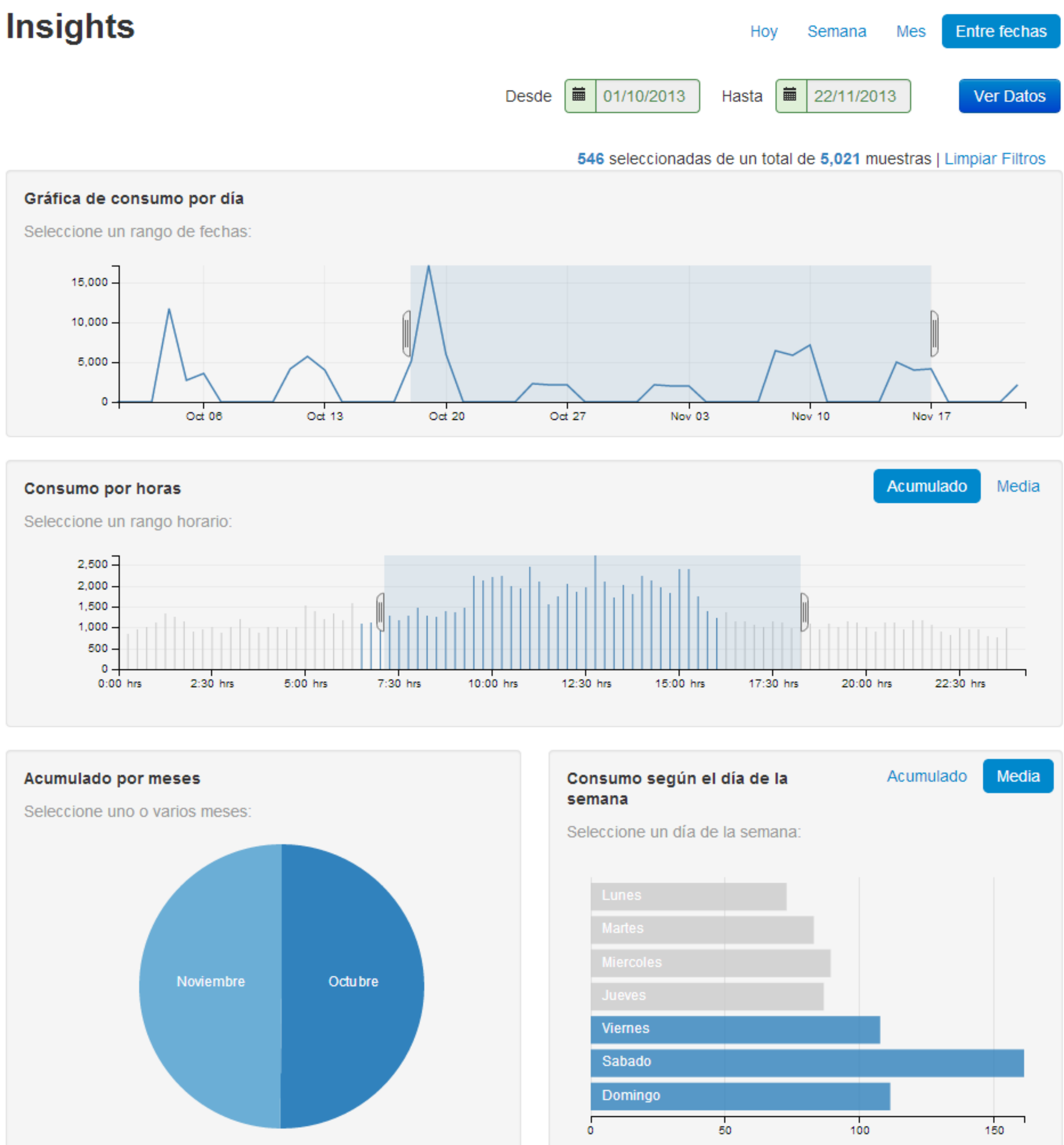

Figure 8: Interface of SIGE: Consumption Insights

Other historical information is presented in different parts of the interface to analyze it and make comparisons. Visual Mining tools are applied to help the user to understand where power is consumed, where it is wasted, etc. In Figure. 9 the weekly user consumption is represented in a heatmap to facilitate the discovering of a behavior pattern visually.

The interface takes into account different aspects of usability, accessibility and, of course, the functional aspects of providing the user with the information that allows monitoring and controlling the appliances presented in the Digital Home.

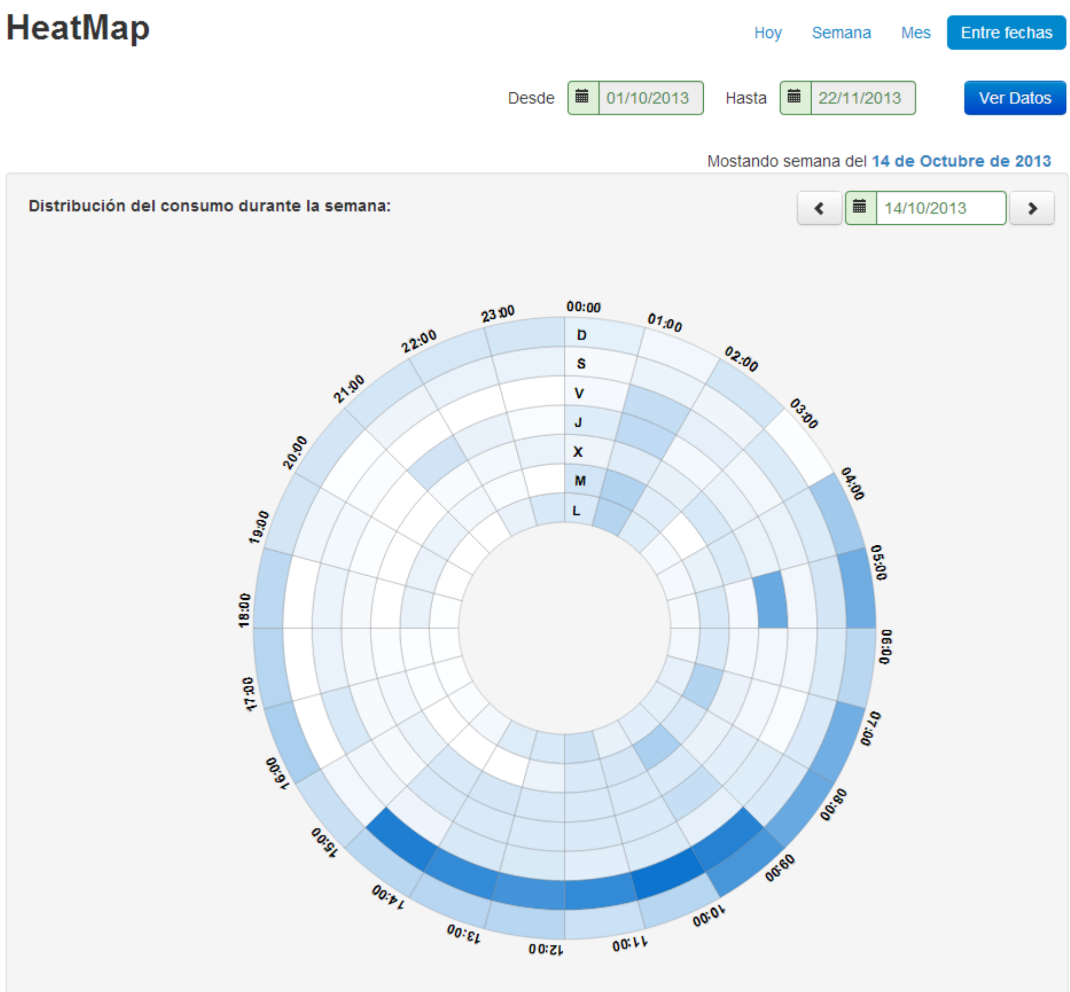

Figure 9: Interface of SIGE: Heatmap

IV. Test Results

After different attempts to match simulated energy demand with multivariate regression models, the next step was to prove implementation of Artificial Neural Network (ANN) models as suggested in [29]. Several studies about prediction of building energy consumption and temperature forecaster [30][31][32] are based on ANNs and demonstrating a high accuracy in predicting energy demand and consumption in buildings. The main drawback is the need of a learning process for identifying the particular patterns, which define the system performance or behaviour. In this case, a simple ANN (3 hidden layers, using a symmetrical sigmoid as activation function) has been tested with the back-propagation algorithm [33], using as input parameters outside temperature, outside humidity ratio, previous hourly energy demand, among others. The obtained results have satisfied survey expectation since using short-term ANN for energy demand prediction has shown an average error of 3% during a complete year simulation what constitutes insignificant deviation compared with typical estimations that usually energy experts make in energy audits (more than 20%). The comparison between the energy demand (heating and cooling) of a small building simulated by EnergyPlus ® and the ANN's outputs is shown in Figure 10.

The test was performed with no seasonal discrimination, which demonstrates that the results could actually be reasonable to predict easily, without high accuracy, the energy demand and thus, the energy consumption, in case of we know the rated efficiency of domestic facilities.

Even, the mentioned accuracy has been achieved with simple ANN composed by 5-neuron layers designed for estimating the thermal energy demand of a house as output, paving the way to design a robust energy forecaster. In order to include the data in the forecaster, the value of input parameters have to be established between 0 and 1 (dimensionless).

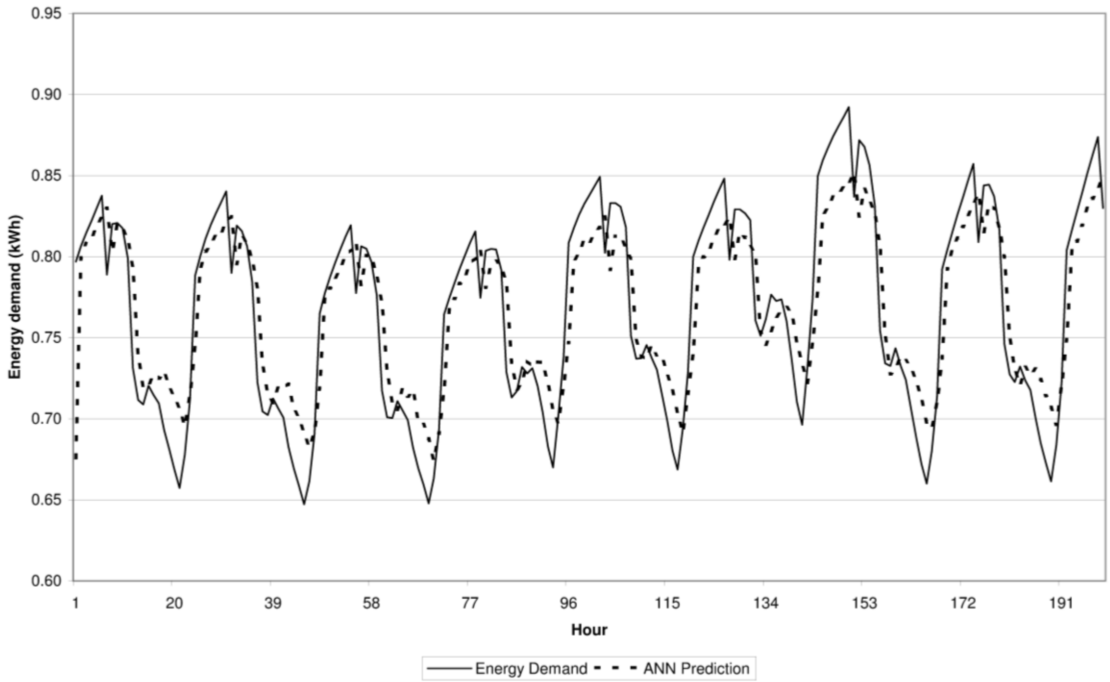

Figure 10: Comparison building energy demand and ANN prediction

For instance, in this study, the outside temperature T_{out}, humidity ratio φ and previous energy demand d_{k-1} have been transformed according with following equations (1), (2) and (3):

$$T_{out}{}^{*} = \frac{T_{out} - T_{\min}}{T_{\max} - T_{\min}} \qquad (1)$$

$$\phi^{*} = \frac{\phi}{100} \qquad (2)$$

$$d_{k-1}^{*} = \frac{d_{k-1} - d_{\min}}{d_{\max} - d_{\min}}, \qquad (3)$$

Min and max subscripts are related to the minimum and maximum historical temperature and potential demand respectively. When ANN calculate the current energy demand d_k^{*}, the inverse transformation is easy to understand according to (3). As mentioned above, ANNs need a learning process to modify the synaptic weights that allow the network to integrate the performance of a complex system.

The current assessment did not consider the different seasons, months, holidays, etc. in order to obtain greater precision since another most sophisticated algorithm called support vector machine (SVM) considers the identification of behavior patterns, related to the likelihood of an event occurs based on input parameters [34]. This mixture of artificial intelligent and statistical approach, e.g., regression models, confers a highly effectiveness in solving non-linear problems, with reduced training data, as our current project, what shows this model as the ideal candidate for energy consumption prediction in buildings. In addition, due to the robustness of this prediction method, potential perturbations, which could appear by adapting the smart home system to new buildings, will be mitigated as it is mentioned in [35].

V. CONCLUSION AND FUTURE WORK

The system described in this paper allows to determine that an open stage of interaction between devices and the Smart Grid can be set by providing more capabilities than pure traditional energy efficiency (such as accounting and reductions in consumption). It also permits the establishment of a consumption profile for the different heterogeneous appliances, which a customer has at home, as well as a referral system in the Cloud associated with business intelligence that allows reducing even more the energy expenditure. All this is done in a distributed way but through a single point where the user interacts. Decisions could be ineffective or even counterproductive if a holistic approach would not have considered.

Cloud technology offers an elastic and resilient solution without requiring a high-capacity storage infrastructure at household level. It also facilitates the management and maintenance of the integrity, security and availability of data. In addition, this solution provides facilities for transparent software updating, because most of the software is centralized and non-distributed on each node.

Specifically, the application of SuperDoop to the metering data allows doing both a batch and a continuous real-time processing of the measurements, working with a large set of data taken along the time from a large set of homes and historical database. It facilitates the generation of configurable and customizable reports, and recommendations, among other functions and independent of the measuring device.

The proposed solution applies ANNs and Machine Learning algorithms using stored and real-time data, thus can be used to acquire personalized consumption knowledge for each home. At the beginning of the learning, real data is temporally replaced with simulated datasets of homes and historical weather data and climate zones, so as the system does not have historical data yet. The prebuilt knowledge can be applied to a classification algorithm, until the system have enough real data, a real customized knowledge progressively learns the real behavior and forgets the knowledge based on simulated data. Thus, the system would acquire the ability of predicting consumption for each home through the customized home energy knowledge.

Summarizing, this technology has advantages over other approaches, because it is open, distributed, and scalable. Besides, it requires little or no configuration by the end user. The use of Big Data techniques does not require initial investment. This method and technology can also be used for other stakeholder solutions that are beyond the scope of this communication.

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