Collaborative Smart Environments for energy-efficiency and quality of life

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[#] SMART BUILDING: LA NUOVA TECNOLOGIA PER L'EFFICIENZA ENERGETICA E LA QUALITÀ DELLA VITA
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Abstract—In line with the goals of Europe 2020 strategy, energy resource saving represent a key issue for smart, sustainable and inclusive growth. Recent developments in ICTs offer home devices featuring local intelligence and connectivity services. So, basing on such technologies, a house becomes Collaborative Smart Environment (CSE), a place where multimedia services are provided to users, while heterogeneous smart appliances are interconnected and interact allowing to save energy, to reduce costs and, at the same time, to improve comfort and safety.

In this paper we propose an interoperable architectural framework and a knowledge-based management model for monitoring and managing energy consumption in CSEs.

Keyword- Energy Efficiency, Collaborative Smart Environment (CSE), Interoperable Home Energy Management Systems (HEMS), Information Management Model, Energy Consumption Forecasting

I. INTRODUCTION

Over recent years, interest in aspects related to sustainability and energy saving has been growing dramatically. In fact, the rising energy demand and the growing evidence for the climate change have created an increased need for energy-efficient and energy-saving solutions around the world. Particularly interesting is the context of energy consumption in the buildings sector: nowadays, commercial and residential buildings account for nearly 40% of yearly worldwide energy consumption and are responsible for a similar level of global CO2 emissions. In particular, houses are becoming one of the major contributors to the countries energy balances: as a matter of fact, it is expected in the near future that the home energy consumption will probably exceed 40% of the total yearly consumption in most of the developed countries [1]. Therefore, energy efficiency in residential buildings is one of the keys to reducing overall energy consumption and greenhouse emissions.

A large number of concepts and solutions can be adopted in order to optimize the energy efficiency in buildings. These include improving the building envelope thermal characteristics, replacing existing heating equipment and household appliances, lighting with higher efficiency devices, and switching to less carbon-intensive fuels for space and domestic hot water heating [2]. Among the various approaches, Home Energy Management Systems (HEMSs) offer a proven and interesting alternative to reduce energy consumption in home environments through the monitoring and the managing in real time of most of the home appliances [3]. Moreover, recent developments in ICT offer home devices featuring local intelligence and connectivity services, making such devices "smart objects", i.e. able to acquire, manage and apply knowledge about an environment, to interact with other smart objects and to adapt their behaviour according to the needs of the home inhabitants [4].

Therefore, basing on the paradigm of the Internet of Things (IOT) [5], it is possible to introduce the concept of "Collaborative Smart Environment" (CSE) as a place where multimedia services are provided to users, while heterogeneous smart appliances are interconnected and interact allowing to save energy, to reduce costs and, at the same time, to improve comfort and safety.

In the scientific literature, different approaches to the design of CSEs are emerging, emphasizing the importance of such a type of applications as a mean to guarantee energy and cost saving. However, most of these approaches are essentially focused on the technological issues, relying primarily on the architectural characteristics of the HEMS [6], [7], [8].

In this work, we propose an innovative system for monitoring and managing energy consumption in CSEs, according to the needs of users and to the particular state conditions of the considered environment. In particular, we intend to highlight how a knowledge-based management model can support the design and the development of innovative HEMSs, ensuring the energy performance improvements of the considered environment and the adaptability to the user's habits.

The paper is organized as follows: in section 2 we present a Methodological approach for the design of a CSE, while in section 3 we propose a CSE System Architecture. Section 4 is related to the Data Management Model, with a particular focus on forecasting methodologies for home energy consumption. Finally, in section 5 we present the conclusions and further developments of such work..

II. METHODOLOGICAL APPROACH FOR THE DESIGN OF CSES

The concept of Smart Environment evolves from the definition of Ubiquitous computing that promotes the ideas of "*a physical world that is richly and invisibly interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly in the everyday objects of our lives, and connected through a continuous network*" [9]. Therefore, a Smart Home (see Fig.1) can be generally referred to a fully equipped environment, featuring interconnected smart devices and a management software which evaluates the gathered information and makes decisions with the aim of ensuring energy and cost saving, as well as improving comfort and safety.

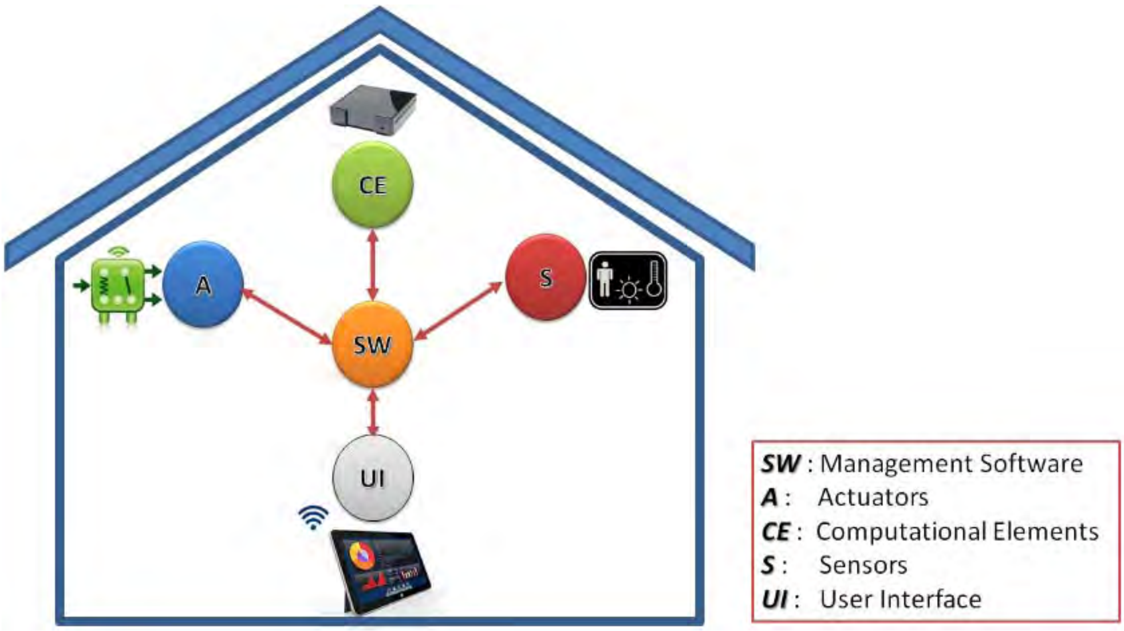

Fig. 1. Typical architecture of a Smart Home

According to these guidelines, the methodological approach adopted for the design of the proposed system is based on the following steps:

- Identification and implementation of technological solutions which provide additional intelligence and connectivity services to existing heterogeneous home devices in order to guarantee their interconnection and interoperability [10].
- Definition of the CSE architecture, based on the use of a centralized management system featuring a central control unit (CCU) and different peripheral devices of sensing and actuating.
- Definition of a data management model for the software of the CCU in order to handle machine-to-machine and machine-to-human interactions [11], [12].
- Define a set of decision algorithms and interoperability rules to perform energy-control services, basing on quantitative forecasting methodologies for analysis of historical data.

III. SYSTEM ARCHITECTURE

A typical smart home is characterized by a distributed system where heterogeneous devices and appliances need to perform joint execution of tasks in an efficient manner to be really interoperable. Indeed, being distributed architectures, smart home environments need a certain degree of interoperability to manage sub-systems which are usually developed in isolation and thus feature different operating systems and connectivity services [10]. Although recent advances in Information and Communication Technologies (ICT) and Internet of

Things (IoT) have led to the development of smart tools intended for smart home environments, the interoperability between typical home appliances still remains an open issue [13].

In order to overcome the issue of the interoperability between existing heterogeneous home devices, the proposed system features a centralized architecture model, shown in Fig.2, where the Central Control Unit (CCU) represents the data-aggregation gateway and the decision-making core of the system, allowing the interconnection and the interoperability of different home appliances, sensors and actuators within the smart home environment through powerline and/or wireless technologies.

More specifically, the communication between the CCU and the existing heterogeneous home appliances is achieved by the use of a set of smart peripheral devices connected to such appliances, called "smart plugs" in Fig.2, which allows providing additional intelligence and connectivity services to the system. In particular, these smart objects carry out the monitoring of the energy consumption and the managing of the activation/deactivation of the connected electrical appliances.

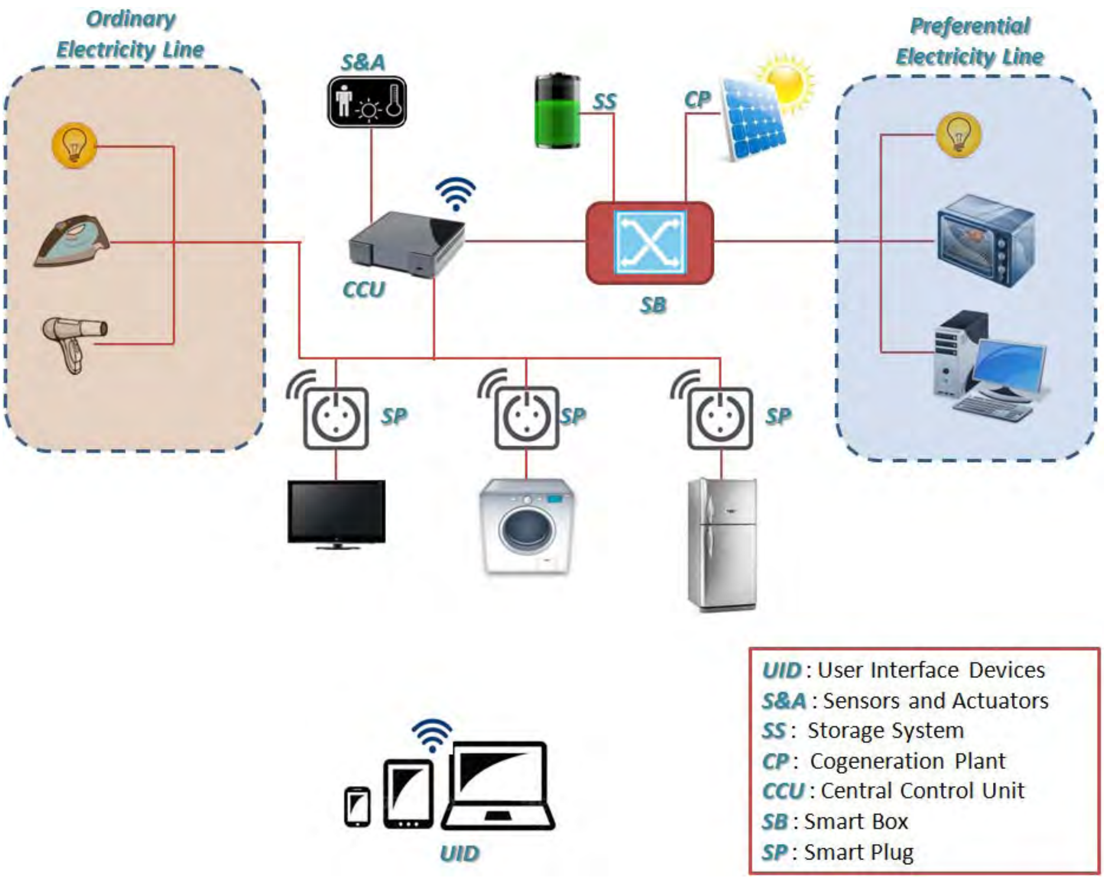

Fig. 2. Architecture of the proposed system

Moreover, in the proposed model, the CCU communicates with another smart peripheral device, called "smart box" in Fig.2, which carries out the monitoring of the overall energy consumption in the considered home environment. The "smart box" is also able to integrate the energy supplied by the power grid with the energy provided by a local cogeneration system and/or a local energy storage system, and to manage the charging of the latter.

In order to achieve the interoperability in existing home environments, our architectural framework, shown in Fig. 1, is based on a centralized model. In particular, the central smart management system, consisting of a Central Control Unit (CCU) with a dedicated software application, "talks" to all involved actors within the home environment (such as users, sensors, actuators, home sub-systems and appliances, energy service providers, etc.) through different technologies (e.g., powerline, Ethernet, wireless, web-based). Therefore, the CCU represent the data-aggregation gateway and the decision-making core of the system: it interacts with all involved actors, collects and processes in real time all information about machine-to-machine and machine-to-human interactions, and, consequently, makes decisions, also on the basis of energy consumption predictions, by taking into account a defined set of decision algorithms and interoperability rules.

In Tab. 1, all the elements of the architectural framework and their related services are described. It is worth noting that, in the proposed model, the communication between the central management system and an existing home appliance (e.g., refrigerator, washer, dishwasher, TV, etc.) is provided by the use of a specific smart peripheral device, shown as “smart plug” in Fig. 2, thus adding intelligence and connectivity services to the related appliance. In particular, this smart object allows the implementation of some energy-control services on the connected appliance, such as the monitoring of device energy consumption and status (on/off), and the activation/deactivation of the appliance in response to CCU and/or user requests.

TABLE I
Architectural Elements of the Proposed SHE Model

Element	Services
Central Control Unit (CCU)	– Communication with all involved actors of the system (smart peripheral devices, sensors, actuators, users, energy service providers, etc.) through powerline, Ethernet, wireless and/or web-based technologies. – Collection, interpretation and elaboration in real time of all data concerning machine-to-machine and machine-to-human interactions (e.g., energy consumption of home appliances, environmental data, user request, etc.) for statistical and training purposes. – Prediction of home energy consumption and environmental conditions. – Sending of control signals to peripheral devices for energy-control services on the basis of a defined set of decision algorithms and interoperability rules, also in response to the performed predictions, as well as to specific user requests. – Detection of abnormal situations and failures, and subsequent generation of alarm signals on user interface devices through an appropriate notification system.
Sensors	– Detection of environmental data (e.g., user presence, temperature, lighting, etc.) – Sending of environmental data to the CCU.
Actuators	– Execution of operational actions on home sub-systems or appliances in response to CCU and/or user requests.
Smart Plugs (SPs)	– Energy consumption monitoring of the connected appliance. – Detection of the operating status (on/off) of the connected appliance. – Sending of energy consumption and status information to the CCU. – Activation or deactivation of the connected appliance in response to CCU and/or user requests.
Smart Box (SB)	– Monitoring of overall energy consumption in the considered home environment. – Integration of the energy supplied by the power grid with the energy provided by a local energy storage system and/or a local cogeneration system in response to CCU and/or user requests. – Managing of the recharge of the local energy storage system in response to CCU and/or user requests.
User Interface (UI)	– Interaction with users through dedicated web-based or mobile Apps.

A fundamental element in our architectural framework is the “smart box” (see Fig. 1 and Tab. 2). This smart peripheral device provides some significant energy-control services to the system. Firstly, it allows the monitoring of overall energy consumption in the considered home environment. Moreover, through the use of such device, the system is able, in response to CCU and/or user requests, to integrate the energy supplied by the power grid with the energy provided by a local cogeneration system and/or a local energy storage system, and to manage the recharge of the latter.

IV. DATA MANAGEMENT MODEL

According to the devices' interoperability and the users' needs, the information management is fundamental to achieve efficient solutions for CSEs in terms of energy and cost saving, as well as comfort and safety. In the proposed architecture model, the presence of a set of peripheral devices, such as sensors, smart plugs and smart box, makes available a large amount of data, which need to be collected and handled to make decisions.

To this purpose, we propose a centralized knowledge-based management model, whose dataflow is shown in Fig.3.

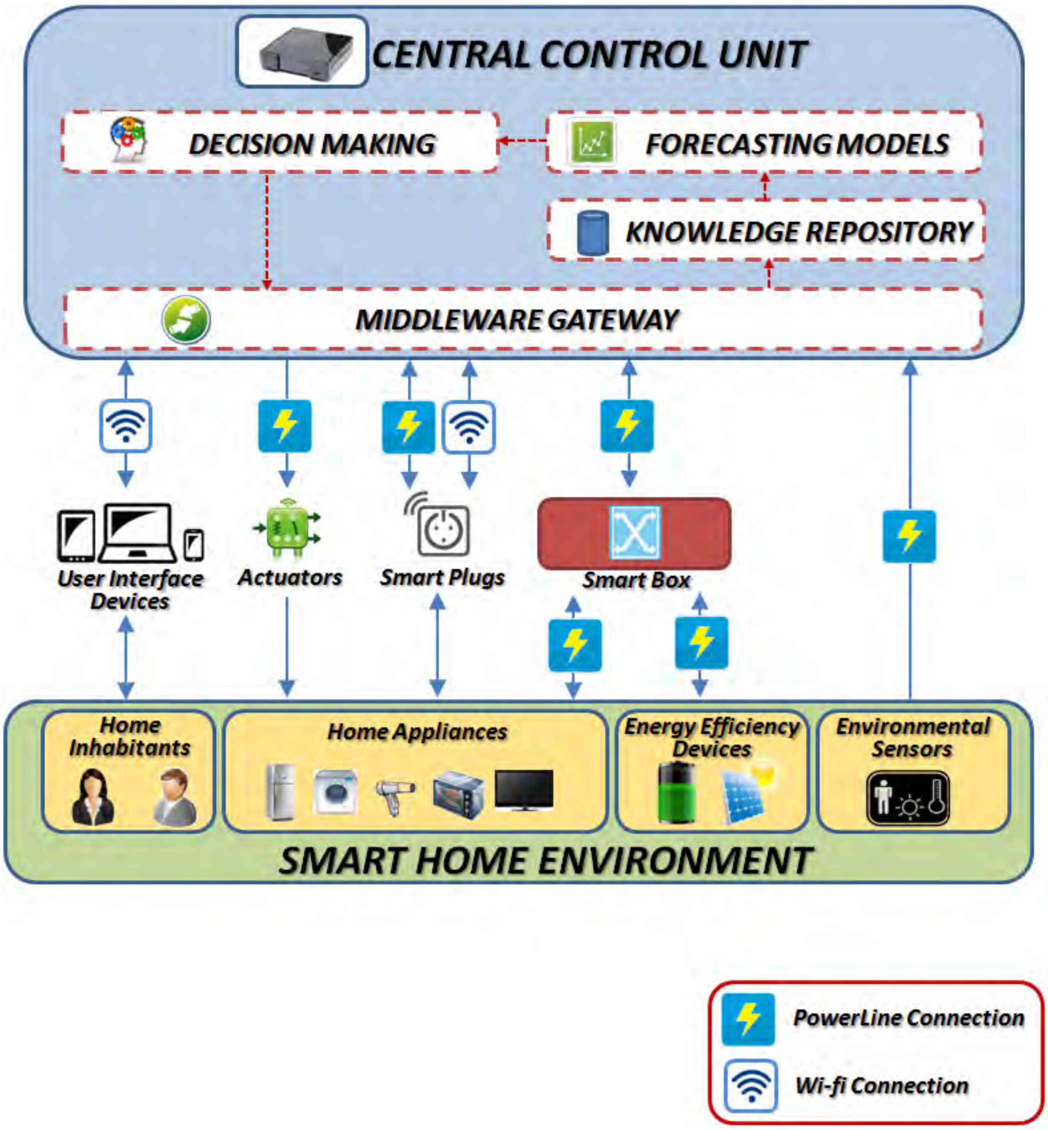

Fig. 3. Flow of information in the proposed knowledge-based management model

As already stated, the Central Control Unit (CCU) represents the data-aggregation gateway of the system. Indeed, it interacts with all the peripheral devices of the systems through powerline and/or wireless technologies, and with the users through web-based or mobile interface Apps. Every information related to machine-to-machine and machine-to-human interactions is collected through a Middleware Gateway and stored in real time in the Knowledge Repository. Then, by taking into account the different information categories and devices' functionalities, data from different devices of the system are interpreted and processed by the CCU for achieving smart home interoperability. Thereby, the management system can perform automatic actions for intelligence-based energy-control services, associated for example to the charging of the energy storage system, to the activation/deactivation of an appliance connected to a smart plug, and so on, with reference to a specific set of decision algorithms and interoperability rules. Clearly, as described in Fig.3, the automated decision-making capability of the proposed system requires the implementation of quantitative forecasting methodologies for analysis of historical data in order to provide the successful prediction of energy consumptions and state conditions of the considered smart home environment and, consequently, the adaptability of the system to the user's habits and needs [14]. For example, accurate forecasting allows planning energy-saving a nd cost-saving actions, such as suggesting which are the best time slots for using some home appliances (e.g., the washing machine, the dishwasher, etc.), or choosing whether to activate/deactivate the electrical appliances connected to the smart plugs, or else suggesting when it is most convenient to recharge and use the energy storage system managed by the smart box or which energy source to be used for charging the energy storage system among those available (i.e., the cogeneration plant or the traditional power grid).

A. Forecasting methodologies for home energy consumption

Energy consumption forecasting is greatly challenging. Worldwide energy consumption is rising fast because of the increase in human population, as well as the continuous pressures for better living standards. Forecasting methodologies are essential not only for accurate investment planning of energy production and distribution, but also to promote best practices in energy consumption in smart home environments.

Over the years, different forecasting techniques have been proposed to model the electricity consumption, both in the classical literature on the time series modeling and in the machine intelligence research. In [15] and, more recently, in [16], reviews of different forecasting methods are provided. In particular, Hahn et al. distinguish forecasting methods firstly by the time-horizon, highlighting the dominance of short-term load forecasting methods in the scientific literature

Taylor and McSharry [17] discuss short-term load forecasting (from one hour- to one day-ahead) using standard forecasting methods with seasonal autoregressions and exponential smoothing which are also carried out in a periodic fashion by treating each hourly load as a daily time series, while Cottet and Smith [18] adopt Bayesian procedures for forecasting high-dimensional vectors of time series. Mohamed and Bodger [19] propose a model based on multiple linear regression analysis, taking into account economic and demographic variables, while Al-Ghandoor et al. [20] define a forecasting method based on multivariate linear regression of time series in order to identify the main drivers behind electricity consumption.

Zhao and Magoules [21] propose a review on forecasting methods for building energy consumption, classifying forecasting methods into two main categories: classical time series and regression methods, and artificial intelligence and computational intelligence methods, underlining benefits and limits of proposed approaches.

Moreover, several authors [21] [22] [23] point out the importance of hybrid approaches which combine two or more different approaches in order to overcome some drawbacks of the original methods.

Starting from the approach presented in [24], we propose a hybrid methodology for forecasting energy consumption and appliances utilization in smart home environment by taking into account the quantitative analysis of historical data. In particular, this methodology is based on a deterministic forecasting method (that includes seasonal component and exponential smoothing) for predicting the overall home energy consumption, and a probabilistic approach for forecasting hourly energy consumption of each smart home appliance.

Firstly, in order to define appropriate models for energy consumption forecasting, it is necessary to identify the characteristics of time series related to the historical energy consumption data. Harris and Lon-Mu [25] have analysed a 30-years data series from South Eastern States of USA in order to study the dynamic relationships between electricity consumption and other variables, such as weather and user behaviour, finding a high component of seasonality in electricity demand.

Even if the exact shape of the load curve depends on the region, the climatic conditions and the consumers' behaviour, long-term time series (about one year) present a specific seasonality: indeed, the electricity demand is generically high on cold days (due to electric heating), as well as on hot days (due to the increased usage of air-conditioning) [26]. In particular, it is possible to observe two seasonal cycles in yearly home energy consumption: an intra-daily cycle (i.e., the daily load curve or load profile) and a weekly cycle. Because of work habits of house occupants, the weekly cycle usually shows two main groups: weekdays and weekends [18]. While in office buildings the operation time is normally in working hours, usually starting from 8am until l7pm, in the residential sector, the electricity usage is maximum in the evening when all family members are at home [23]. Of course, additionally ‘‘regular” exceptional cases (e.g. holidays), can be identified [24].

These considerations about characteristics of time series related to home energy consumption lead to choose, among forecasting methods based on quantitative analysis of time series, those that take into account the seasonality component. To this purpose, the standard Holt–Winters exponential smoothing formulation has been extended in order to catch the two seasonal cycles (i.e., intra-daily and weekly) observed in the electricity demand time series. This leads to the introduction of an additional seasonal index in the original formulation, as well as an additional equation for the introduced index.

Let us consider $y_t, t = 1, \dots T$ as the historical time series of hourly load in a smart home environment. We indicate with D and W, respectively, the intra-daily and the weekly seasonality components. Assuming that $y_t, t = 1, \dots T$ is a continuous and regular time series, we indicate a and b as the smoothed level and the linear trend in the long run, respectively. Moreover, indicating with C_D the duration of the daily cycle and with C_W the duration of the weekly cycle, we assume, without loss of generality, that the available historical data are sufficient to cover an integer number $k_D = \frac{T}{C_D}$ of daily cycles and an integer number $k_W = \frac{T}{C_D}$ of weekly cycles.

Therefore, the formulation of the chosen forecasting model, based on the multiplicative seasonality, is given by

$$\begin{cases} a_t = \alpha \dfrac{y_t}{D_t\, W_t} + (1-\alpha)a_{t-1} + b_{t-1} & t = 1, \dots, T \quad (1) \\ b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} & t = 1, \dots, T \quad (2) \\ D_t = \delta\left(\dfrac{y_t}{a_{(t-C_D)}\, W_t}\right) + (1-\delta)D_{(t-C_D)} & t = C_D + 1, \dots, T \quad (3) \\ W_t = \gamma\left(\dfrac{y_t}{a_{(t-C_W)}\, D_t}\right) + (1-\gamma)W_{(t-C_W)} & t = C_W + 1, \dots, T \quad (4) \\ p_T(\tau) = (a_T + \tau\, b_T)D_{T+\tau}\, W_{T+\tau} + \omega^\tau \left(y_T - \left((a_{T-1} + b_{T-1})D_T\, W_T\right)\right) & \quad (5) \end{cases}$$

Assuming that the forecast origin is T, in equation (5) $p_T(\tau)$ represents the τ-step-ahead forecast, while the term involving ω^τ represents an adjustment for first-order autocorrelation. The smoothing parameters $\alpha, \beta, \delta, \gamma \in [0, 1]$ and ω are estimated in a single procedure by minimizing the sum of squared one step-ahead forecast errors, while the initial values for the level, trend and seasonal components are estimated by averaging the early observations. In our implementation of the method, the duration of the daily and weekly cycles, i.e. C_D and C_W, have been set as follows: $C_D = 24$, $C_W = 168$.

While this approach is useful for appropriately predicting the overall energy consumption in a smart home environment (because of the regularity of the electricity demand time series), such model is not well suited for forecasting the energy consumption of each device/appliance within the CSE, essentially due to the presence of many null values in the time series of single appliances (because of their discontinuous usage). For this reason, in this case, we treat each hour of the day as a separate time series, according to what reported in [24].

Let us assume $A = \{A_1, \dots, A_n\}$ as the set of appliances in our CSE and $J = \{j_1, \dots, j_m\}$ as the set of days accounted in the time series horizon. Therefore, for each appliance A_i, and for each hour *h* of the day, we consider a binary vector $v^{i,h}$ where each element $v_j^{i,h}$ can assume the following values:

$$\begin{cases} 1 & \text{if the appliance } i \text{ was turned on at hour } h \text{ of the } j\text{-th day} \\ 0 & \text{otherwise} \end{cases}$$

In other words, for each appliance *i*, we have a set of 24 *m*-length vectors (where *m* represents the number of days accounted in the time series horizon), whose $v_j^{i,h}$ elements represents the state (on/off) of the *i-th* appliance during the *h-th* hour of the *j-th* day. Similarly, we consider a vector $w^{i,h}$, where each element $w_j^{i,h}$ contain the load absorbed by A_i during the *h-th* hour of the *j-th* day.

In order to identify a certain regularity in the binary sequence $v^{i,h}$, and then predict if the next value (i.e., *m*+1) will be 0 or 1, each vector has to be analysed. Initially, the pattern to be searched has unit length and corresponds to the last value of the vector $v^{i,h}$. Therefore, it is necessary to count the number of times that this pattern is repeated (*count pattern*) in the vector $v^{i,h}$ and the number of times that such pattern is followed in the sequence by a 1 (*count one*) or a 0 (*count zero*). This allows calculating the probability of the next value as follows:

$$P(0|pattern) = \frac{count\ zero}{count\ pattern} \qquad P(1|pattern) = \frac{count\ one}{count\ pattern}$$

This procedure has to be repeated by increasing, in each iteration, the length of the pattern to be recognized (therefore, in the second iteration, the pattern will be composed by the last two values of the vector $v^{i,h}$, in the third iteration by the last three values of $v^{i,h}$, and so on). Of course, the predicted next value will be associated to the one with the highest probability among the various analysed patterns. If such value will be 0, the algorithm stops, otherwise it is necessary to estimate the load $w_{j+1}^{i,h}$ that the appliance A_i will absorb during the next day at the *h-th* time slot. In this case, we consider the probability distribution of the absorbed load $w^{i,h}$, excluding null entries

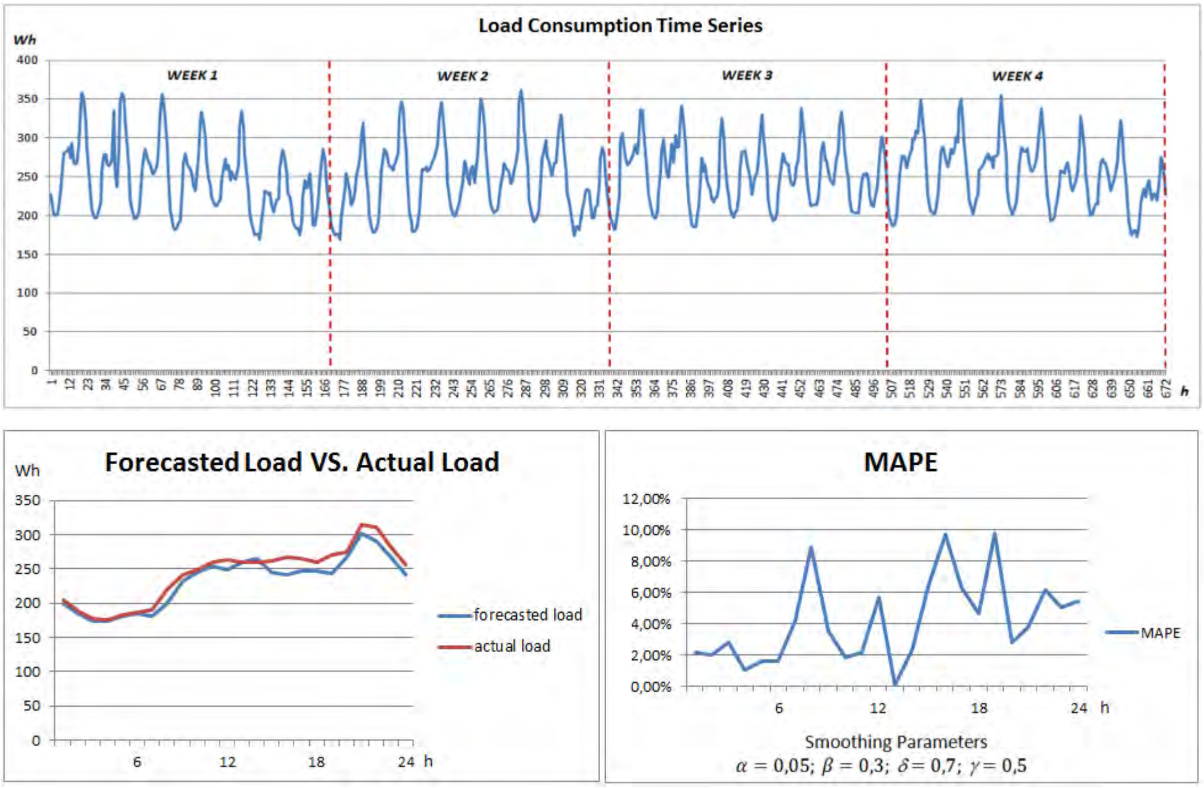

Fig. 4. The considered energy consumption time series in our test (on the top) and the comparison between forecasted and measured values (on the bottom)

For testing purposes, we have applied the proposed forecasting model to a real home energy consumption time series, taken from the website of the Italian grid operator for electricity transmission [27]. In particular, the considered energy consumption time series (see Fig. 3) refers to a 28-days time horizon, from 17th of March to 13th of April 2014. Fig. 3 also reports the comparison of the results obtained through the implementation of our forecasting model with the real data measured in 14th of April 2014, showing a good fit between the forecasted values and the real ones. The smoothing parameters α=0.05; β=0.3; δ=0.7; γ=0.5 have been obtained by minimizing the Mean Absolute Percentage Error (MAPE). The calculated overall value of MAPE is 4,17%. A more complete discussion is available in [28].

V. Conclusions and Future Works

In line with the goals of Europe 2020 strategy, energy resource saving represent a key issue for sustainable development [29] [30]. Among the various technological solutions for reducing energy consumption in home environments, the so called “building automation and control systems” (BACS) represent high performance and low impact solutions for energy efficiency. In this context, the proposed system offers in prospect the opportunity to improve the energy performance and electricity cost saving of residential buildings, featuring at the same time a low architectural impact due to the use of wireless and/or powerline technologies. This makes such kind of solution well suitable to existing houses.

The development of the hardware components (such as smart plugs, smart box and Central Control Unit) as well as the knowledge-based management software of the system is still ongoing. Further works will concerns the testing of the system prototype in laboratory and in real home environments with different characteristics in order to validate our CSE architectural framework and the proposed management model in terms of cost and energy saving. For what concerns the forecasting methodology, we intend to compare the performance of our model with other sophisticated models proposed in literature, such as the seasonal ARIMA (Autoregressive integrated moving average) models, SVM (Support Vector Machine) and neural network approaches.

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