A Framework for Energy-Efficiency in Smart Home Environments

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[1] SMART BUILDING: LA NUOVA TECNOLOGIA PER L'EFFICIENZA ENERGETICA E LA QUALITÀ DELLA VITA
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Abstract. A resource-efficient Europe is a pillar of the EU 2020 program which aims at smart, sustainable, inclusive growth. The diffusion of smart networked environments, wherein humans, intelligent agents and devices collaborate, is fundamental for achieving energy-efficiency in buildings. In this context, this paper deals with the topic of Smart Home Environments (SHEs), where users can exploit multimedia services to interact with heterogeneous and interconnected smart appliances in order to save energy, reduce costs and improve users' comfort and safety. In particular, we propose an interoperable architectural framework and a related knowledge-based management model, associated with a specific forecasting model, for monitoring and managing energy consumption in SHEs.

Keywords: Energy Efficiency, Smart Home Environment (SHE), Interoperable Home Energy Management Systems (HEMS), Information Management Model, Energy Consumption Forecasting.

1 Introduction

Recent years have been characterized by a growing awareness towards sustainability and energy-efficiency issues, which have taken a central role in the debate on energy policies. In this scenario, it has been clearly shown that energy efficiency in the buildings sector is one of the keys for reducing overall energy consumption and greenhouse emissions [1]. Nowadays, commercial and residential buildings represents nearly 40% of yearly total energy consumption in most developed countries and are responsible for a similar level of global CO_2 emissions [2]. In particular, residential buildings are becoming one of the major contributors to the countries energy balances, due to growth in population, increasing demand for home services and comfort levels, and rise in time spent in them.

A large number of options can be implemented to reduce the end-use energy consumption and greenhouse gas (GHG) emissions in the residential sector. These also include optimizing the home energy efficiency through improving the building envelope characteristics, replacing existing heating equipment and household appliances, using higher efficient lighting sources and switching to less carbon-intensive fuels for space and domestic hot water heating. Among the various approaches for optimizing energy efficiency in buildings, collaborative and interactive Home Energy Management Systems (HEMSs) offer an interesting alternative to save energy, reduce costs and, at the same time, improve users' comfort and safety in home environments [3].

Until a few years ago, the lack of really interoperable and collaborative HEMSs has represented a matter for monitoring and managing in real time energy consumption in a home environment [4]. Recent advances in Information and Communication Technologies (ICT) tools and Internet of Things (IoT) approaches have led to the development of various solutions of HEMSs for "Smart Home Environments" (SHEs), featuring heterogeneous and interconnected smart home devices with local intelligence and connectivity services and, therefore, able to acquire, manage and apply knowledge about the environment, to interact with other smart objects and to adapt their behaviour according to the needs of the home inhabitants [5]. A deep review of such systems and technologies is presented in [6]. Nevertheless, the interoperability between typical home sub-systems and appliances still remains an open issue, also due to the different system architectures, device characteristics, communication protocols and syntactic rules of the different proposed solutions [6].

In this context, we propose a general architectural framework and a knowledge-based management model for monitoring and managing in real time energy consumption in typical real home environments, where most of the existing heterogeneous sub-systems and appliances are lacking of intelligence and connectivity services. In particular, in order to achieve energy and cost saving, as well as users' comfort and safety, the proposed architecture features smart peripheral devices and a central management system, which provide the network interoperability and the implementation of some energy-control services, also performed on the basis of energy consumption predictions by exploiting a specific forecasting model.

2 Smart Home Environment Architectural Framework

The traditional concept of collaborative networks as aggregation of companies and their supply chains is evolving toward a wider concept [7] known as "collaborative ecosystems", i.e. smart networked environments wherein humans, organizations, intelligent agents and devices collaborate. In fact, notions such as sensing enterprises, collective awareness systems, smart cities, and ambient intelligence, that are emerging in recent years, are expressions of new collaborative ecosystem paradigm, being applicable in many fields, such as security, transportation, construction, education and manufacturing.

This concept can be also applied for energy-efficiency in SHEs, where heterogeneous devices need to perform joint execution of tasks in an efficient and collaborative manner to be really interoperable [6], also according to the users' needs and habits, and to the particular state conditions of the considered environment. Indeed, being distributed architectures, SHEs need a certain degree of interoperability to manage sub-systems and appliances which are typically developed in isolation and, consequently, feature different operating systems and connectivity services [4].

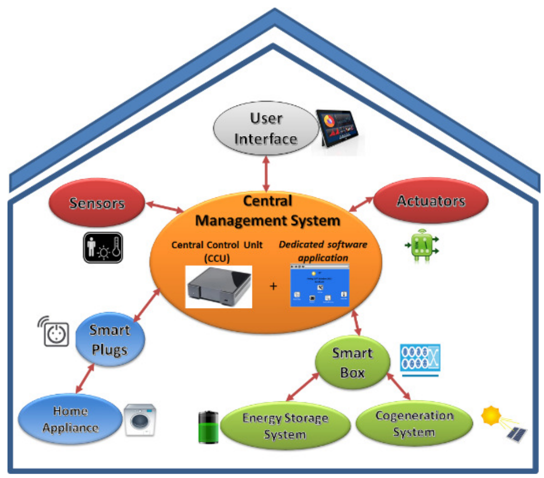

Fig. 1. Proposed architectural framework for SHE.

In order to achieve the interoperability in existing home environments, the proposed 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, TV, etc.) is provided by the use of a specific smart peripheral device, shown as "smart plug" in Fig.1, thus adding intelligence and connectivity services to the related appliance. In particular, as reported in Tab. 2, 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.

Another fundamental element in the proposed framework is the "smart box" (see Fig. 1 and Tab. 1). This 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.

Table 1. 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 based on 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.

3 Information Management Model for Energy-Control Services

The proposed architectural framework features a set of peripheral devices, such as sensors, smart plugs and smart box, which make available a large quantity of data within the considered home environment. In order to fully exploit such amount of information and the device interoperability, it is needed to define a fruitful knowledge-based management model whereby all data can be collected, interpreted and handled to support real-time decisions for energy- and cost-control services, as well as for comfort and safety purposes, also on the basis of users' needs.

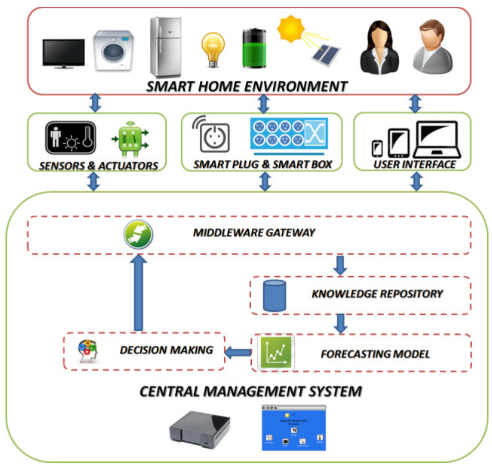

Fig. 2. Proposed information management model for SHE.

Fig. 2 shows the proposed information management model, according to the previously described architectural framework. As already stated, the central smart management system operates as data-aggregation gateway. Indeed, the CCU interacts with all involved actors within the SHE through different technologies: for example, it can communicate with all the peripheral devices (smart plugs, smart box, sensors and actuators) through powerline and/or wireless technologies, and with the users and the energy service provider through dedicated web-based interface Apps. Therefore, all information about machine-to-machine and machine-to-human interactions is collected through the Middleware Gateway, and stored in real-time in the Knowledge Repository, as described in Fig. 2. Then, the central management system interprets and processes all data in order to make real-time decisions and, consequently, to perform automatic actions for intelligence-based energy-control services (such as the smart scheduling of events and scenarios, the energy overload management, and the smart scheduling of the recharge of the local energy storage system), also on the basis of energy consumption predictions.

4 Energy Consumption Forecasting Model

As highlighted in Fig. 2, in most cases, the implementation of management services requires a foregoing prediction of energy consumptions and environmental state conditions in the considered SHE, through the application of quantitative forecasting methodologies for analysis of historical data, in order to provide the adaptability of the system to the user's habits and needs [8]. For example, accurate forecasting allows scheduling energy- and cost-saving actions, such as suggesting which are the best time slots for using some home appliances or else when it is most convenient to recharge and use the energy storage system managed through the smart box, or else 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).

In order to define an appropriate model for home energy consumption forecasting, firstly, it is necessary to identify the characteristics of time series related to the historical energy consumption data. To this purpose, several authors have been observed that, even if the exact shape of the energy load curve depends on the region, the climatic conditions and the users' behaviour, long-term series present a specific seasonality component and, consequently, a certain degree of regularity [9-10]. In particular, it is possible to observe two seasonal cycles in yearly home energy consumption: an intra-daily cycle (i.e. the daily load profile) and a weekly cycle [10]. By taking into account these considerations about the characteristics of time series related to home energy consumption and basing on the results shown in [11], in this work we propose an extension of the Holt–Winters exponential smoothing formulation for the energy consumption forecasting model in SHE, 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 $y_t, t = 1, \ldots T$ as the historical time series of hourly energy load in a SHE. We indicate with *D* and *W*, respectively, the intra-daily and the weekly seasonality components. Assuming that $y_t, t = 1, \ldots T$ 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 proposed forecasting model, based on the multiplicative seasonality, is given by

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

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. It is worth noting that the prediction is carried out for a day-ahead time horizon. 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: $C_D = 24$, $C_W = 168$. 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 time series.

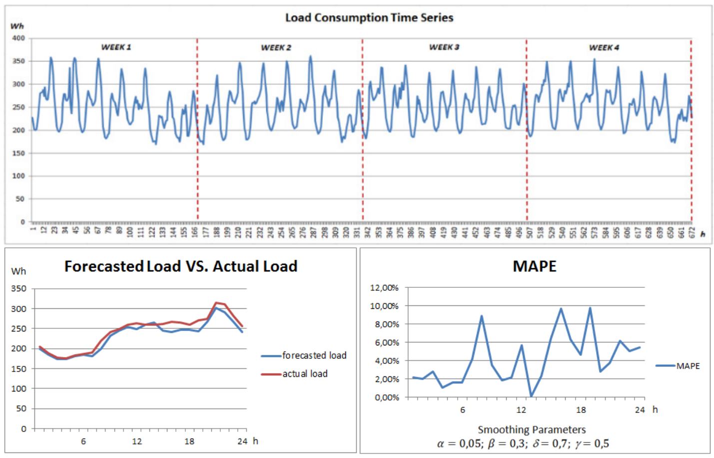

Fig. 3. The considered energy consumption time series in our test (on the top) and the comparison between forecasted and measured values (on the bottom).

For testing purposes, we have applied the proposed forecasting model to a real home energy consumption time series (see Fig. 3), taken from the website of the Italian grid operator for electricity transmission [12]. In particular, the considered energy consumption time series 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%.

4 Conclusions and Future Works

An energy resource-efficient Europe is a pillar of the EU 2020 strategy which aims at sustainable development. Over recent years, it has been widely shown that the diffusion of smart networked environments, wherein humans, intelligent agents and devices collaborate, is fundamental for achieving energy-efficiency in buildings. In this context, this paper proposes a general architectural framework and a related knowledge-based information management model, associated with a specific energy consumption forecasting model, for monitoring and managing SHEs, where heterogeneous and interconnected smart devices interact with the goal of saving energy, reducing costs, and as well as improving users' comfort and safety. Moreover, the proposed SHE framework, featuring a centralized model and a set of smart peripheral devices, is characterized by a low architectural impact, also due to the use of wireless and/or powerline technologies, thus making it well suited to existing home environments. The development of the hardware components (such as smart plugs, smart box and Central Control Unit), as well as of the knowledge-based management software of the system prototype is still ongoing, according to what presented in this paper. Once completed the development of the HW and SW components, future works will concern the testing of the system prototype in laboratory and in real home environments in order to validate our SHE architectural framework and the proposed information management model in terms of cost and energy saving.

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References

1. Perez-Lombard, L., Ortiz, J., Pout, C.: A review on buildings energy consumption information. Energy and Buildings, vol. 40, pp. 394-398, (2008).
2. D&R International, Ltd: 2011 Buildings Energy Data Book. Prepared for the Building Technologies Program Energy Efficiency and Renewable Energy, (2012).
3. Niyato, D., Xiao, L., Wang, P.: Machine-to-machine communications for home energy management system in smart grid. IEEE Communications Magazine, 49(4): 53-59, (2011).
4. Perumal, T., Ramli, A.R., Leong, C.Y., Mansor, S., Samsudin, K.: Interoperability among Heterogeneous Systems in Smart Home Environment. IEEE International Conference on Signal Image Technology and Internet Based Systems, (SITIS '08), pp. 177-186, (2008).
5. Elmenreich, W., Egarter, D.: Design guidelines for smart appliances. Proc. of the Tenth Workshop on Intelligent Solutions in Embedded Systems (WISES), pp. 76-82, (2012).
6. Peruzzini, M., Germani, M., Papetti, A., Capitanelli, A.: Smart Home Information Management System for Energy-Efficient Networks. Collaborative Systems for Reindustrialization, vol. 408, pp. 393-401, (2013).
7. Volpentesta, A. P., Felicetti, A. M.: Identifying opinion leaders in time-dependent commercial social networks. 13th IFIP Working Conference on Virtual Enterprise, Collaborative Networks in the Internet of Services, PRO-VE 2012. Springer Berlin Heidelberg, pp. 571-581, (2012)
8. Das, S.K, Cook, D.J.: Designing Smart Environments: A Paradigm Based on Learning and Prediction. Lecture Notes in Computer Science, Pattern Recognition and Machine Intelligence, vol. 3776, pp. 80-90, (2005).
9. Hippert, H.S., Pedreira, C.E., Souza, R.C.: Neural networks for short-term load forecasting: A review and evaluation. IEEE Transactions on Power Systems, 16 (1): 44–55, (2001).
10. Taylor, J. W., McSharry, P. E.: Short-term load forecasting methods: An evaluation based on european data. IEEE Transactions on Power Systems, 22 (4): 2213-2219, (2007).
11. Soares, L. J., Medeiros, M. C.: Modeling and forecasting short-term electricity load: A comparison of methods with an application to Brazilian data. International Journal of Forecasting, vol. 24, no. 4, pp. 630-644, (2008).
12. Terna S.p.A., www.terna.it