A framework for home energy management and its experimental validation

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Abstract With the Smart Grid revolution and the increasing interest in renewable energy sources, the management of the electricity consumption and production of individual households and small residential communities is becoming an essential element of new power systems. The electric energy chain can greatly benefit from a flexible interaction with end-users based on the optimization of load profiles and the exploitation of local generation and energy storage. This paper proposes a framework for the development of a complete energy management system for individual residential units and small communities of domestic users, taking into account both the power system and the final users' perspectives. All the main elements of the framework are considered, and contributions are provided on the users' habits profiling, electricity generation forecast, energy load, and storage optimization. Specifically, we propose a linear regression model to predict the photovoltaic panels production, a stochastic method to forecast the home appliances usage, and two optimization models to optimize the electricity management of residential users with the goal of minimizing their bills. The study shows that it is possible to reduce the energy bill of residential users through the electricity optimization driven by dynamic energy prices. Moreover, remarkable improvements of the electric grid efficiency can be achieved with the cooperation among users, confirming that services for the coordination of the demand of groups of users allow huge benefits on the power system performance.

Keywords Smart grids · Demand side management · Linear regression modeling · Users profiling · Mixed integer linear programming · Final user's awareness

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Nomenclature

Acronyms

CPP	Contractual peak power
DG	Dispersed generation
DSL	Digital subscriber line
DSO	Distribution system operator
ESS	Energy storage system
EV	Electric vehicle
GCPP	Global contractual peak power
GUI	Graphical user interface
HEM	Home energy management
HVAC	Heating, ventilation, and air conditioning

ICT Information and communication technology
MILP Mixed integer linear programming
PV Photovoltaic
RES Renewable energy source
TOU Time of usage
WPSN Wireless power meter sensor network
WSN Wireless sensor network

Mathematical notations

η Charge/discharge efficiency of the ESS $[p.u.]$

$\eta_{rel}(Ir', T')$ Efficiency of the PV power plant, depending on the solar radiance acting on the PV panel, Ir', and on the PV modules temperature, T' $[p.u.]$

$\omega_{bt}^{C}, \omega_{bt}^{D}$ Binary variables equal to 1 if the ESS $b \in B$ is charging $\left(\omega_{bt}^{C}\right)$, or discharging $\left(\omega_{bt}^{D}\right)$, in the time slot $t \in T$ and 0 otherwise

π_t^{CPP} Contractual peak power limit at the time slot $t \in T$ $[W]$

π_t^{GCPP} Global contractual peak power limit at the time slot $t \in T$ $[W]$

π_t^{PV} PV power generation at time $t \in T$ $[W]$

σ Variance of the critical profile representing, in each time slot $t \in T$, the probability that an appliance is turned on $[min.]$

$\tau_b^{max}, \tau_b^{min}, \vartheta_b^{max}, \vartheta_b^{min}$ Maximum and minimum charge (τ_b) and discharge (ϑ_b) rates of the ESS $b \in B$ [Wh/(15 min)]

A Set of home appliances of each user considered in the energy optimization model

C_b Capacity of the ESS $b \in B$ $[Wh]$

c_t, g_t Purchase (c_t) and selling (g_t) energy prices at the time slot $t \in T$ [€$/Wh$]

d_a Real duration of the appliance activity $a \in A$ [min]

$d_{an}^{\star}$ Predicted duration of the n^{th} starting of the appliance $a \in A$ for the next day, with $n \in \{1, 2, .., N_a^{\star}\}$ [min]

DB^{PF}, DB^{NPF} Perfect and Not Perfect Forecasting based Daily Bill [€]

$E_{status}, E_{time}, E_{duration}$ Forecasting error of the device status [p.u.], starting [min] and duration [min]

E_t Forecasting error of the PV power generation at the time slot $t \in T$ $[W]$

e_t Value of the conventional PV error profile at the time slot $t \in T$ $[p.u.]$

F_a Set of phases of each appliance $a \in A$ considered in the energy optimization model

G_t Proportionality coefficient representing the PV power plant model as evaluated in the time slot $t \in T$ $[m^2]$

I Status string I, whose elements, i, are equal to 1 if the device has been used on the day i, and 0 otherwise

ir_t Value of solar radiance made available by the Web service provider for the time slot $t \in T$ $[W/m^2]$

Ir' Value of solar radiance normalized with regard to the STC: $Ir' = Ir/Ir_{STC}$ $[p.u.]$

L Length of the daily status string S used to predict the devices usage $[p.u.]$

m Mean value of the PV forecasting error $[W]$

l_{af} Energy load required by the activity $a \in A$ in the phase $f \in F_a$ $[Wh/(15min.)]$

N Number of days of the learning period of the devices usage forecast algorithm $[p.u.]$

$N_a^{\star}$ Number of times the appliance $a \in A$ is predicted to be used on the next day $[p.u.]$

NO Number of Occurrences in I of S $[p.u.]$

n_a Run-time of the activity $a \in A$ expressed in terms of time slots $[p.u.]$

p_{at} Amount of energy requested by the activity $a \in A$ in the time slot $t \in T$ $[Wh/(15min.)]$

$P\left(Ir', T'_{mod}\right)$ Power generation of the PV power plant $[W]$

P^E, P^F Effective and forecast system parameters

P_{STC} PV power in the STC $[W]$

p_t Estimated power generation of the PV power plant at the time slot $t \in T$ $[W]$

p'_t Actual power generation of the PV power plant at the time slot $t \in T$ $[W]$

q_a Activity of the appliance $a \in A$ $[p.u.]$

S String representing the status of the device in the last L days of the monitoring period

SOC_{bt} State of charge of the ESS $b \in B$ at the time slot $t \in T$ [%] $[p.u.]$

SOC_b^{ini} Initial value of the state of charge of the ESS $b \in B$ [%]

SOC_b^{max}, SOC_b^{min} Maximum and minimum state of charge of the ESS $b \in B$ [%]

$Sq(G)$ Sum of the squares of the deviations between the estimated (p_t) and the actual $\left(p'_t\right)$ PV generation $[W^2]$

$S+0, S+1$ Status strings followed by 0 or 1

S^F Forecast-based scheduling

ST_a, ET_a Starting and ending time of the activity $a \in A$ [min]

STC Standard Test Conditions equivalent to an irradiance intensity of 1 kW/m^2

T Set of home time slots considered in the energy optimization model

T' Temperature of the PV module reported to the STC: $T' = T_{mod} - T_{modSTC}$ $[K]$

$t_{an}^{\star}$ Predicted start time associated with the n^{th} predicted usage of the device $a \in A$ for the next day, with $n \in \{1, 2, .., N_a^{\star}\}$ [min]

t_a Real start time of the appliance $a \in A$ $[min.]$

U Set of users involved in the multi-user optimization model

u_a Real status of the appliance $a \in A$, which is equal to 1 if the device is used and 0 otherwise $[p.u.]$

$u_a^{\star}$ Forecast status of the appliance $a \in A$, which is equal to 1 if the device is predicted to be used on the next day and 0 otherwise $[p.u.]$

v_{bt}^C, v_{bt}^D Charge $\left(v_{bt}^C\right)$ and discharge $\left(v_{bt}^D\right)$ rates of the ESS $b \in B$ at the time slot $t \in T$ [Wh/(15 min)]

W^C Set of the clustering windows, w_a^C, of the appliance $a \in A$

w_a^C Clustering window of the appliance $a \in A$ [min]

x_{at} Binary variable equal to 1 if the activity $a \in A$ starts in the time slot $t \in T$, and 0 otherwise $[p.u.]$

z_t, y_t Amount of energy bought (z_t) and sold (y_t) at the time slot $t \in T$ $[Wh]$

z_t^u, y_t^u Amount of energy bought $\left(z_t^u\right)$ and sold $\left(y_t^u\right)$ at the time slot $t \in T$ by user $u \in U$ in the multi-user optimization model $[Wh]$

Introduction

In the future Smart Grid scenario, residential users are expected to play a key role in the power systems operations, by efficiently and flexibly managing their electricity demand. Residential users are indeed responsible for a significant portion of the world electricity needs (i.e., approximately 30 %), but this demand is currently mainly driven by habits of users that are unaware of the grid requirements (European Environment Agency 2014).

In the domestic context, time of use (TOU) tariffs are a clear attempt to make users responsible for the issues related to the electricity supply: TOU tariffs have been recently introduced (generally with small impacts on users' habits and on the network performance) to drive the users to shift their consumptions out of the peak hours (European Parliament 2009). Another case of users involvement in the power systems management is represented by the limitation of the instantaneous power absorption introduced to reduce demand peaks and to attenuate the impact of loads on the electricity grid (US Department of Energy 2012). The just mentioned initiatives demonstrate that an improvement of the users' awareness is essential to significantly increase the power system performance.

Today, the integration of renewable energy sources (RESs) is one of the most critical challenges of the electric grid: The increasing diffusion of RESs is changing the traditional approach of managing the generation of electricity, amplifying the need of a more strict control, and predictability of power flows over the grid. In fact, in the past, the generation was centralized in a small number of large power plants on the transmission system; nowadays, there is a huge number of medium-small size power plants connected to distribution electricity networks. Unlike the traditional power plants, such units are unable to change their power injections according to the power system requirements. As a consequence, the power dispatching results more difficult than in the past, and new instruments are required to ensure the real-time balance between load and generation. Loads management is one of the tools available for this purpose: It allows the (partial) adjustment of the power demand according to the generation and can be used to turn the once-intermittent and uncontrollable load into a programmable one. Energy storage systems (ESSs) are another powerful resource of flexibility that can be used to balance electricity demand and generation over time.

Although the network operation cannot be analyzed without considering the final users' perspective, loads, RESs, and ESSs management cannot be left to the users, since this new difficult task would significantly affect their everyday life. Therefore, an intelligent infrastructure based on information and communication technologies (ICTs) tools is needed, which can deal with all the decision variables while minimizing the effort required to end-users and providing them with information and suggestions on their electricity consumption (Álvarez Bel et al. 2013). Although a single house has a small impact on the overall system performance, the optimal management of its electricity demand may produce a significant efficiency improvement. Further, by coordinating and optimizing a set of households, greater benefits may be obtained, without requiring additional flexibility to single users.

In this paper, we propose a home energy management (HEM) framework that includes a set of tools for managing the electricity demand of individual households and small users communities, by exploiting the potentials of the Smart Grid and of ICTs. Specifically, in the Smart Grid, a huge amount of data will be available to the users, such as real-time information on the economic value of energy. At the same time, users will be able to send data to the grid, providing, for example, a feedback on the energy consumption of each home appliance. All these data can be used by demand-side management mechanisms that can support residential users in shaping their load profile, with a twofold aim, reducing their bills or saving energy, but also using the energy in a more efficient way in accordance with the power system requirements. The described framework (BEE Project 2013) has been implemented within the BEE Project, a multi-area research project activated by a multidisciplinary research group of Politecnico di Milano (Department of Energy and ICT Department).

We carefully analyze all the key elements of the system and provide contributions to:

- Modeling and optimizing users' electricity consumption and storage according to the given price signals (to this purpose, the Italian TOU and dynamic tariffs are considered as possible signals).
- Forecast of system parameters in terms of both the electricity generation of the domestics PhotoVoltaic (PV) power plant and the users' habits, so as to reduce the effort required to users in managing the proposed system.

The paper is organized in eight sections: section "Power system needs for home energy management" introduces the motivations on the basis of the deployment of HEM solutions; section "State of the art on home energy management" presents the state of the art on HEM systems; section "The BEE home energy management architecture" depicts the proposed energy management architecture, deepening in sections "Prediction of devices usage," "Prediction of electricity generation", and "Electric energy optimization" each module of the framework. In section "Experimental tests methodology," the case study, as well as the methodology used in our tests, is explained, while in section "Experimental tests: numerical results", the numerical results of these tests are provided. Finally, in section "Discussion on results and contributions", the achievements of the research are discussed, and in section "Conclusion," conclusions are provided.

Power system needs for home energy management

The Smart Grid is an electricity network that can cost-efficiently integrate the behavior and actions of all users connected to it (i.e., generators, consumers, and prosumers) in order to ensure economically-efficient and sustainable power systems with low losses and high levels of quality and security of supply and safety (European Regulators' Group for Electricity and Gas 2009). The Smart Grid concept ranges over all the electric power systems architecture, from centralized to dispersed generation (DG) (typically based on RESs), from transmission to distribution grids, and from classical inelastic load models to new demand response services.

The main driver for Smart Grids is represented by the DG increasing diffusion and the issues related to it. The Smart Grid is the strategy to address these issues by means of exploiting innovative products and services combined with intelligent monitoring, control, communication, and self-healing technologies.

On distribution grids, DG power injections can lead to power quality problems, such as transients and harmonic distortions. The grid protection also becomes an issue, mainly to avoid unintentional islanding (Delfanti et al. 2010). Another factor limiting the DG diffusion is the voltage rise caused by mismatching production and demand: Every time the production exceeds the demand, power flows over the network reverse. In this condition, if DG injections are low, there are beneficial effects on voltage drops along distribution feeders, on customers voltages, as well as on network losses. However, if DG injections are too high (i.e., low load conditions), the voltage can potentially exceed the prescribed limits, currents increase, and thus losses, worsening the overall efficiency of distribution service (Delfanti et al. 2013).

In the future, DG impact on distribution networks will be attenuated and/or avoided by the implementation of "smart" solutions within distribution grids (Italian Regulatory Authority for Electricity and Gas 2010b). However, the extensive integration of DG, especially from solar and wind sources, affects the power system operation also on a larger scale. RES intermittent injections, for example, impacts on the power system stability and conventional power production (Widén et al. 2009), thus motivating an improvement in the flexibility and management of the load/generation resources underlying the grids.

In the new Smart Grid paradigm, in addition to the new needs in terms of sustainability and energy savings, there is a great expectation on domestic users energy management to improve the system efficiency, also in reference to DG issues. The attention is growing even more with the increasing penetration of microgeneration units, i.e., with the new market actor called "prosumer" (Eurelectric 2011; European Regulators' Group for Electricity and Gas 2011).

Generally, load management solutions are used to schedule the appliances of domestic users (according to given economical quantities), for a single house or for multiple users (Lappegard Hauge et al. 2013), in order to yield potential savings in the whole power system. Although the economic benefits for each single user due to the energy management may be limited, the control of single houses can drive to important savings at national level on the whole electric energy chain (e.g., postponement of network reinforcements and improvements in efficiency), motivating the integration and coordination of a large number of houses and buildings.

By using loads shifting solutions to reduce peak loads, investments needed to provide additional network capacity can be avoided or deferred, and the utilization of transmission and distribution assets can be thus improved. This result, given by the loads flexibility (Faruqui et al. 2013), is particularly beneficial especially if considering that the peak consumption typically occurs only in a few hours a year.

The energy management is also a useful solution to increase the predictability of users' exchange profiles. In this way, the impact of RESs unpredictability on power system can be attenuated, liming the costs needed to acquire the relevant ancillary services on the market, and consequently achieving a greater efficiency in the electricity supply service (Clastres et al. 2010).

Demand management tools are also effective in managing electricity costs by means of shifting consumptions to low-priced electricity hours, arbitrating in the wholesale market. In the literature, it is commonly accepted that the new Smart Grid approach possibilities can be fully exploited only applying dynamic pricing structures (Geelen et al. 2013). However, in the authors' opinion, domestic users cannot be directly charged of an active role in the energy pool due to the huge effort required: They should not be required to operate as single actors on the market (an aggregator is needed to match the grid and customers requirements) (Biegel et al. 2014) or subjected to the complex rules today applied to industrial users (e.g., multiple market sessions and penalties for imbalances). An interesting example of tariffs providing electricity prices varying according to the system status is represented by TOU tariffs, consisting in simplified price structures that reflect the system status by means of time bands (Italian Regulatory Authority for Electricity and Gas 2010a), with the aim of introducing a cost-of-service regulatory approach (i.e., to charge each customer with the actual costs of the electricity supplied). These regulations represent clear attempts to increase the users' awareness on their energy behavior. In fact, awareness is considered a first significant step toward a better exploitation of the electric grid infrastructure (BeAware Project 2013; Plugwise 2013; IEA Demand Side Management Programme 2013).

State of the art on home energy management

As mentioned, a significant portion of the whole electricity consumption is related to houses and more in general buildings. For this reason, a clever load management can greatly improve the power systems performance. The new paradigm, commonly identified as Smart Grid, allows the achievement of such improvement by introducing, through the recent ICT advances, a suitable communication channel between the system and the end-users. Therefore, in the literature, a great attention is paid to issues related to HEM.

In the present section, we provide a review of the literature concerning the power systems evolution toward Smart Grids, specifically focusing on the development of HEM solutions devoted to improving the efficiency of the electricity grid and to reducing the users' electricity bill. In section "Discussion on results and contributions", this literature analysis will be used as a reference in discussing the novel contributions provided by our work.

The Smart Grid paradigm is open to many different interpretations, motivating a huge scientific interest and research (European Commission 2006; IEEE Smart Grid 2013; European Energy Regulators 2012).

To exploit the Smart Grid and ICT potentials within a HEM framework, two main issues must be investigated: the data forecast (e.g., weather and PV production forecast, users' habits forecast) and the schedule of the house appliances activities. Both topics have been investigated in the literature, although usually separately.

Photovoltaic generation forecast The forecasting of electricity generation from PV power plants is addressed in several papers and projects. In particular, the PV prediction requires the estimation of both the weather conditions (first of all the solar irradiation) and the PV modules parameters (to evaluate the generation efficiency). In the literature, many methods are proposed for the PV generation estimation such as: ARIMA, k-NN, ANN, and ANFIS models (Fernandez-Jimenez et al. 2012); Medium-Range Weather Forecasts coupled with PV power plant models (Lorenz et al. 2009); and multilayer perception networks (Voyant et al. 2011). Despite the accuracy of these methods in estimating the PV production, the wide set of data that they require, regarding the weather conditions and the PV power plant, could be an issue, especially if small users (domestic users) are involved. For example, the model proposed by Huld et al. (2010) requires to know the efficiency of the PV panels as a function of ambient parameters, in addition to the solar radiation and temperature. In Fernandez-Jimenez et al. (2012), surface sensible and latent heat flux, surface downward short- and long-wave radiations, top outgoing short- and long-wave radiations, and temperature are used to estimate the PV generation up to 39 h in advance. In Lorenz et al. (2009), to refine the irradiance forecasts provided by the ECMWF model (e.g., by spatial averaging and temporal interpolation, improved clear sky forecasts, and post processing with ground data), additional data regarding the PV plant are needed (i.e., location, orientation, and PV panels characteristics) in order to obtain site-specific hourly-forecasts. Similarly, with the purpose to evaluate the PV production of the next day, the Multilayer perception model proposed in Voyant et al. (2011) processes global radiation (direct-, diffuse-, and ground-reflected radiations), pressure, nebulosity, ambient temperature, wind speed, peak wind speed, wind direction, sunshine duration, relative humidity, and rain precipitations.

Users' habits forecast The main problem of HEM frameworks is that, in spite of the great evolution in terms of communication and control capabilities, an effort is still required to users to provide information to the system regarding their "electricity preferences" (e.g., at what time of the day they prefer to use home devices), thus reducing practical usability of HEM solutions. For this reason, in designing elec-tricity management systems, power meter networks can be used (Bressan et al. 2010) to monitor the con-sumption of home appliances (Jiang et al. 2009; Rowe et al. 2010). By processing data provided by power meters, it is possible to extract meaningful information that can be used to provide inputs to HEM systems automatically, thus reducing the users' effort. To this purpose, forecasting methods are required in order to predict people preferences in using electricity for future periods. Several data-driven algorithms are proposed in the field of Smart Grids to forecast daily building electric consumption (Neto and Fiorelli 2008; Newsham and Birt 2010), but usually no attention is paid to predicting single devices usage, hence preventing their applicability to HEM systems, such as the one proposed in this paper, which require detailed information on each appliance. However, users' habits profiling is extensively studied in other areas, such as ambient assisted living and home automation (Ha et al. 2006; Gallicchio and Micheli 2011), where daily life routines are automatically learned and predicted in order to control home devices, assist elderly people, and so on. For this reason, some of the solutions proposed in these fields may be reused for developing HEM systems. Specifically, two families of methods are promising to be applied in the Smart Grid field: fuzzy logic and neural networks. Fuzzy logic algorithms (Lee 1990), aiming at mathematically emulating human decision-making, can be used to design intelligent control systems, while neural networks (Hagan et al. 1996), which are mathematical models of the human neural network, are a very efficient solution for recognizing patterns. Both these methods are used to learn users' preferences and needs (e.g., light intensity and temperature) and automatically control some appliances (e.g., air conditioner, light, and water heating) (Hagras and et al. 2004; Hunt et al. 1992; Mozer 1998). However, with regard to HEM systems, neural networks represent the most promising method to profile and predict users' preferences in consuming electricity, even though some limitations may prevent their applicability in the Smart Grid domain: The optimal neural network topology strictly depends on the home environment in which it is used, and determining the optimal topology and parameters for efficient learning can be a non-trivial task.

Electricity management models The forecasting of the electricity production and consumption can be used within an HEM framework in charge of optimally controlling the flexible home appliances and ESSs of residential users. In this kind of systems, an intelligent local controller is used in order to manage the operation of the users of the power system and to adapt local responses to system and market conditions (Chuang and McGranaghan 2008).

The solutions proposed in the literature generally provide the mechanisms that, based on the electricity tariffs and data forecasts for future periods (e.g., devices future usage and users' presence), automatically and optimally schedule the home devices activities and define the whole energy plan of users (i.e., when to buy and sell energy to the grid). Their main goal is to minimize the electricity costs while guaranteeing the users' comfort; this can be achieved through the execution of logics based on optimization models (Jacomino and Le 2012; Agnetis et al. 2011) or heuristics, such as Genetic Algorithms (Soares et al. 2013; Zhao et al. 2013) and customized Evolutionary Algorithms (Allerding. F. et al. 2012), which are used to solve more complex and advanced formulations of the problem.

Since RESs diffusion is rapidly increasing, several works include renewable plants into HEM frameworks. In these cases, devices are scheduled also based on the availability of an intermittent electricity source (e.g., PV plants), and users' profits from selling renewable electricity to the energy market are considered (Clastres et al. 2010). The uncertainty of RESs production forecasts, as well as that related to load demand predictions, requires some effort to preserve the efficiency of HEM solutions. This problem is tackled by using different approaches, such as the offline definition of robust energy plans (Duy Ha et al. 2006) and the designing of real-time mechanisms to adjust the usage of load/generation resources dynamically to cope with variations with respect to forecast data (Duy Ha et al. 2007). Specifically, in the field of offline approaches, stochastic models are the most used methods (Bu et al. 2011; Adika and Wang 2013) with a special focus on stochastic dynamic programming, which is a very suitable tool to address the decision-making process of energy management systems in the presence of uncertainty, such as the one related to the electricity produced from weather-dependent generation sources (Livengood and Larson 2009).

The efficiency of HEM solutions can be notably improved by including ESSs that can increase the system flexibility in optimizing the electricity usage. Specifically, storage systems can be used to harvest the renewable generation in excess for later use or to charge the ESS when the electricity price is low, with the goal of minimizing the users' electricity bill (Guo et al. 2012). To this end, batteries of electric vehicles (EVs) could be used (Lujano-Rojas et al. 2012; Pedrasa et al. 2010) given their future wide penetration.

In the solutions analyzed above, the energy plans of residential users are individually and locally managed. However, more relevant results can be achieved when HEM systems are specifically designed to manage groups of users (e.g., a micro-grid) (Mohsenian-Rad and Leon-Garcia 2010). In this case, indeed, differences and inherent randomness among consumers in terms of electricity consumption needs and preferences can be exploited to obtain a flatter demand profile, thus reducing its peak and to efficiently adapt the overall load demand to the DG generation, hence improving the RESs penetration into the power system. In the case of multi-user systems, two different approaches have been proposed in the literature to manage the load/generation resources of customers: cooperative and non-cooperative. In the first case, the HEM system is applied to a group of cooperative residential users, in some cases equipped with a PV power plant and an ESS, and a global scale optimization method is defined to control the users' demand and the electricity resources of the whole group of houses (Hatami and Pedram 2010; Molderink et al. 2009). The cooperative approach is particularly beneficial when applied to thermostatically controlled loads (e.g., heating, ventilation, and air conditioning, HVAC, and fridges), which can be viewed as distributed ESSs because of their thermal inertia (Perfumo et al. 2012).

Cooperative solutions require some sort of centralized coordination system run by the aggregator in order to collect all the electricity requests and define the optimal solution. This central controller is not required in non-cooperative scenarios, in which decisions are taken locally by the users. In this case, game theory is usually used to design HEM systems (Saad et al. 2012). Specifically, users' electricity scheduling problem is formulated as a game, where the players are the consumers and their strategies are the daily schedules of their loads. The goal of the game is to reduce either the peak of the total energy demand, the total energy costs, or each user's daily electricity bill (Barbato et al. 2013; Mohsenian-Rad et al. 2010).

HEM frameworks In recent years, the research activities aimed at developing novel HEM architectures and strategies to assign an active role to the end-users, performing the energy management of the home environment, have grown in number. In particular, AIM European Project (2013) proposes a harmonized technology for profiling and managing the energy consumption of home appliances. The research activity focuses on designing sensor networks to monitor environmental parameters, such as user's presence, temperature, and light (Barbato et al. 2009). These data are used to control the home appliances automatically and efficiently, with the aim of saving energy (Tompros et al. 2009). To this end, basic control algorithms are defined and limited attention is given to modeling the house environment. The project Energy@Home (2013), involving telecommunication companies, manufacturers of home appliances, energy vendors, and distribution system operators (DSOs), proposes an interoperable and fully-integrated system including smart gateways, smart meters, smart plugs, and smart domestic appliances. In the project, a set of technical specifications of the home area network is defined, integrated with the state of the art of communication protocols (ZigBee Home Automation 1.2 standard). In the Energy@Home framework, the scheduling of home appliances has to be set by the user or according to external signals (e.g., price signal from the energy vendor). Address Project (2013) defines a first prototype of interactive distribution energy network, with the target to enable the "Active Demand" of small and commercial consumers (i.e., their active participation in energy market and the provision of ancillary services to the power system). The project proposes some easy-to-use system tools to monitor and display the customers' devices electric consumption, to increase the users' awareness on energy usage, and to improve their energy behavior. However, the proposed optimization models are mainly focused on the needs of the power system, not including methods for the prediction of home appliances and electricity generation within the HEM architecture. In the SESAME-S project (Fensel et al. 2013), an ontology-based modeling approach is used to describe a home and the relationships between the objects and actors within its control scenario, in order to assist end-consumers in making decisions and controlling their electricity consumption. The solution provided by the project is easily expandable, being the proposed architecture based on simple correlation rules among objects/actors, but the peculiarities of the specific components of the home energy framework are not considered (e.g., forecasting models for the PV generation), as well as the contribution to the HEM of ESSs. The iDEaS project focuses on developing algorithms and methodologies to enable intelligent appliances (Rogers et al. 2013) and energy storage devices (Rogers et al. 2011) to foster an optimal use of energy. The optimization of the home as a whole energy system, including different typologies of loads and DG, also in this case is not explored in depth.

The BEE home energy management architecture

In this paper, a hybrid approach is proposed, which focuses on residential users' electricity management, taking into account the electric grid requirements depicted in section "Power system needs for home energy management", in an ancillary services market perspective. The approach embraces also a retailer perspective, i.e., a company active on the energy pool in charge of selling energy (and services) to the final users. The retailer interacts with a set of customers optimizing their electricity behavior to fully exploit the dynamic pricing structure and acts as an aggregator (Piette et al. 2013).

The considered scenario is shown in Fig. 1. Householders can both buy and sell the electricity to the market (prosumer concept). Residential houses are equipped with a PV power plant that generates electricity, an ESS that allows the users to store energy, and a set of home appliances that have to be used during the day; for each of them a reference start time and end time are provided according to users' preferences.

In order to support the users in managing their electricity plan, a novel architecture allowing real-time electricity consumption monitoring and control is proposed. The main elements of the framework, called BEE framework because developed with the BEE project, are listed below:

- Management core (here called BEE Box): It is the core of the proposed architecture; it consists in a processing unit that manages and optimizes the home electricity planning, based on demand management mechanisms, and exchanges information with other actors of the electric system, such as other users, the electricity provider, and the electricity market.
- Meters: Smart meters are used for monitoring the consumption of house appliances; other meters, such as the gas and water meters, can be added in a future development of the architecture.
- The local generation: The forecasting of the production of DG (i.e., PV power plant) is integrated in the system, in order to improve the predictability of the power exchanges with the grid.
- Energy storage system: The usage of storage devices allows the system to be flexible in managing the power exchanges with the grid.
- User Interface: A graphical user interface (GUI) is developed for both fixed and mobile terminals. The graphical interface is used for the set-up and maintenance of the sensor networks and to display the data and results provided by the system in a simple, effective, and intuitive way.

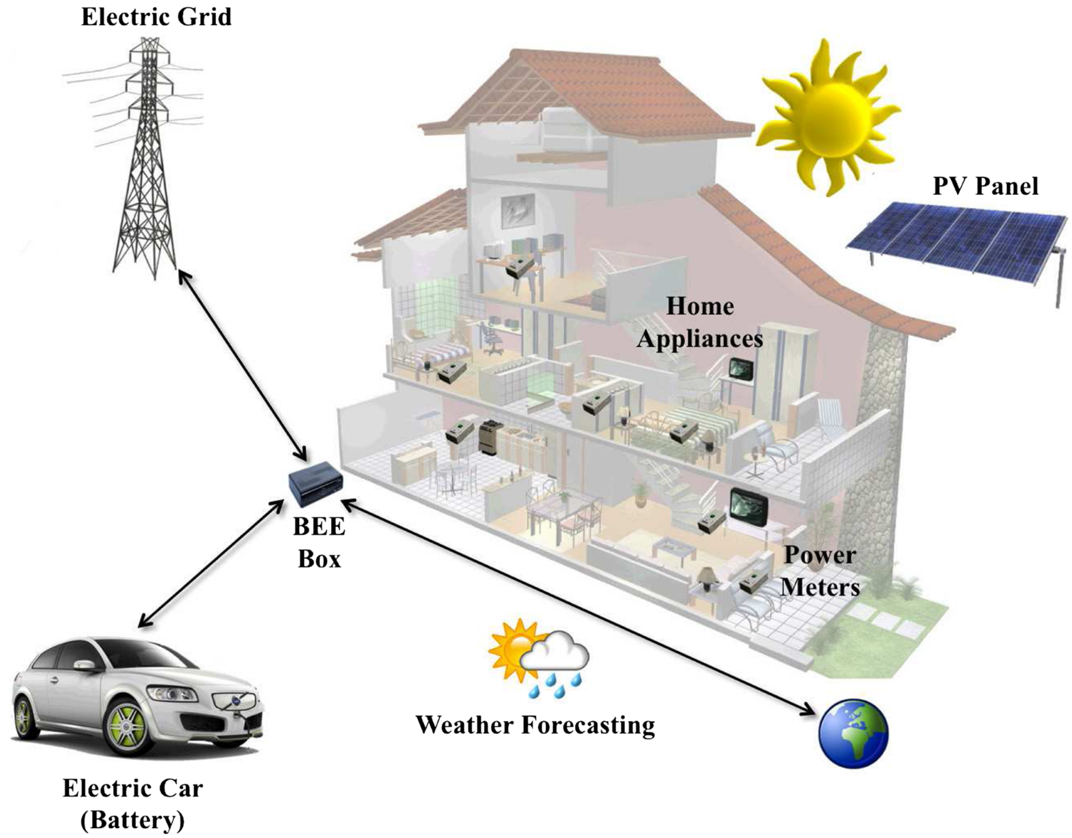


Fig. 1 BEE system architecture for a single house scenario

The management core is introduced with the task of scheduling house appliances activities and power exchanges with the grid over a 24-h time period, by means of optimization models. The proposed models require predictions on both the PV generation and devices future usage. Regarding the PV power plant, we have defined ad hoc learning methods that, based on weather forecasting, are able to predict the panels production for the next 24 h. In particular, the weather forecasting is made available by a Web service provider, while the PV power plant is modeled through an adaptive method (based on linear regression), which does not require to be set-up according to the type of PV technology (e.g., monocrystalline silicon and polycrystalline silicon) installed. In order to predict the house load demand (i.e., which home appliances are used and at what time of the day), we have also defined other forecasting algorithms to predict the home devices usage. In this case, power meters are used for monitoring the power withdrawals of home appliances; predictions of electricity demands for the next 24 h are generated by processing the sequence of measured withdrawals, in order to provide inputs automatically to the electricity optimization models. Prediction tools allow minimizing the configuration effort required to users and improving the system usability. Notice that the PV and device forecasting algorithms are both deployed in the BEE Box and use data provided by power meters and local electricity generators.

PV and device data predictions are employed by the management core to define the home energy plan for the next day. To this end, we have designed some optimization models (implemented in the BEE Box) that, as shown in Fig. 2, define the electricity plan minimizing the daily bill, according to the output of forecasting algorithms and electricity tariffs. Specifically, this plan is determined by optimally deciding and planning when to use each home appliance, when to buy and inject power into the grid, and how to use (i.e., charge and discharge) the ESS over the next 24-h time period.

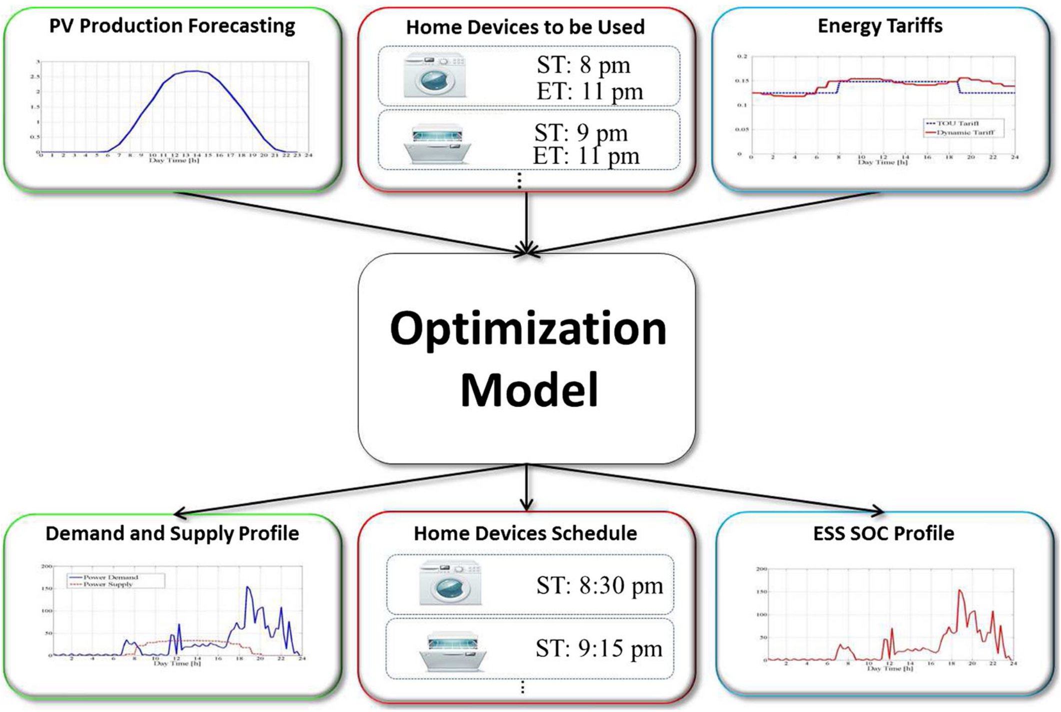


Fig. 2 BEE HEM operating diagram

In the following, the algorithms at the basis of the BEE HEM architecture are explained.

Prediction of devices usage

One of the main problems of load demand management systems is that they require users to provide a large number of inputs to the system, for example, concerning the preferred time of use of each home appliance, thus reducing their practical applicability to real-life scenarios. For this reason, in the framework described in the paper, forecasting methods have been designed to predict people preferences in using electric appliances for the next day. In the proposed architecture, the HEM core requires the following input data that can be automatically computed through the prediction algorithm:

– which home devices have to be used;
– at what time of the day;
– for how long.

The designed forecasting process includes two procedures: a mechanism for recording data on home devices usage (i.e., electricity consumption) and a prediction algorithm that allows extracting, from all these data, some settings of the demand management system that is expected to meet the users' requirements.

Our approach, in particular, consists in deploying a wireless sensor network (WSN) that provides the basic tools for gathering information on the user's behavior to predict the above mentioned parameters. To do this, a wireless power meter sensor network (WPSN) is used, with sensor nodes attached to each household appliance. Data provided by the WPSN are processed in order to forecast devices activities for the next day.

The sensor network can be implemented using several available communication technologies (Batista et al. 2013). Generally speaking, WSNs are today considered the most promising and flexible technology for creating low cost and easy to deploy networks in many scenarios, including HEM systems for the Smart Grid. In our prototype implementation, in order to collect information on the state of appliances, we use ACme nodes designed at UC Berkeley (Jiang et al. 2009). ACmes are sensors based on CC2420 communication chipset with IEEE 802.15.4 technology able to measure AC electricity usage of devices they are connected to.

Since in the considered scenario, the area to be monitored is usually relatively small, it would be possible to consider a single WPSN interconnecting all the sensing devices. However, in order to define a flexible and reliable sensor network, we propose a hierarchical hybrid architecture consisting of different islands of sensor nodes (homogeneous WPSNs in our case, but also heterogeneous technologies may be included in future development of the system) interconnected through gateways. These gateways are higher layer devices able to communicate via heterogeneous links that can be either wireless (e.g., WiFi and ZigBee) and wired (e.g., PLC and ethernet), and to perform some data aggregation and processing tasks. The network topology created among the gateways is meshed to ensure reliability and resilience to failure.

The final outcome of the WPSN activity is the collection, for every day and household appliance, of a profile representing the daily power consumption of the appliance itself. The power profile is then processed in order to obtain the daily device status:

- the 24 h are divided into time slots of 1 min each;
- for every time slot, the device is said "On" if the average power consumption is higher than a threshold (experimentally defined for each appliance), "Off" otherwise.

An example of power consumption and device status profiles is shown in Fig. 3. Notice that start times and stop times, hence devices activities, can be easily identified by analyzing this profile.

One key obstacle to predict appliances usage is that status profiles have a lot of irregularities that could badly affect the performance of the proposed system. Specifically, temporary suspensions of devices cause

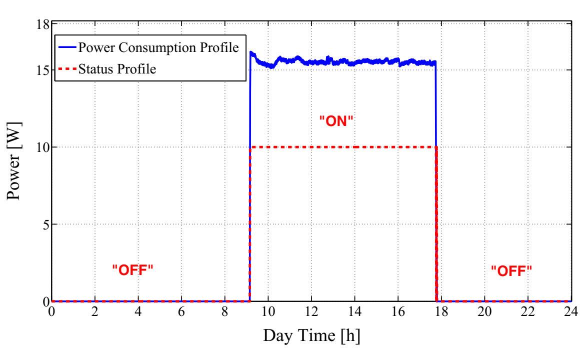


Fig. 3 Daily power consumption and status profiles for a PC monitor

the status profile to have "Off" periods within a single activity window. This may be misinterpreted by the system, hence confusing a single device activity with multiple ones (i.e., the system would recognize multiple startings, thus supposing that the device has been used more than once). This kind of misinterpretations may lead to errors in predicting the devices start time and the usage duration associated with each starting. To avoid this issue and increase the appliances predictability, a filtering procedure to apply to status profiles has been defined. Specifically, the filtering process consists in merging devices activities that happen within a given period of time, called clustering window. Let t_a^1 and t_a^2 be two consecutive starting times of a generic appliance a. The corresponding device activities, q_a^1 and q_a^2, are merged if:

$$t_a^2 - t_a^1 \leq w_a^C \tag{1}$$

where w_a^C is the clustering window whose value is strictly dependent on the appliance (e.g., the microwave oven has a very short clustering window since its activities duration is usually quite short, hence it is very unlikely to have long temporary suspensions). If condition of Eq. 1 is verified, the two activities q_a^1 and q_a^2 are merged into a single activity $\tilde{q}_a$ whose start time, $\tilde{t}_a$, and duration, $\tilde{d}_a$, are computed as follows:

$$\tilde{t}_a = \frac{t_a^1 + t_a^2}{2} \tag{2}$$

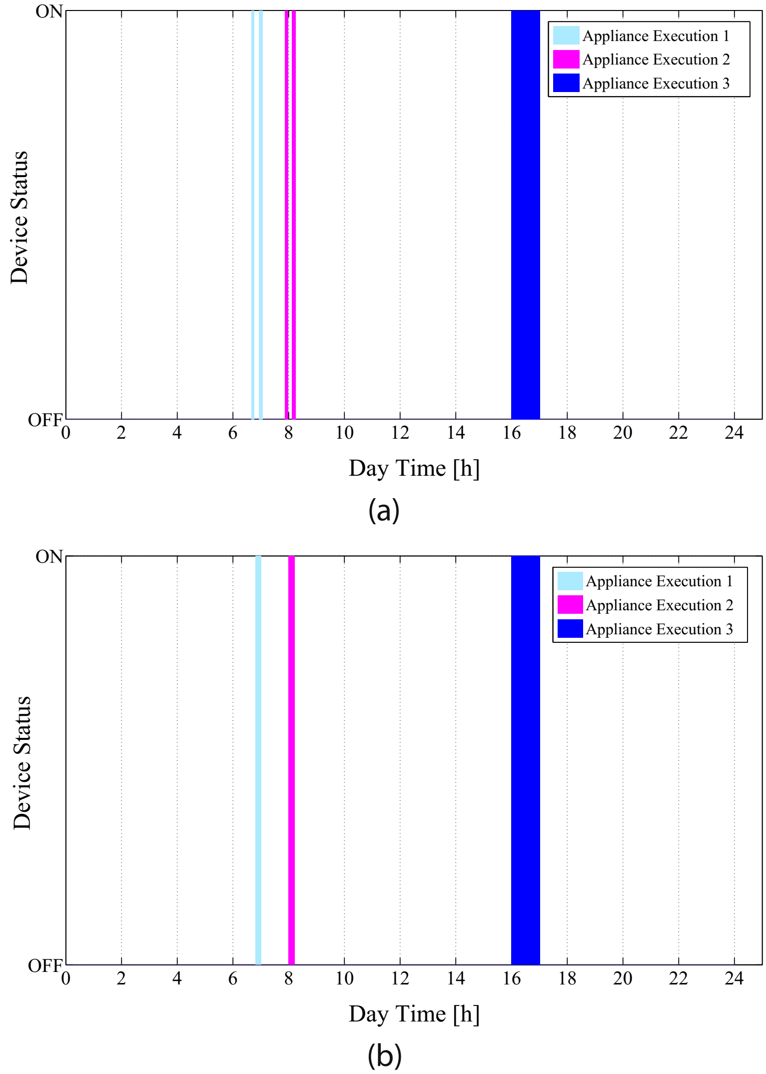
$$\tilde{d}_a = d_a^1 + d_a^2 \tag{3}$$

The new activity $\tilde{q}_a$ replaces q_a^1 and q_a^2 in the status profile of the appliance a, and the filtering procedure is iterated until no more merging is required. Figure 4 shows an example of the filtering procedure applied to a generic device used three times during the day. In the first two executions, two temporary suspensions are found (a) and the corresponding activities are replaced with the merged ones (b).

The proposed forecasting algorithm processes, every 24 h, the filtered status profiles collected in the last N days (i.e., the learning period of the algorithm), in order to predict the following data for the next day:

- Which devices will be used: status prediction.
- At what time of the day: time prediction.
- For how long: duration prediction.

Fig. 4 Device status profile before (**a**) and after (**b**) the activities filtering procedure



By using these predictions, some settings of the demand management system can be made automatically. Notice that the system is not able to forecast devices usage during the very first N days of activity because not enough information is available for the status, time, and duration predictions.

In the following, the three prediction steps are described with reference to a generic household appliance a. The basic idea used in the forecasting procedure is that people habits in using a device are nearly periodic. Thereby, by processing data collected in the past, the behavior period can be extracted and used to predict how the device will be used in the future.

Status prediction

The goal of this step of the devices forecasting system is to predict if the device a will be used or not on the next day. To this end, the independent binary variable, $u_a^{\star}$, is defined, which is set equal to 1 if a is predicted to be used and 0 otherwise. In order to determine the value of this variable, the status prediction algorithm proceeds as follows. Daily status profiles are used to create a string, here called "I", of N characters, each one corresponding to a day of the monitoring period. The element in the position i of the string has value 1 if the appliance a has been used on day i, 0 otherwise. The goal of the status forecasting algorithm is to predict if the device will be used or not on the day following the monitoring period "I" (i.e., last N days). To this purpose, the probability that 1 or 0 occur at the end of the string is computed, by applying the following method:

1. A status string "S" of length L (starting from L=1) is selected, representing the status of the device in the last L days of the monitoring period.
2. The number of occurrences (NO) in "I" of the patterns "$S+1$" and "$S+0$" are counted, and the probability that 1 or 0 occur at the end of the sequence "S" is computed as follows:

$$Prob[1|S] = \frac{NO[S+1]}{NO^{I\{N\}}[S]}, \; Prob[0|S] = \frac{NO[S+0]}{NO^{I\{N\}}[S]} \tag{4}$$

where $NO^{I\{N\}}[S]$ is the number of occurrences of "S" in the string "$I[1:N-1]$" (i.e., all the days of the monitoring period except the last one).

3. If $Prob[1|S]$ ($Prob[0|S]$) is equal to 100 % the algorithm stops, the variable $u_a^\star$ is set to 1 (0), hence the device is predicted to be used (not used) on the next day and "S" is said "Prediction Sequence"; otherwise, L is increased by 1 and the algorithm goes back to step 1 (if $L = N-1$, the procedure stops anyway and returns the most probable status, i.e., 1 or 0, computed till that iteration).

Notice that from a qualitative point of view, when the algorithm stops, it means that in the learning period, on the days following the "Prediction Sequence" and here called "critical days", the device a has always been used (not used) so that the same behavior is likely to be experienced in the future. An example of the proposed algorithm is presented in Table 1, stopping for L=2 and predicting the device to be used on the next day. In this case, the "Prediction Sequence" is "$S = 00$" and the 'critical days" are days 4 and 7. If the device is predicted not to be used, the forecasting procedure stops, otherwise the time and duration prediction steps are performed.

Time prediction

The second step of the algorithm for the prediction of home appliances usage has the goal to forecast how many times and at what time of the day the device will be turned on. To this end, we define the integer non-negative variable $N_a^\star$, which represents the number of times the device a is predicted to be used on the next day, and $N_a^\star$ continuous non-negative variables $t_{an}^\star$, with $n \in \{1, 2, .., N_a^\star\}$, which represent the start time associated with each predicted usage of the device a. In order to determine the value of these variables, not all the days of the learning period are used, but just a subset composed by the "critical days" found in the status prediction (i.e., day 4 and 7 in the example of Table 1), which are indeed supposed to be a good representation of what will happen in the next 24 h. For each of these days, in particular, the corresponding status profile is selected and a critical profile is defined by introducing a normal function, with variance σ minutes, for every detected start time of the device, thereby representing the probability that the appliance is turned on at a given time of the day (an example is shown in Fig. 5).

In order to forecast when the appliance a will be used, the sum, sample by sample, of all critical profiles is computed. The variable $N_a^\star$ is set to the number of peaks of the resulting profile, hence representing the number of times the device a is predicted to be used. Moreover, for each peak $n \in \{1, 2, .., N_a^\star\}$, the corresponding variable $t_{an}^\star$ is set equal to the day time associated with the peak, thus representing the predicted start time of the device a for the next day. In Fig. 6, an example of time prediction is presented, with reference to the instance described in Table 1.

Duration prediction

The goal of this step of the devices forecasting procedure is to predict for how long the device a will

Table 1 Status prediction algorithm with $N = 9$ and a learning period string I="100100100"

	"S"	NO(S)	NO(S+1)	NO(S+0)	$Prob[1\|S]$	$Prob[0\|S]$
L=1	S='0"	5	2	3	40 %	60 %
L=2	S="00"	2	2	0	100 %	0 %

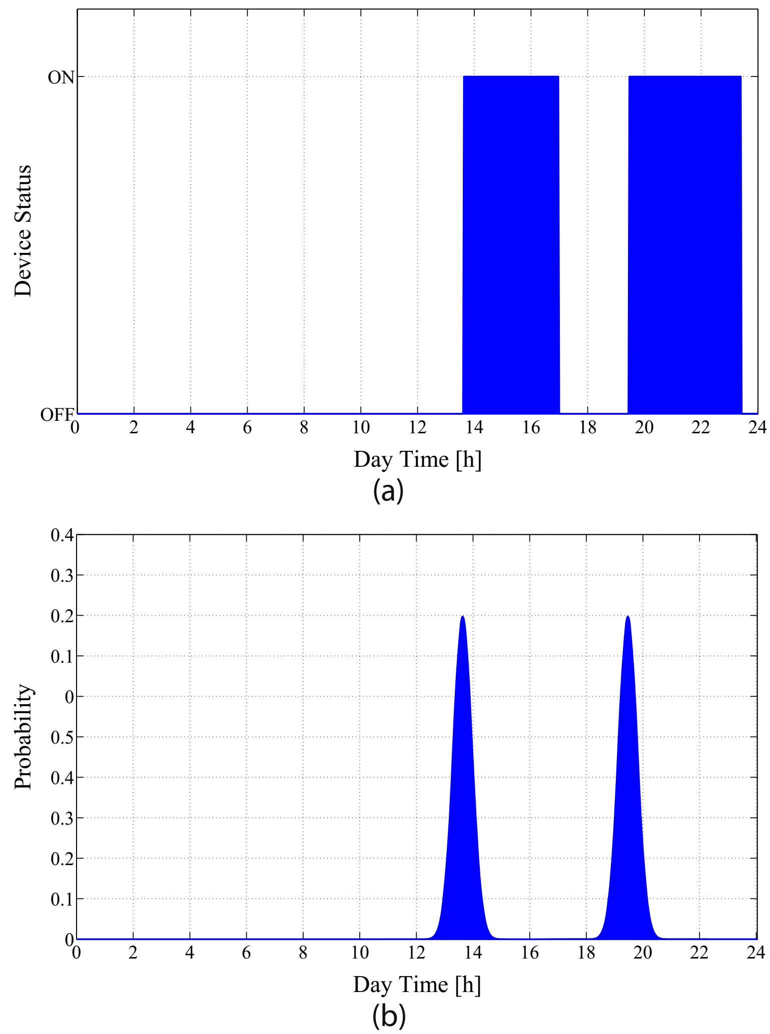


Fig. 5 Daily status (**a**) and critical profiles (**b**)

be used since it will be turned on. To this end, for each of the $N_a^\star$ predicted starting times, the independent continuous variable $d_{an}^\star$ is defined, which represents the duration of the forecast device activity. In order to determine the value of this variable, the duration prediction algorithm processes the critical profiles. Specifically, for each normal function composing this profile, we compute the duration, d_a, of the device activity it is associated with. For each peak $n \in \{1, 2, .., N_a^\star\}$ detected in the time prediction step, normal functions numerically contributing to the peak value are selected and the variable $d_{an}^\star$ is set equal to the average value of the corresponding parameters d_a, hence representing for how long the device will be used. Figure 6 shows an example of duration prediction, as already mentioned, with reference to the instance in Table 1.

Parameter identification procedure

The proposed devices forecasting method requires some parameters to be determined: the learning period, N, the set of clustering windows of each appliance a, w_a^C, and the variance, σ, of the critical profile normal function. To this end, a training method has been defined, consisting in solving an optimization problem. Specifically, in the training procedure, a set A of appliances is considered, and usage data are acquired for K consecutive days. The parameters of

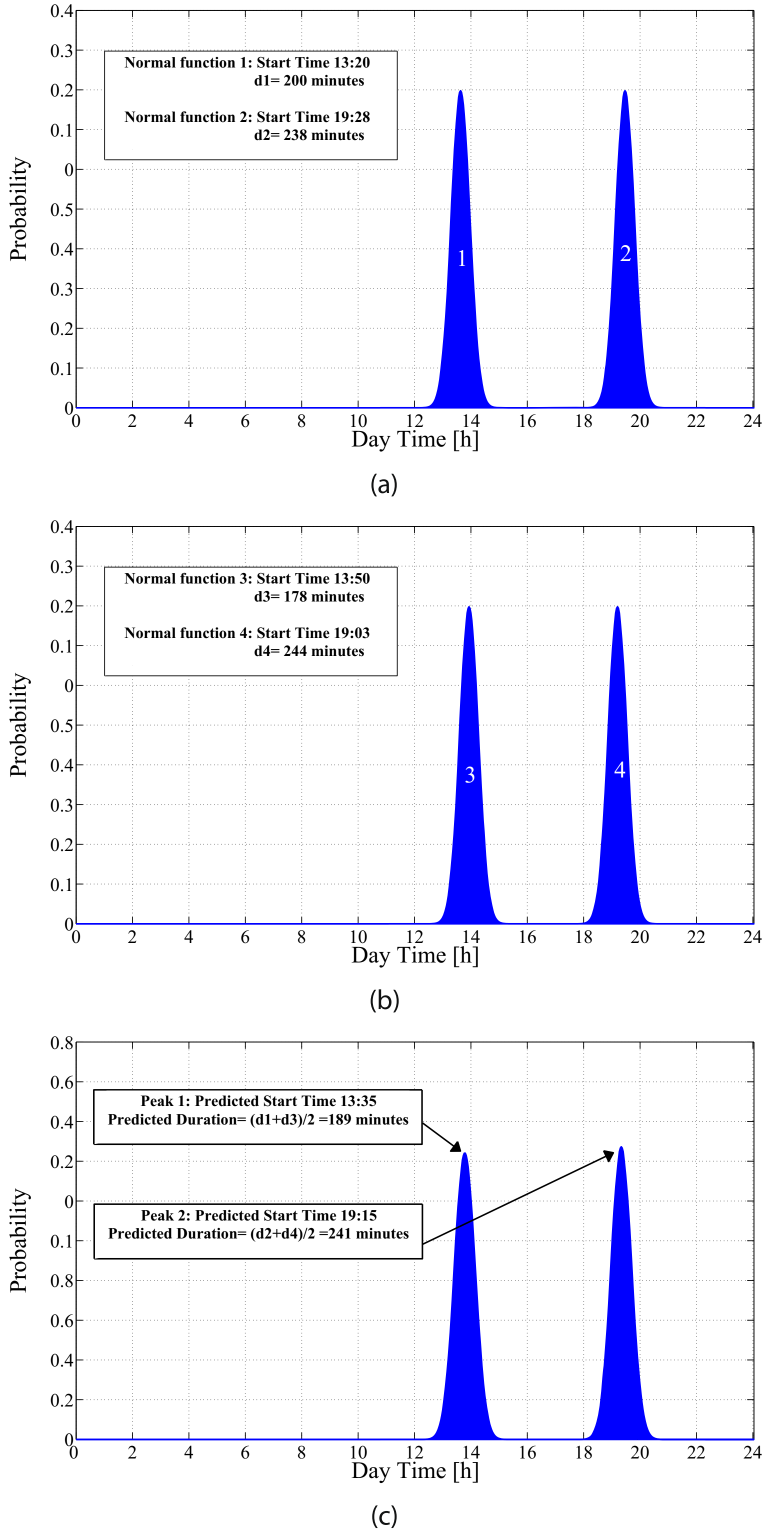


Fig. 6 Device time and duration prediction based on critical profiles (**a**) and (**b**) and the final critical profile (**c**)

the forecasting algorithm are those that minimize the total prediction error:

$$\begin{aligned}&\underset{w_a^C \in W^C, N, \sigma}{\arg\min} \quad \alpha\ E_{status} + \beta\ (|E_{time}| + |E_{duration}|)\\ &\quad s.t.\\ &w_a^C \geq 0 \ \ \forall a \in A, N \in \mathbb{N}, \sigma \geq 0\end{aligned} \tag{5}$$

where E_{status}, E_{time}, and $E_{duration}$ are, respectively, the average error of the device status, starting, and duration predictions computed over a period of $K - N$ days (as noticed before the algorithm is not able to forecast the devices usage during the very first N days because of the required learning period of the model). Weights α and β are used to combine, in the same objective function, the numbers with different metrics (E_{time} is a percentage, while E_{time} and $E_{duration}$ are expressed in minutes). In the error minimization process, the parameters w_a^C, N, and σ are constrained. Specifically, w_a^C and σ must be positive and N must be a natural number.

As the proposed model is a nonlinear optimization problem (E_{status}, E_{time}, and $E_{duration}$ are not linear functions of the model variables), it would be quite hard to solve it using an optimization problem solver. For this reason, a recursive formulation is implemented, which is able to define the optimal values of the variables through an exhaustive research process.

Prediction of electricity generation

The PV is the DG technology most widespread among domestic users. However, PV generation is subject to fluctuations due to weather conditions that can make the task of controlling the power balance (frequency regulation and generation dispatching) more difficult.

In the BEE HEM framework, a scheme to forecast the PV generation is proposed. Its objective is to give an accurate estimation of generation injections, necessary to provide a reliable prediction of the users' profiles, assuring, at the same time, an easy set-up of the electricity management system according to the PV power plant technical characteristics.

The main input of the PV production prediction is given by the weather forecasts. These are acquired from a Web service provider, exploiting the communication channel between the user and the system operator (e.g., Digital Subscriber Line: DSL). The data considered are the information typically provided by the weather services (e.g., solar irradiation, temperature, humidity, and wind) referring to the user's location.

The core of the proposed prediction scheme is a mathematical model of the generation plant (PV cells and inverter). The purpose of the model is to give an estimation of the effective power injections of the PV power plant starting from the weather data collected by the Web service. In order to implement an easy-to-use infrastructure, the architecture developed is able to autodetect the parameters needed for the mathematical model of the PV plant and does not require additional data to retrieve.

The proposed model is based on the following equation:

$$p_t = G_t \cdot i_t \tag{6}$$

where p_t is the estimated power production of the PV power plant in the time slot t $[W]$; G_t is the proportionality coefficient representing the PV power plant model as evaluated in the time slot t $[m^2]$; and i_t is the value of solar radiance made available by the Web service provider for the time slot t $[W/m^2]$.

In each time slot t, the developed procedure automatically evaluates the proportionality coefficient of the PV model, G_t, through the analysis of the data of historical production and weather forecasts of the previous 100 h. The model coefficient better representing the PV power plant is determined by the linear regression Levenberg–Marquardt algorithm (Seber and Wild 2003), which minimizes, on an iterative basis, the sum $Sq(G)$ of the squares of the deviations between the estimated production values assessed by the fitting curve (p_t) and the actual production values (p_t'):

$$Sq(G) = \sum \left[p_t' - f(p_t, G)\right] \tag{7}$$

For a numerical application of the proposed approach, see section "Prediction of electricity generation".

Electric energy optimization

The management core is designed to cope with the electricity load and generation over a 24-h time horizon, with the final goal of both minimizing the electricity daily bills and improving the efficiency of the whole electricity grid. Residential houses are equipped with a PV power plant, an ESS allowing the system to store energy, and a set of home appliances.

An activity is associated to each appliance, which must be executed during the day. For each activity, starting and ending times are provided according to users' preferences. Figure 2 reports the input and output of the management core. It receives as input the forecast of the PV production, the users' requirements and the electricity tariff, and provides a schedule of the next day appliances activities. It decides:

- when to start/stop home appliances;
- when to buy, sell and store energy.

The management core is based on optimization models that can manage two different scenarios:

1. Non-cooperative users scenario: Users autonomously manage their electricity demand; in this case, the optimization model has to schedule the electricity plan of a single house under TOU tariffs.
2. Cooperative users scenario: Users accept to cooperate in managing their electricity resources; in this case, the optimization models are used for scheduling the electricity plan of the whole group of users, taking into account constraints on the overall peak absorption.

In both scenarios, the objective function is to minimize the daily bill. Intuitively, by optimally scheduling house appliances activities and managing the power exchange with the network, the user is able to reduce his bill. Since electric energy is a cheap commodity, the economic saving might be very small for the domestic users. Nevertheless, other important benefits correlated with the better exploitation of the electric system will fall down indirectly on final users. However, modeling such benefits is complex and thus the mathematical model takes into account only the direct economic benefit for domestic users.

Non-cooperative user optimization model

To represent the problem as a mixed integer linear programming (MILP) model, the considered 24 h time horizon is divided into 96 time slots of 15 min each, modeled by the set T. The model must decide when to buy and sell electricity from the grid, with the aim of minimizing the daily bill. The purchase and selling electricity prices, in each time slot $t \in T$, are denoted by c_t and g_t, respectively. Continuous non-negative variables z_t and y_t represent the amount of electric energy bought and sold, respectively, in each time slot t.

Objective function

The objective function can be modeled as:

$$\min \sum_{t \in T} (c_t \cdot y_t - g_t \cdot z_t) \tag{8}$$

The first term of Eq. 8 is the purchase electricity price, while the second one is the selling price of the electricity injected into the grid.

Constraints description

Activity scheduling The house appliance activities to be executed in the considered time horizon are represented by the set A. For each activity $a \in A$, which is associated with a house appliance, a starting time ST_a, an ending time ET_a, and a run time n_a are given. To describe the activities schedule, binary variables x_{at} are defined for each activity $a \in A$ and for each time slot $t \in T$, which are equal to 1 if the activity a starts in the time slot t, and 0 otherwise. Such variables must satisfy several constraints. The first set of constraints guarantees that the activity a starts in exactly one time slot and it is carried out in the required interval (ST_a, ET_a). Such constraints are written as follows:

$$\sum_{t=ST_a}^{ET_a - n_a + 1} x_{at} = 1 \qquad \forall a \in A \tag{9}$$

Notice that the bigger is $(ET_a - ST_a)$, the more the system is flexible in scheduling house appliance activities.

The activity of each appliance a is divided into phases, described by the set F_a, whose duration is equal to that of a single time slot (i.e., 15 min in the scenario considered in this paper). For each $f \in F_a$, the power, l_{af}, required when executing that phase is given, hence defining a power consumption profile for the appliance under analysis. Specifically, the consumption l_{af} of a device $a \in A$ in each phase $f \in F_a$ is an average of the real consumption of the device within the corresponding 15-min time window (Fig. 7a shows the load profile of a dishwasher, consisting in eight 15-min phases).

In this paper, we only consider the devices whose power consumption profile is given and can merely

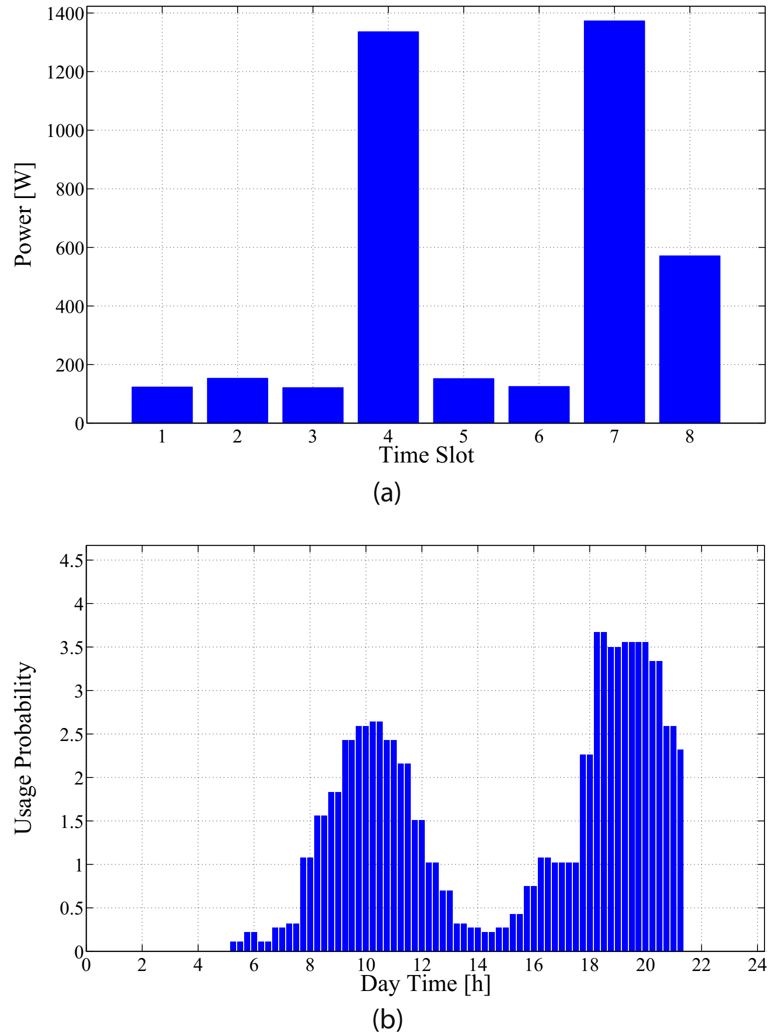


Fig. 7 Dishwasher machine load profile (**a**) and statistical data on the washing machine usage (**b**)

be shifted in time, depending on the starting time decided by the proposed optimization model. Additionally, other kinds of appliances whose instantaneous power consumption can be directly controlled (e.g., HVAC devices whose consumption can be set based on indoor, outdoor, and set-point temperatures) may be considered and integrated into the system. However, the integration of these devices into the proposed framework is out of the scope of this paper: Our framework has been specifically defined and tested based on the usual configuration of Italian domestic users, whose total consumption coming from directly "controllable" appliances is almost negligible (i.e., gas is used for space heating with no impact on the electric grid).

The amount of energy requested by each appliance in each time slot is computed according to the following constraints:

$$p_{at} = \sum_{f \in F_a : f \leq t} l_{af} x_{a(t-f+1)} \qquad \forall a \in A, t \in T \qquad (10)$$

Eq. 10 forces the power required by each appliance in each time slot to be equal to the load profile l_{af} of the phase carried on in the considered time slot. Indeed, $x_{a(t-f+1)}$ is equal to 1 if phase f is carried on in the time slot t and 0 otherwise.

Energy storage systems Five sets of variables are introduced to model the ESS. Two binary variables, ω^C_{bt} and ω^D_{bt}, are defined for each ESS $b \in B$ and each time slot $t \in T$: ω_{bt}^{C} is equal to 1 if the ESS b is charging in time slot t and 0 otherwise, while ω_{bt}^{D} is equal to 1 if the ESS b is discharging in time slot t and 0 otherwise. Such variables are subjected to the following constraints:

$$\omega_{bt}^{C} + \omega_{bt}^{D} \leq 1 \qquad \forall b \in B, t \in T \tag{11}$$

Eq. 11 guarantees that each ESS, in a given time slot, can be in only one of the three possible modes: charge, discharge, and off.

The charge and discharge rates must be decided by the model as well. They are represented by continuous non-negative variables v_{bt}^{C} and v_{bt}^{D}. Such variables are bounded, for each $t \in T$, according to the following constraints:

$$\begin{aligned} \tau_b^{min} \cdot \omega_{bt}^{C} \leq v_{bt}^{C} \leq \tau_b^{max} \cdot \omega_{bt}^{C} & \\ & \qquad \forall b \in B, t \in T \\ \vartheta_b^{min} \cdot \omega_{bt}^{D} \leq v_{bt}^{D} \leq \vartheta_b^{max} \cdot \omega_{bt}^{D} & \end{aligned} \tag{12}$$

where τ_b^{max} and τ_b^{min} $\left(\text{and } \vartheta_b^{max} \text{ and } \vartheta_b^{min}\right)$ are the maximum and minimum charge (and discharge) rates, respectively. Equation 12 guarantees also the consistency between the values of v_{bt}^{C} and v_{bt}^{D} and their binary counterparts ω_{bt}^{C} and ω_{bt}^{D}.

A continuous non-negative variable SOC_{bt} is defined for each ESS b and each time slot t, which is the state of charge of the ESS b at time t. The SOC of an ESS in a time slot depends on the SOC of the same ESS in the previous time slot and on the charge and discharge rates, according to the following constraints:

$$\begin{aligned} SOC_{bt} \; = \; & SOC_{b(t-1)} \\ & + \frac{1}{4 \cdot C_b} \left(\eta v_{bt}^{C} - \frac{1}{\eta} v_{bt}^{D} \right) \quad \forall b, t : t \geq 2 \end{aligned} \tag{13}$$

where C_b and η represent, respectively, the capacity of the battery b and the charge/discharge efficiency (the efficiency of the whole charge and discharge process is η^2). For each ESS, the SOC is bounded according to the following constraints:

$$SOC_{bt} \geq SOC_b^{min}, SOC_{bt} \leq SOC_b^{max} \qquad \forall b, t \tag{14}$$

where SOC_b^{max} and SOC_b^{min} are, respectively, the maximum and minimum allowed SOC of the ESS $b \in B$ needed to avoid damages to the ESS itself.

Finally, for each ESS, the SOC at the initial time slot is set to a given parameter SOC_b^{ini}, which represents the charge level at the beginning of the day, while the initial charge and discharge rates are 0.

$$SOC_{b1} = SOC_b^{ini}, v_{b1}^{D} = 0, v_{b1}^{C} = 0 \qquad \forall b \in B \tag{15}$$

Energy balancing The scheduling variables and the ESS variables must be related with the sold and bought electricity variables through a set of balancing constraints. The following constraints force the balance between the used and the available electricity, the sold and bought one, in each time slot:

$$y_t + \pi_t^{PV} + \sum_{b \in B} v_{bt}^{D} = z_t + \sum_{a \in A} p_{at} + \sum_{b \in B} v_{bt}^{C} \qquad \forall t \tag{16}$$

where π_t^{PV} is the PV production in the time slot t. The left hand side of Eq. 16 represents the available electricity (bought, generated by the PV power plant, or injected by the ESS) while the right hand side is the sum of the absorbed electricity, by the ESS or appliances, and the sold one.

Finally, the amount of electricity that can be bought from the grid cannot exceed the contractual peak power (CPP) limits, denoted by π_t^{CPP}. To this end, the following constraints are defined:

$$y_t \leq \pi_t^{CPP} \qquad \forall t \in T \tag{17}$$

Multi-user optimization model

In this scenario, a set U of users is supposed to cooperate in managing the power exchange with the grid. The goal of the problem is now to minimize the global daily electric energy bill of the set of users. The resulting optimization model is similar to the one described in section "Non-cooperative user optimization model". The objective function slightly changes as the purchase and selling prices are summed over all users:

$$\min \sum_{u \in U} \sum_{t \in T} \left(c_t \cdot y_t^u - g_t \cdot z_t^u \right) \tag{18}$$

The first term is the electricity purchase price, while the second one is the selling price of the electricity injected into the grid. Moreover, additional constraints must be introduced:

$$\sum_{u \in U} y_t^u \leq \pi_t^{GCPP} \qquad \forall t \in T \tag{19}$$

Eq. 19 limit the total amount of electricity purchased, in each time slot, by the set of users: Such value cannot exceed the global contractual peak power (GCPP) limit π_t^{GCPP}. By setting the parameter π_t^{GCPP}, it is possible to control the peak demand of users, thus providing a benefit in sizing grid assets.

Experimental tests methodology

The proposed architecture has been tested on realistic instances in order to evaluate the performance of each part of the framework: the PV and device usage prediction tools and the optimization core. Both the single-user scenario and the multi-user cooperative scenario have been considered in the test phase. The experimental tests aim at assessing the behavior of the proposed framework in terms of:

- performance of the optimization core, improvement with respect to non-optimized solutions, efficiency and efficacy of the optimization models;
- performance of the forecasting tools;
- sensitivity of the obtained solutions with respect to errors in the forecast parameters.

This section is devoted to the methodology adopted for the analysis, and it is organized as follows. First, the considered instances are presented and the involved parameters are described (section "Case study"). Then, the assessment of the sensitivity to errors of the proposed framework is discussed (section "Impact of the prediction error on the system performance").

Case study

In this study, the benefits of the HEM architecture on users' behavior are evaluated with reference to the current Italian scenario. The assessment is performed according to two alternative electricity tariff structures applied to residential users: TOU and dynamic pricing tariffs (Fig. 8).

For the TOU tariff, the Italian tariff structure is used. In Italy, TOU tariff has been applied to domestic users since July 2010 (Italian Regulatory Authority for Electricity and Gas 2010a), with the aim of introducing a cost-of-service regulatory approach, hence to charge each customer with the actual costs of the electricity supplied. Two time bands are defined: shoulder, off-peak (i.e., from 7 pm to 8 am), and week-end hours, with a low electric energy price and peak hours (i.e., from 8 am to 7 pm), with a high electricity price. Specifically, the price of the electric energy during off-peak and week-end hours is 15 % lower than in the peak hours.

On the other hand, in the case of the dynamic pricing tariff, users are assumed to have an active role in the day-ahead market: The price changes every hour with higher values at peak hours. In Italy, this approach is not (yet) applied to residential users, but only to large industrial consumers. In order to realistically define this tariff, the Italian energy market is taken as a reference, and the dynamic pricing is computed by adding to the day-ahead market clearing prices (for a standard 2010 spring day), the costs of ancillary services (e.g., electricity transport, distribution and dispatching, frequency regulation, and power balance).

For both the TOU and dynamic pricing tariffs, the price of the electricity produced by the PV power plant and sold to the grid is always supposed 20 % lower than the price of the electricity bought from the network (20 % is a gross estimation of the costs of the electric system ancillary services; indeed, in Italy, about 20 % of the electric energy price for residential users is devoted to the compensation of the costs for the energy transport, distribution, measurement, and dispatching service (Acquirente Unico 2013)).

It is worth noting that, as better clarified in section "Discussion on results and contributions", despite the tariff structures change according to national frameworks, the HEM architecture proposed in this work has a general validity since the optimization algorithms can suitably manage different pricing signals.

As mentioned, tests have been run on two different scenarios: the single-user case, in which only one residential user is involved, and the multi-user cooperative case, in which many cooperating residential users are involved.

In the single-user problem, we consider a basic configuration consisting of one house having 11 appliances (i.e, namely, washing machine, dishwasher, boiler, vacuum cleaner, refrigerator, purifier, lights,

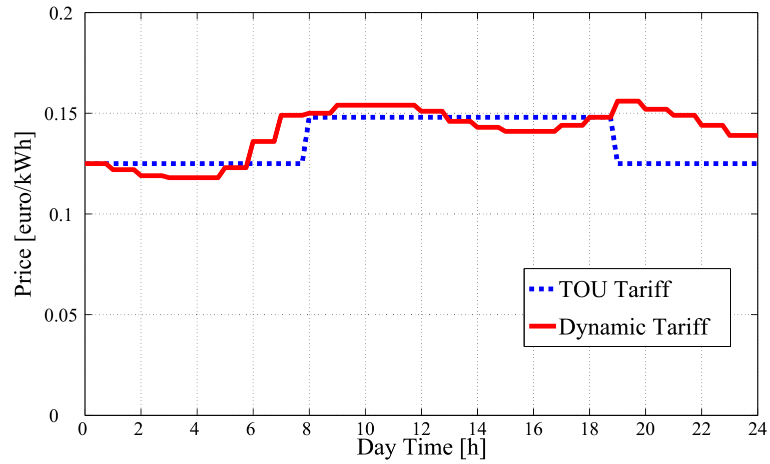


Fig. 8 Price of electricity bought from the grid

microwave oven, oven, and TV/PC) connected to the grid at the contractual peak power of 3 kW $\left(\pi_t^{GCPP} = 3 \text{ kW}, \forall t \in T\right)$. The basic domestic configuration is obtained from literature data relevant to the Italian standard user (ECORET Project 2013), while the load profile consumption of each appliance is defined by adopting data reported in Micene Project (2013). Figure 7a, for example, shows the standard load profile associated with a dishwasher, where each time slot corresponds to a period of 15 min. Moreover, Fig. 7b reports the statistical distribution of the usage of a washing machine.

Starting from the base configuration, multiple scenarios, with and without a 1 kWp PV power plant and a 10 kWh/3 kWp ESS, and with different energy price functions and scheduling constraints, are defined. The PV power plant electricity production is determined by applying the forecasting model described in section "Prediction of electricity generation". The ESS parameters are set as follows: $\eta = 0.95$ (the efficiency of the whole charge and discharge process, being equal to η^2, is 0.9), $\tau_b^{min} = 500$ W, $\tau_b^{max} = 3{,}000$ W, $\vartheta_b^{min} = 500$ W, $\vartheta_b^{max} = 3{,}000$ W, and $\forall b \in B$.

As reported in section "Electric energy optimization" for each appliance, a bound is introduced for both the starting and the ending time (i.e., ST_a and ET_a), representing the period of time in which the appliance activity has to be executed. The activity duration n_a is given, as well. Such data may be manually provided by the users or automatically computed by the prediction algorithm. In our experimental tests, the prediction algorithm is used, which computes the above mentioned parameters as follows:

- ST_a and ET_a are computed using the outcome of the time prediction step; indeed, since we know at what time the device will be turned on (i.e., $t_a^\star$), ST_a and ET_a will be the starting and ending time of a time window, centered at $t_a^\star$, with a time length defined by the flexibility level of the model (this parameter will be introduced hereinafter).
- n_a is the parameter defined by the duration prediction step $\left(\text{i.e., } d_a^\star\right)$.

Four scenarios are analyzed in order to take into account different flexibility levels according to the activity execution window (the higher the flexibility, the larger the execution window):

- *Zero Flexibility* The appliances scheduling is fixed and can't be optimized, hence:

$$ST_a = ET_a - n_a + 1 \qquad \forall a \in A \tag{20}$$

- *Low Flexibility* The average number of feasible starting times (i.e., time slots that satisfy constraints of Eq. 9) of each appliance is equal to 3:

$$\sum_{a \in A} \frac{ET_a - n_a + 2 - ST_a}{|A|} = 3 \tag{21}$$

Notice that the number of feasible starting times is not the same for all devices. Specifically, for those appliances that are more dependent on users' activities and interaction (e.g., TV, lights, and microwave oven), only two possible starting times are given (i.e., the maximum delay with respect to the preferred starting time is 15 min), while other appliances have a greater flexibility, so that the average number of scheduling is 3. The same consideration can be done for the medium flexibility case.

– *Medium Flexibility* The average number of feasible starting times of each device is 15:

$$\sum_{a \in A} \frac{ET_a - n_a + 2 - ST_a}{|A|} = 15 \quad (22)$$

– *High Flexibility* The execution window corresponds to the whole day for every appliance considered in the tests:

$$ST_a = 1, ET_a = 96 \qquad \forall a \in A \quad (23)$$

Figure 9, for example, shows the medium flexibil-ity scenario used in some instances of the problem. Specifically, both the activity duration n_a and the execution window (i.e., interval $ET_a - ST_a$)are shown for each home appliance. These parameters are defined according to the Italian statistical data available in ECORET Project (2013) and Micene Project (2013).

The multi-user cooperative case is defined by considering a group of 10 identical houses with 11 appliances each, with different combinations of PV power plants, ESSs and GCPPs.

Impact of the prediction error on the system performance

In the numerical results presented in section "Experimental tests: numerical results", initially, a perfect forecast of both the PV production and the devices usage is assumed. Then, in order to verify the performance of the whole HEM system, additional tests are presented, aiming at evaluating the impact of the error in the prediction algorithms on the performance of the optimization models. Three errors are considered in the forecasting phase, namely:

– Errors in the devices status forecast: In this case, we simulate errors in predicting which devices will be used or not based on the probability distribution functions presented in Fig. 13 and described in section "Prediction of devices usage".
– Errors in the devices start time forecast: In this case, we simulate errors in predicting at what time the devices will be turned on based on the probability distribution functions presented in Fig. 14 and discussed in section "Prediction of devices usage".
– Errors in the PV power plant production forecast: We introduce errors in the PV prediction, properly modeled in section "Model of the PV forecasting error".

For all the three considered errors, the impact of the prediction error on the optimization models performance is evaluated by using the following approach, also shown in Fig. 10.

– The energy consumption and production are optimized according to the day-ahead forecast of both the PV production and devices usage; such values are generated by introducing a prediction

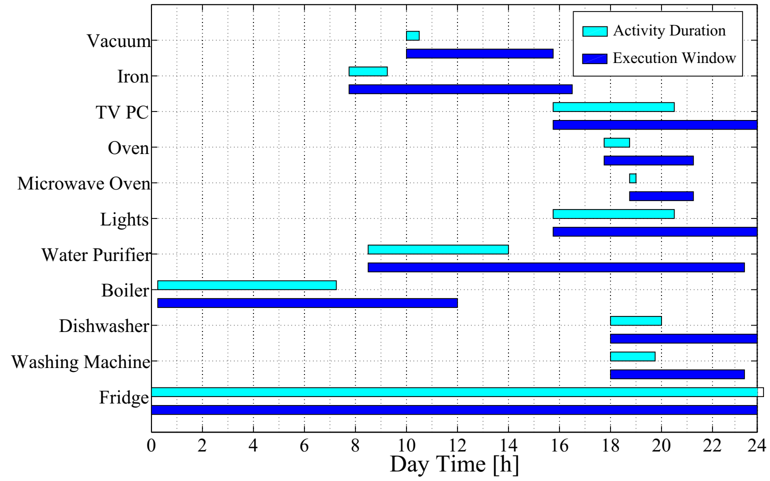


Fig. 9 Medium flexibility scenario considered in our tests

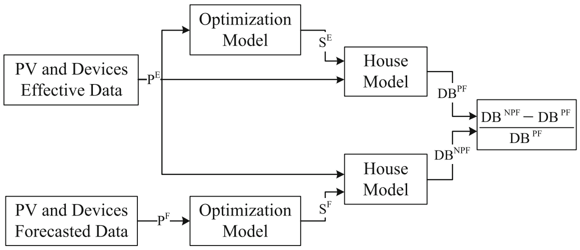


Fig. 10 Daily bill error evaluation outline when introducing errors in the PV production forecast

error on the effective data of PV production and devices usage by applying the probability density functions mentioned in sections "Model of the PV forecasting error"and "Prediction of devices usage". We call P^F (i.e., forecasted values based profile), the daily profile associated with the prediction, and S^F (i.e., forecast based scheduling), the output of the optimization model that we obtain at this step; the scheduling S^F is then applied in the current day.

- The energy consumption and production are optimized according to the effective values of PV production and devices usage. When evaluating the impact of PV forecasting error, device forecast is assumed to be perfect; the other way around, when evaluating the impact of device usage forecast error, PV production forecast is assumed to be perfect. We call P^E (i.e., effective values-based profile) the daily profile that is associated with the real data, S^E (i.e., effective values-based scheduling) the output of the optimization model that we obtain at this step, and DB^{PF} (i.e., perfect forecasting-based daily bill) the corresponding daily bill; DB^{PF} is the minimum electricity cost of the considered day. However, such cost might not be reached as the real data are not known in advance.
- The daily bill is recomputed by applying the scheduling based on the forecast S^F but according to the real values P^E, thus obtaining a cost DB^{NPF} (i.e., non-perfect forecasting-based daily bill). In this way, we obtain the real bill which must be paid by users, when applying the optimized scheduling with real data. The bill DB^{NPF} can therefore be compared with DB^{PF}, which is the optimal bill associated with P^E.
- Finally, the increasing percentage of DB^{NPF} with respect to DB^{PF} is computed.

Model of the PV forecasting error

In order to evaluate the impact of the inaccuracy of the PV production forecasting on the optimization process, a suitable probabilistic characterization of the error affecting the predictions is required; this will allow also an adequate repeatability of the analysis. To this purpose, the gap between predictions and effective PV production is modeled through a conventional profile (Fig. 11), modulated on the basis of the forecasting error observed on field tests (Fig. 12). This model allows representing, in a simplified way, the correlation among the forecast errors along the day, without requiring the use of a complex full probabilistic model.

The conventional characteristic of Fig. 11 is the typical curve of solar irradiation over a day. In each simulation, the mean value of the characteristic is changed according to the mean of the daily error evaluated on the data set. Specifically, the following equation is applied:

$$E_t = m \cdot e_t \tag{24}$$

where E_t is the forecasting error of the PV power generation at the time slot t $[W]$; m is the mean value of the forecasting error, constant for the whole simulation under analysis, drawn according to the pdf of Fig. 12 $[W]$; and e_t is the value of the conventional error profile at the time slot t $[p.u.]$.

The errors data are the mismatches assessed between the power generation measures collected on a real PV plant located in the north of Italy and the weather forecasts made available by a Web service provider for the PV installation site, during the period between August and December 2011.

Notice that the considered approach produces conservative results, since it assumes that the mismatches in the PV forecasts are maintained with the same sign (but with different amplitudes) for the whole day: for example, if the PV production is overestimated, the overestimation is kept for all the day (with greater impact on the performance of the optimization model).

Experimental tests: numerical results

In this section, the results of the numerical simulations performed to define the system parameters and to test the prediction algorithms are presented. In the first

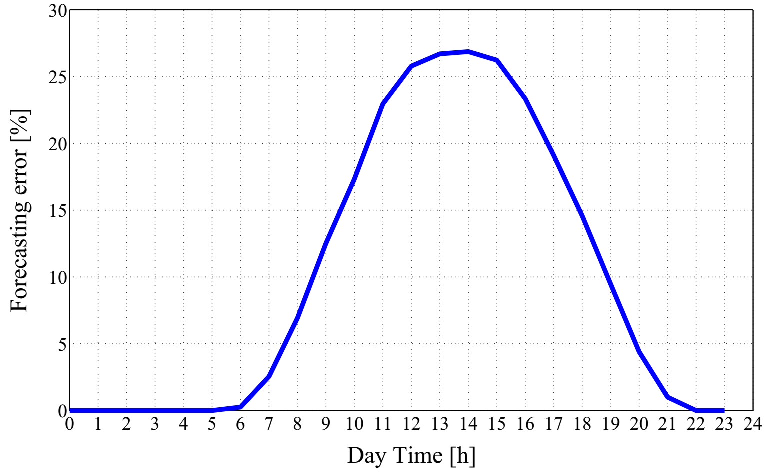


Fig. 11 Conventional characteristic of the forecasting error in p.u. according to the PV rated power and the daily mean error of Fig. 12

part of the study, we assume a perfect forecast of the device usage and PV production. The performance of the prediction tools is analyzed in sections "Prediction of devices usage" and "Prediction of electricity gene-ration", while the computational tests on the optimiza-tion models are reported in section "Energy optimiza-tion". Then, in section "Impact of the prediction error on the system performance", the impact of the pre-diction error on the system performance is assessed, thus evaluating the sensitivity to errors of the pro-posed framework. The results obtained are discussed in section "Discussion on results and contributions".

Prediction of devices usage

The training of the devices prediction method is realized through the parameters identification procedure described in section "Parameter identification procedure". To this end, simulations are used to define the system parameters based on a large data set that would have been hard to obtain in an experimental scenario, mainly because of the long period of time required for gathering data. In the training process, 11 appliances are considered (see section "Case study"), with a simulating period of 1 year. However, for the sake of brevity, only the results obtained with four appliances are reported here: oven, boiler, dishwasher, and TV. For each device, a sequence of realistic power consumption and status profiles is defined, introducing random variations and exceptions in the way users run appliances in order to simulate a real use-case scenario (see section "Prediction of devices usage"). Users, in particular, change their habits in running home devices during the 365 days (e.g., the boiler usage is increased

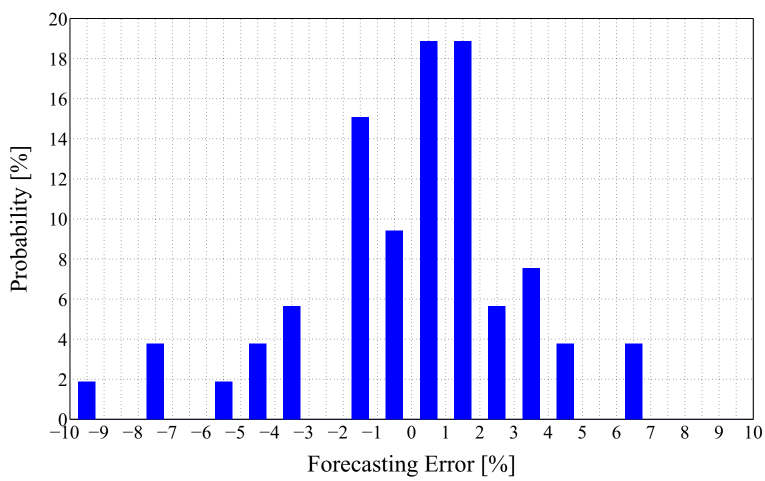


Fig. 12 Probability distribution function of the forecasting error of the PV production

in winter and autumn). Moreover, in 20 isolated days of the year, users run devices contrary to their habits.

The training model of Eq. 5 is solved by defining a recursive formulation which is able to find the optimal values of the variables w_a^C, N and σ through an exhaustive research process whose results are the following:

- $w_{oven}^C = 15$ min, $w_{boiler}^C = 29$ min, $w_{dishwasher}^C = 16$ min, and $w_{tv}^C = 18$ min;
- $N = 28$ days;
- $\sigma = 30$ min.

Notice that in the exhaustive research process, weights α and β of the learning model of Eq. 5 are experimentally set to 0.9 and 0.015.

Table 2 presents the numerical results obtained by varying the duration of the learning period, N, when using the optimal values of parameters w_a^C and σ shown before. As one can see, a small value of N brings to bad performances of the algorithm in predicting home appliances usage for the next day. By increasing the length of the learning period, the system becomes more and more accurate, even if no major improvement is observed for N higher than 28. As for time and duration prediction, the numerical results presented in Table 3 show a very good accuracy of the system, except for the time prediction of the oven. Actually, in our simulations, we suppose that users run this device about 2 h later on the weekend than on the working days, hence explaining the errors of the system in predicting the oven starting time.

In addition to numerical evaluations, we have also performed experimental tests in order to evaluate the performance of the system in a real use-case scenario. For this reason, a prototype version of the proposed power meter sensor network has been implemented. The WPSN has been used for monitoring the power consumption of the appliances listed in section "Case study" for a period of 60 days. The numerical results obtained are presented in Figs. 13 and 14 and in Table 4. In Table 4, for the sake of brevity, only the results obtained with some of the home appliances are reported: oven, boiler, dishwasher, and TV. In fact, with the other devices (seven house appliances), no significant variation of the forecast algorithm perfor-mance has been observed and results coherent to those presented in Tables 2, 3, and 4 have been obtained. The experimental tests confirm the system performance experienced with numerical analyses. The algorithm, in particular, has a good accuracy in predicting the devices status and usage duration, while a perfor-mance degradation is detected in the time prediction, reflecting the fact that users' habits are just partially predictable.

Prediction of electricity generation

As for the prediction of device usage, numerical analyses are carried out in order to test the efficiency of the model adopted for the PV production forecasting. It is worth noting that in the proposed framework the weather forecasts are acquired from a Web service provider, and therefore, they are subject to an intrinsic estimation error that cannot be limited or removed. For this reason, in the following, only the performance of the mathematical model exploited to represent the PV power plant technical characteristics is assessed (the evaluation of the overall PV prediction error, necessary to measure the sensitivity to errors of the optimization procedure, is discussed in section "Model of the PV forecasting error").

Table 2 Average percentage of correct status predictions for different lengths (N in days) of the learning period

	Status prediction			
N [days]	Oven	Boiler	Dishwasher	TV
11	38 %	40 %	42 %	35 %
21	78 %	81 %	84 %	77 %
28	94 %	95 %	95 %	93 %
45	96 %	96 %	95 %	95 %
60	96 %	96 %	95 %	95 %

Table 3 Average difference in minutes between the predicted device start time (duration) and the observed one with $N = 28$ days

	Oven	Boiler	Dishwasher	TV
Time prediction error	91 min	26 min	22 min	28 min
Duration prediction error	14 min	18 min	8 min	31 min

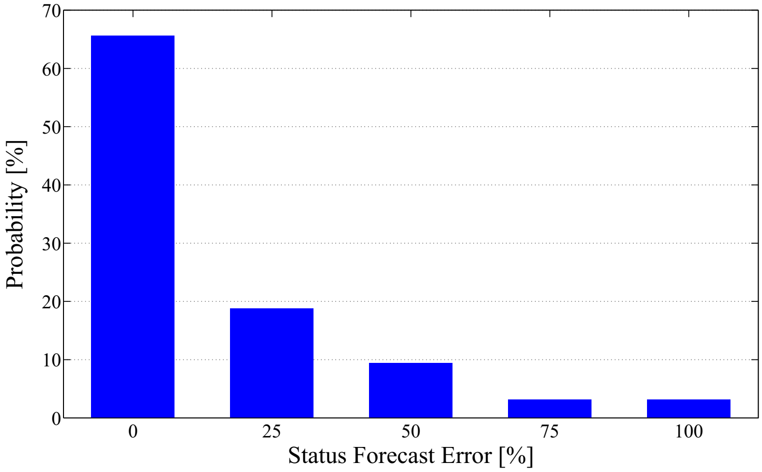


Fig. 13 Probability distribution function of the devices status forecast algorithm error

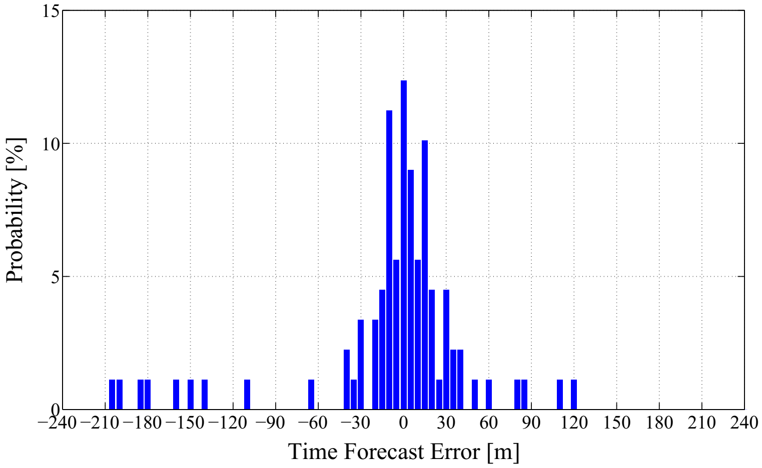


Fig. 14 Probability distribution function of the devices start time forecast algorithm error

Table 4 Status, time and duration prediction performance evaluated through experimental tests

	Oven	Boiler	Dishwasher	TV
Average status prediction accuracy	78 %	90 %	93 %	81 %
Average time prediction error	71 min	29 min	42 min	32 min
Average duration prediction error	7 min	18 min	32 min	22 min

The performances of this approach are evaluated on the data collected on a real PV power plant (sited in the north of Italy), with a rated power equal to 9.18 kWp. The database consists of information about the produced power and global solar irradiation, on an hourly basis, for the period from January 2009 to December 2010.

Through the Eq. 6 and a linear regression algorithm, in each time slot t, the proportionality coefficient of the PV model G_t is evaluated (see section "Prediction of electricity generation"). The data considered are the historical production and weather forecasts of the previous 100 h. The results obtained are reported in Fig. 15 and represent the correlation between the values of the PV generation estimated through the PV model and the values actually measured on the real power plant. Numerical results show a good accuracy of the method, confirmed also by the analysis of the error in Fig. 16. The graph shows the percentage of hours in which the forecasting error (in percentage with respect to the PV plant rated power) is equal to the value on the x-axis. The production forecasting error, in the most of cases (59.66 %), is lower than 2 % of the rated power of the PV power plant (the root mean square error is equal to 2.39 %). Moreover, in almost every hour (99.45 %), the prediction error is lower than 10 %.

Although the performance of the PV production estimation could be improved further by using more complex approaches, as for example in Sulaiman et al. (2008) where neural networks allow the production to be estimated with a root mean square error of about 1 %, the production forecasting is strictly reliant on weather conditions affecting the PV plant (in particular, solar irradiance): if the prediction is performed on long time horizons (e.g., the day-ahead, as in our case), the weather uncertainty is the most impacting factor for the accuracy estimation (Lorenz et al. 2007). According to our analysis, the linear regression method is a suitable tradeoff between the estimation accuracy and the simplicity of the proposed architecture. We underline the crucial importance of this last aspect, due to the need to limit the final cost of the HEM system and its impact on users' habits.

Energy optimization

The proposed optimization models have been implemented in A Mathematical Programming Language (AMPL) and solved using CPLEX (a state-of-the-art optimization software package from IBM ILOG) on a Intel Pentium Duo 3.0 GHz, with a 3.5 GB RAM.

The results of our tests on the single-user case are reported in Table 5 for the TOU tariff and in Table 6 for the dynamic tariff. The zero flexibility case (i.e., the starting time of each activity is given and cannot be modified by the model) is used as a reference value and reported in the first row. For each ESS, PV power plant and flexibility combination, the percentage of improvement with respect to the corresponding zero flexibility daily bill is reported. It is possible to evaluate the best theoretical bill reduction, as the difference between the most expensive and the cheapest energy price: for the TOU and dynamic tariffs, these reductions are, respectively, 15 and 32 %. As a consequence, the improvements obtained in our tests and

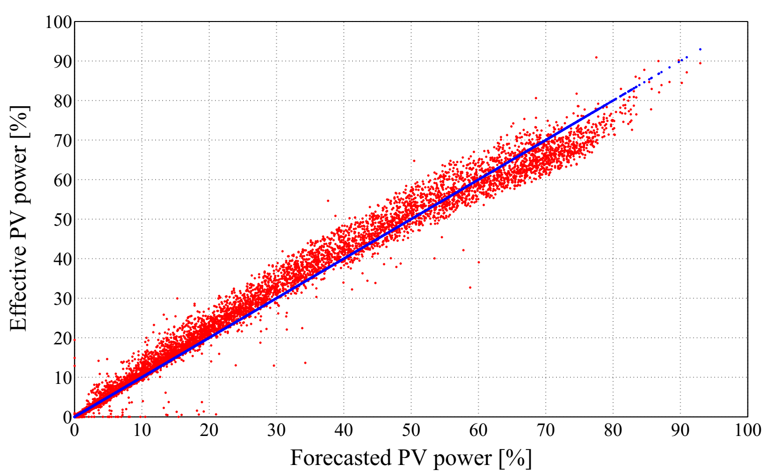


Fig. 15 Correlation between the production measured on the PV and the production estimated with the linear regression model

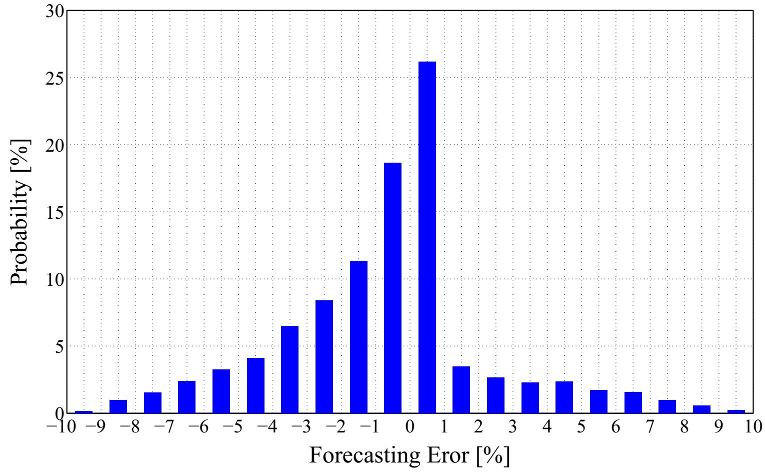


Fig. 16 Probability distribution function of the adopted linear regression model

presented in Tables 5 and 6 are reasonably close to the theoretical ones.

Test results show that the reduction of the daily bill achieved by applying the proposed models, as for the TOU tariff, is between 10 and 12 % depending on the specific configuration. This reduction is just slightly dependent on the flexibility configuration, so that even in the low flexibility scenario, the achieved improvement is close to the best one. In this case, in fact, it is quite easy for the model to reduce the bill by means of shifting only loads used during peak hours to off-peak hours. For this reason, only a few users' scheduling changes are required to minimize the electricity bill and even a low flexibility case can allow obtaining very good results. On the other hand, in reference to the dynamic tariff case, major differences are shown between different flexibility scenarios. In this case, devices flexibility is a pivotal element for the system to take best advantage of the complexity of the electricity price profile, especially when the ESS is not available. Moreover, dynamic tariffs allow the system to achieve better results in terms of bill minimization than in the TOU tariff case. Indeed, in the dynamic scenario, there is a greater margin for optimization at the cost of greater complexity that can be efficiently managed if enough flexibility is given to manage appliances, and if batteries are available.

Table 5 Single-user daily bill (within a 0.05 % of the optimal solution) for a TOU tariff

		ESS and PV power plant configuration			
		0 ESS/0 PV	0 ESS/1 PV	1 ESS/0 PV	1 ESS/1 PV
Flexibility	Zero	1.502 €	1.166 €	1.482 €	1.145 €
	Low	−10 %	−11 %	−10 %	−11 %
	Medium	−10 %	−11 %	−11 %	−11 %
	High	−11 %	−12 %	−11 %	−12 %

Table 6 Single-user daily bill (within a 0.05 % of the optimal solution) for a dynamic price

		ESS and PV power plant configuration			
		0 ESS/0 PV	0 ESS/1 PV	1 ESS/0 PV	1 ESS/1 PV
Flexibility	Zero	1.541 €	1.203 €	1.388 €	1.094 €
	Low	−5 %	−6 %	−8 %	−10 %
	Medium	−5 %	−6 %	−8 %	−12 %
	High	−16 %	−19 %	−20 %	−21 %

Tables 5 and 6 show that, in minimizing the electricity bill, a key role is also played by PV plants and ESSs. PV power plants allow a reduction of the daily bill, since the domestic load is partially supplied through the local generation. Specifically, when using the PV power plant, the bill decreases up to 22 % even with no ESS and device scheduling flexibility. A significant saving can be also obtained by using the ESS, which allows users to store electric energy during low-price hours to use it in peak hours. In particular, by adding an ESS to the house framework, a cost improvement up to 10 % can be achieved even without PV power plant and devices optimization.

One of the main advantages of the proposed model is that it ensures the reduction of the electricity demand during peak hours, when the energy is more expensive. In Fig. 17, the electricity demand resulting from the proposed method is compared to that of an unmanaged house, in the TOU tariff scenario. As one can see, the demand during peak hours (i.e., 8 am–7 pm) is significantly lower, a desirable property from the DSO perspective (the peaks of PV injections are not significant, being limited, in the worst case, to 1 kW). Although in some cases the peaks reach the maximum allowed value, they have been shifted from the peak hours to the less expensive ones.

For the electric grid efficiency, even more benefits can be achieved by applying the proposed approach to the multi-user cooperative case. Cooperation can indeed allow the community of users to reduce their GCPP. The results for the TOU tariff and low flexibility scenario are shown in Table 7 in terms of aggregated users' bill. Different scenarios are considered: They differ for the maximum global absorption allowed, which is kept smaller than the sum of single maximum absorption due to the meter limit. For each scenario, the increasing price with reference to the corresponding single-user case (i.e., houses daily bills are independently optimized) is reported. Notice that for some specific configurations, the problem is not feasible since there is no solution that fulfills the corresponding maximum global absorption constraint (i.e., Eq. 19).

The ESS is a key element in order to allow the group of users to reduce their GCPP with a negligible cost increase if compared to the non-cooperative scenario. The same peak power reduction is unlikely to be achieved in the non-cooperative case because it would require users to significantly change their habits in terms of household appliances usage. People, in fact, could not use multiple appliances simultaneously, unlike to what happens in their everyday life. Notice that reducing the GCPP would bring advantages to the electric grid (i.e., better exploitation of network assets): These benefits in perspective would be reflected to residential users in terms of reduction of costs for the energy transport and dispatching services, with economic benefits for them notably higher than the spending increase reported in Table 7.

The electricity demand during peak hours significantly benefits from the cooperation. The absorption peak is shifted from peak hours to less expensive ones (it is also kept limited). A demand profile for a particular case is shown in Fig. 18, in which selfish and cooperative cases are compared.

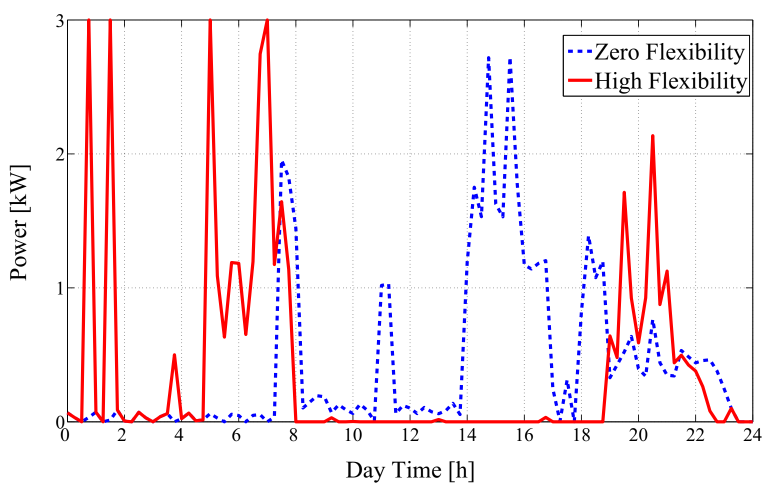


Fig. 17 Electricity demand for zero and high flexibility with a TOU tariff, a PV power plant and an ESS

Table 7 Single-user/multi-user aggregated users daily bill (within a 0.11 % of the optimal solution) for a TOU tariff and low flexibility scenario.

	ESS and PV power plant configuration				
	0 ESS/0 PV	0 ESS/5 PV	5 ESS/0 PV	5 ESS/5 PV	10 ESS/10 PV
Single-user, GCPP=30 kW, CPP=3 kW	13.509 €	11.934 €	13.410 €	11.822 €	10.344 €
Multi-user GCPP=9 kW, CPP=3 kW	Not Feasible	Not Feasible	+0.003€	+0.002€	+0.001€
Multi-user GCPP=12 kW, CPP=3 kW	Not Feasible	Not Feasible	+0.001€	+0.002€	+0.001€
Multi-user GCPP=15 kW, CPP=3 kW	+0.077€	+0.075€	+0.001€	+0.002€	+0.001€
Multi-user GCPP=18 kW, CPP=3 kW	+0.007€	+0.070€	+0.001€	+0.001€	+0.001€
Multi-user GCPP=21 kW, CPP=3 kW	+0.004€	+0.070€	+0.001€	+0.001€	+0.001€

Impact of the prediction error on the system performance

In order to test the impact of the prediction error on the system performance, the same residential scenario presented in section "Case study" is adopted, considering a low degree of flexibility. Numerical results on the impact of PV production forecast error are shown in Figs. 19 and 20. In Fig. 19, in particular, we report the increasing percentage of DB^{NPF} with respect to DB^{PF} as the error in the PV prediction changes. As it can be seen, the error on the daily bill is, in general, very small and grows slightly when increasing the error in the PV prediction. Moreover, as expected, when using the TOU tariff the impact of the PV error on the system performance is weaker than in the dynamic price case. In the first case, in fact, changes in the daily bill occur only when shifting an activity from peak hours (i.e., 8 am–7 pm) to the remaining hours of the day, or vice versa. On the other hand, when using a dynamic price, changes in the daily bill are more frequent since they occur every time an activity is shifted from an hour of the day to another. As a consequence, it is very likely that an error in the PV forecasting will cause an error also in the daily scheduling and bill. Figure 20 shows the probability density function of the increasing percentage of DB^{NPF} with respect to DB^{PF}. The error in the daily bill triggered by the

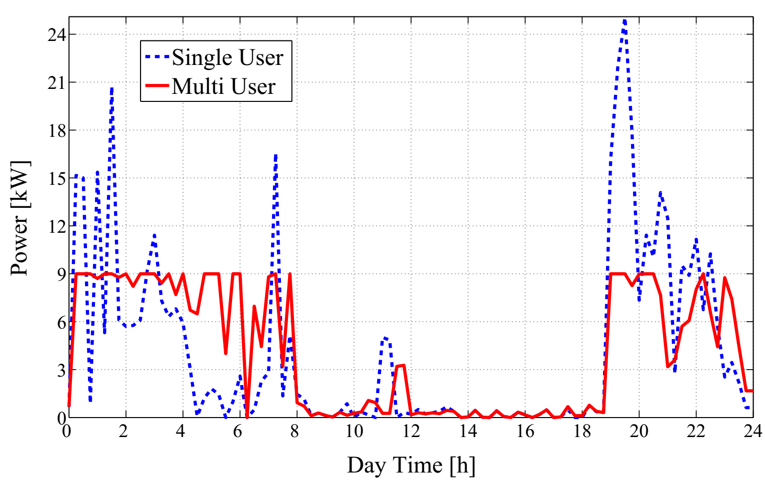
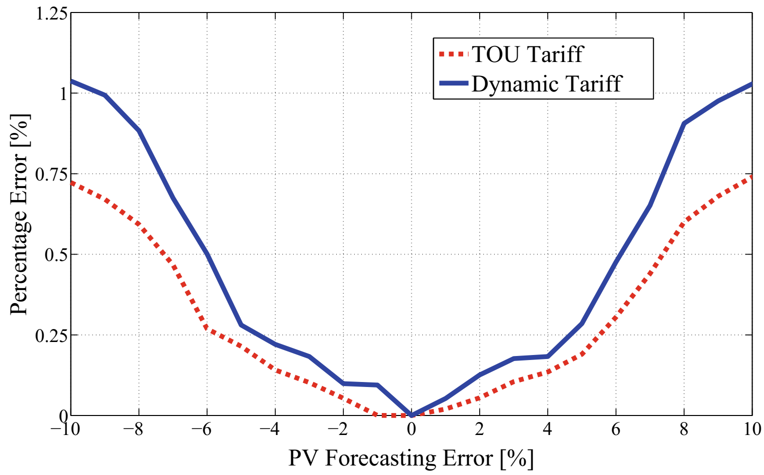


Fig. 18 Single-User and Multi-User electricity demand for low flexibility, 5 PV power plants and 5 ESSs with a TOU tariff

Fig. 19 Increasing percentage of DB^{NPF} with respect to DB^{PF} as the error in the PV prediction changes

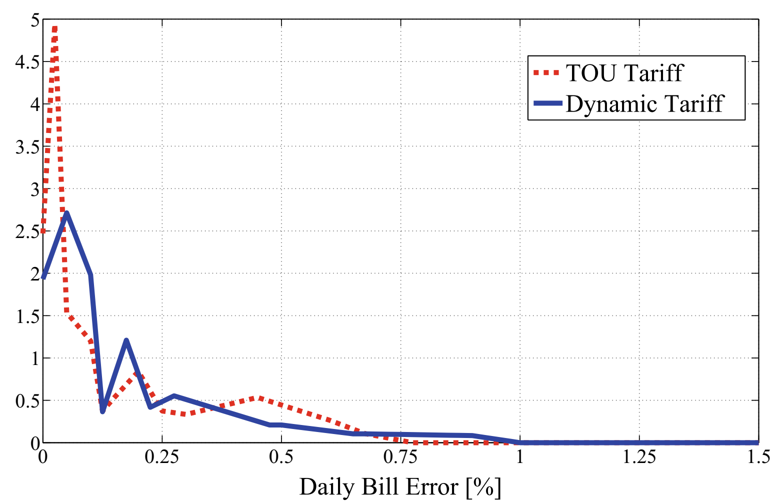


error in the PV prediction is, in most of cases, very low.

Additional tests have also been performed to verify how the effect on the system performance, coming from the errors in the PV forecast, varies depending on the presence of the 10 kWh/3 kWp ESS. Figure 21 shows the results obtained when using the TOU tariff. Although the ESS allows the user to improve appreciably his electricity bill, in the scenario with ESS, the variations of the daily bill with respect to the DB^{PF}, caused by prediction errors, are greater than those obtained without ESS. As shown in Table 5, in fact, the optimal daily bill obtained with no error in the PV forecast is lower when a storage system is available because of the flexibility given by the ESS in managing electric energy exchanges with the grid. However, when errors in the PV forecast are committed, the usage plan of the ESS defined by the energy management model becomes non-optimal, hence reducing the bill saving obtained by using the storage system. On the contrary, obviously, when no ESS is used there is no negative effect on the bill saving coming from the non-optimal usage of the ESS. Nevertheless, even if the efficacy of ESSs is reduced when committing errors in the PV forecast, its impact on the daily bill saving and peak reduction is not compromised, since the performance variations triggered by PV prediction errors are very low.

We have performed similar tests (on the house configuration presented in section "Case study", again with low flexibility level) for evaluating the effect on the system performance of errors in the devices forecasting algorithm. Results are shown in Figs. 22 and 23. Figure 22, in particular, reports the absolute

Fig. 20 Probability density function of the daily bill error



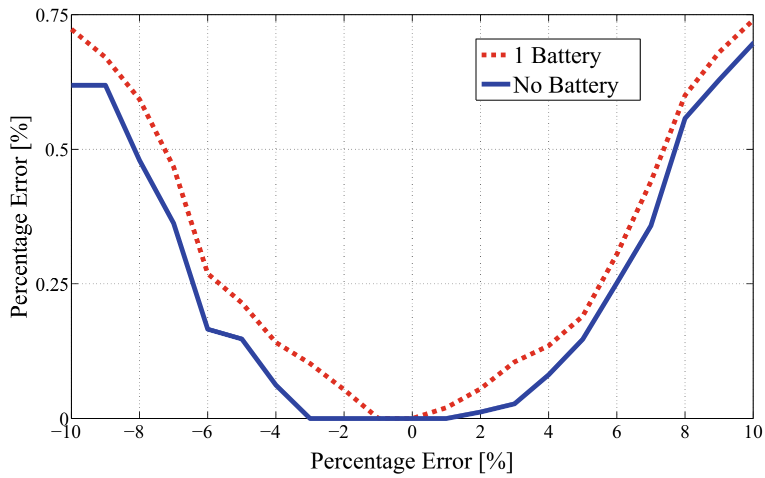


Fig. 21 Increasing percentage of DB^{NPF} with respect to DB^{PF}, with and without the ESS when using the TOU tariff

value of the increasing percentage of DB^{NPF} with respect to DB^{PF} as the error in the prediction of the devices starting time (status) changes. Once again, as expected, when using the TOU tariff the impact of the forecast error on the system performance is weaker than in the dynamic price case. In the first case, in fact, changes in the daily bill occur only when an activity is moved from peak to off-peak hours, or vice versa. On the other hand, when using a dynamic price, changes in the daily bill occur every time the scheduled starting time of an activity is changed, with a direct impact on the daily bill. However, as it can be seen in the first two columns of Table 8, the expected net error in the daily bill is, also in this case, very small. Notice that the numerical results of Table 8 have been obtained by weighting the functions presented in Fig. 22 by the probability distribution function of the forecast starting time error presented in Fig. 14.

Finally, we have tried to increase the flexibility of the optimization module in scheduling the home appliances in order to verify the impact of this feature in mitigating the effect of errors in the devices usage forecast. Figure 23, in particular, shows the results obtained with errors in the devices starting time forecast, when using the TOU tariff. As expected, the greater is the flexibility of the system, the more the error on the daily bill shrinks. The same effect can be observed when an error in the devices status forecast occurs.

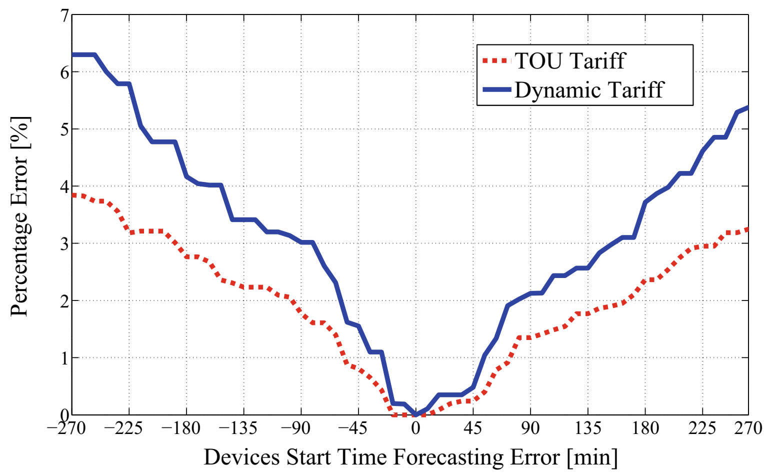


Fig. 22 Increasing percentage of DB^{NPF} with respect to DB^{PF} as the error in devices starting time changes

Fig. 23 Increasing percentage of DB^{NPF} with respect to DB^{PF} as the error in devices starting time and the flexibility of the model change

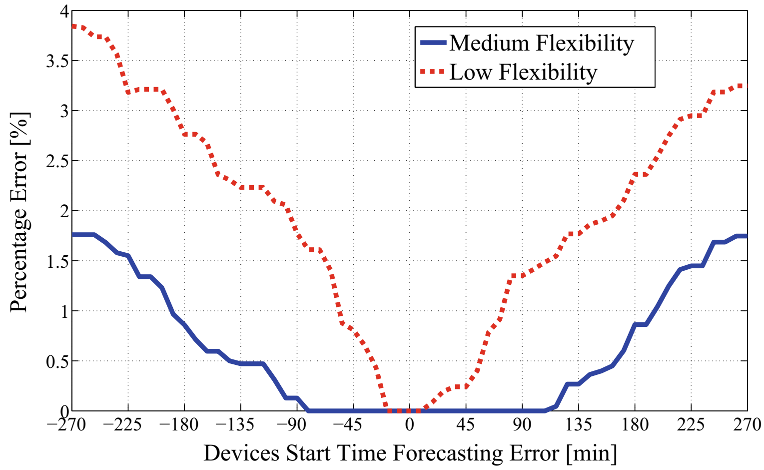


Table 8 Mean percentage and standard deviation of the error of the daily bill with errors in the devices starting time and status forecast

	Starting time error		Status error	
	Mean error	Standard deviation	Mean error	Standard deviation
TOU Tariff	0.88 %	0.41 %	1.52 %	0.79 %
Dynamic Price	1.45 %	0.78 %	2.05 %	0.98 %

Discussion on results and contributions

This section reports a discussion of the results obtained in this research work, focusing on the benefits for the users given by the HEM framework and on its practical applicability in real-life scenarios, with particular attention to the costs of the overall infrastructure. Then, the differences between the cooperative and non-cooperative HEM approaches, and the impact of the system parameters on results, are discussed. Finally, the novel contributions of the work with respect to the state of the art are depicted.

Benefits of the HEM framework The analyses performed show that substantial benefits can be achieved by using the proposed HEM architecture. From the point of view of the final user, the cost of the monthly bill can be reduced by shifting loads of home appliances to time periods in which the electric energy price is low. In the case of a low flexibility for the devices scheduling (i.e., the maximum delay of home appliances with respect to the preferred start time is 15 min), the economic savings are appreciable, although quite limited (5–10% of the overall electric bill). However, if users have a more flexible behavior (in the extreme case, the execution window is set up to the whole day), the advantages can be considerably greater (up to 20–30 %, according to the presence of ESSs/PVs and on the tariff).

Numerical results presented in section "Energy optimization" are obtained by considering two specific electricity tariffs, TOU and dynamic tariffs, since they are the tariff structures with the greatest (respectively, current and future) applicability to the residential sector. Electric energy tariffs reflect, through a supply/demand mechanism, the costs incurred by the system to satisfy the "energy needs" of users (e.g., higher during peak hours and lower in off-peak hours). As a consequence, tariffs evolve based on the needs of the actors of the power system (Charles River Associates 2005). In Italy, for example, in the last few years, DG has been altering the daily profile of the electric energy price, especially in the areas characterized by greater PV plants diffusion. Specifically, since the PV electricity generation is limited to daylight hours, users must be incentivized to shift loads to the central hours of the day so as to meet the PV supply. Similarly, in the future, the diffusions of HEM systems could substantially modify users' habits in using home appliances, thus requiring users to adjust the electricity price accordingly. The numerical results presented in this paper are reliant on the tariff structure considered, so assuming different tariffs for users will result in variations in the numerical quantities obtained, i.e., the bill savings achieved. However, the approach proposed has a general validity (the management core can be adapted to take into account also different price signals), because it assesses the performance of the proposed HEM architecture in exploiting the users' flexibility needed by the power system, as well as ESSs and DG resources.

Cost of the HEM framework The cost of the HEM infrastructure is a pivotal aspect that has to be taken into account in evaluating its actual applicability in real-life scenarios. In fact, despite the economic savings for the user being quite significant, they could not justify the investments required for the HEM system. For this reason, the main components of the infrastructure have been designed to keep costs down. The HEM core (i.e., the processing core), for example, can be installed in the smart meter, and a television, a PC monitor, or a smartphone could be used as user interface.

It is important to point out that, although the objective of the proposed approach is the minimization of the daily bill, the effectiveness of the HEM system also relies on the value-added services that the HEM architecture could provide to customers. The communication interface, for example, could be useful to foster users' energy awareness: The user could improve his awareness on energy consumption and costs based on the information coming from the grid and the home itself (e.g., user and contract references, current power use, historical consumption data, current tariff and tariff time frames, and overload alarms) (The Energy@home Technical Team 2011). In addition, the aggregator could exploit the new communication channel to transmit commercial information and maintenance notices to customers, as well as to make users faithful customers.

The inclusion of ESSs into the HEM architecture is a critical aspect, requiring a particular attention. Despite ESSs having shown great benefits on the savings achievable by the system, their cost greatly limits their applicability in real-life scenarios. In general, nowadays, ESSs potential as regulating resource for the power system still must be fully proven: Some countries have started to foster a massive ESSs deployment on their transmission and distribution electricity networks (e.g., California, Germany, and Italy), while other governments still rely completely on conventional resources. In the authors opinion, the use of ESSs within the HEM system can be effective only in a multi-purpose framework, i.e., if the ESS is exploited to perform, in addition to the energy management, also other services useful for the grid (e.g., ancillary services, such as frequency regulation and voltage control) (Delfanti et al. 2014).

Cooperative HEM solutions The cooperative optimization of home buildings is, in the perspective, the most promising strategy to be implemented in a real scenario: By admitting only a small rise in the users' daily bill if compared to the individual houses optimized one, the impact of domestic load on network can be considerably reduced, limiting the peak power required to the system (Table 7). In fact, an aggregated approach to the HEM problem allows the coordination of users power exchanges, thus reducing the peaks and consequently avoiding the over-investments in network assets. The great benefits achievable through the cooperative approach have to be attributed to the different optimization perspective of the central energy controller with respect to the single-household model. In fact, a set of energy plans and devices scheduling can be found for each user, whose electricity bills are within a very small margin of the optimal one (e.g., in the flexibility scenario presented in Fig. 9 and when using the TOU tariff of Fig. 8, the iron can be started at whatever time from 8:00 to 16:30 with no variation of the daily bill). When applying a single-household model, each customer selects one of the schedulings that minimize his bill, without contemplating the effect of his decisions on the overall power demand. On the other hand, the cooperative case considers the net effect of each user's plan on the overall system performance, and also suboptimal users' energy schedulings can be selected by the central controller when improving the overall bill of the community of customers or reducing the peak power required to the system. As a consequence, the cooperative model can exploit the differences among different optimal (and suboptimal) schedulings and inherent randomness among users, in terms of electricity consumption needs and preferences, to obtain a flatter demand profile. An aggregated approach could also allow the optimization of the flexibility resources on the grid, such as the ESSs used to manage the power flows. The cost of investing and operating a few large batteries, each one aimed, for example, to manage the houses in a neighborhood, is substantially lower than operating many ESSs installed in the single houses (Lund et al. 2011).

It is important to point out that in analyzing the cooperative model, we have considered the worst condition for the HEM optimization: All users are assumed to have the same load/generation profile, thus there is no compensation among the power profiles of different buildings. Differences and inherent randomness among users can be exploited to obtain even better performance of the HEM architecture in optimizing the users' behavior in real scenarios.

Tests parameters and numerical results In the analyses performed in this work, a domestic configuration obtained from the literature data relevant to Italian standard users is considered. Specifically, the house is supposed to be equipped with 11 appliances modeled as shiftable devices and four different flexibility levels are considered to optimize their usage: zero (i.e., activities scheduling is not optimized), low, medium, and high. In the low flexibility case, the maximum variation of the starting time with respect to the preferred one is, on the average, 15 min: Based on the literature data, this is considered a passable variation in real-use case scenarios. On the other hand, the medium and high flexibility cases may be seen as less realistic conditions since they would require users to modify their habits in a more drastic way. Nevertheless, in this paper, these cases are considered in order to verify the system performance achievable in more favorable scenarios (i.e., the greater the flexibility, the larger the degree of freedom in optimizing the appliances usage).

As already mentioned in this paper, a specific case study is taken as reference: The set of devices considered consists of the basic appliances used by an Italian family on a typical spring day and the energy tariffs are defined according to this period of the year. Actually, we have run additional tests on other instances of the problem in order to evaluate the sensitivity of the proposed methods with respect to the system parameters. Specifically, the set of appliances has been modified in terms of both number and kinds of appliances in order to simulate small (i.e., seven appliances) and large family units (i.e., 15 devices). Numerical results have shown that the larger the set of devices is, the higher the bill saving is because of the increased number of variables (i.e., appliances) that can be optimized by the system. However, in terms of percentage variation of the bill with respect to the non-optimized one, no significant variation was found with regard to the results presented in section "Energy optimization". Indeed, in all the cases considered, the gap between the percentage electricity bill reduction obtained when using the basic 11 appliances configuration and the others was always lower than 3 %. The same consideration can be also applied to the difference between the system performance observed during working days and weekends, as well as the variation of the bill reduction during the different seasons of the year. In the authors opinion, this consideration may change when including in the model other kinds of appliances (e.g., HVAC devices) whose use is strictly determined by the season and whose instantaneous power consumption can be directly controlled, hence giving the system a greater degree of freedom in optimizing their operation.

Work contributions This research work provides important contributions to the state of the art of HEM solutions. One distinctive feature of our approach, if compared with most of the literature works, is that it provides an in-depth analysis of the overall framework, including forecasting and optimization methods, also assessing the impact of prediction errors on the system's performance. In the BEE HEM system, in fact, the optimization models are integrated with PV and devices usage forecast tools. Moreover, also in regard to the single components of the system proposed, some novel contributions are provided. Specifically, as for the devices usage forecast method, the solutions presented in the literature usually have several limitations since they have not been explicitly developed for HEM systems. Indeed, these methods allow the assessment of the energy consumption only at an aggregate level (i.e., homes or buildings), without providing any detail regarding the use of individual household devices. Moreover, scalability problems severely limit the applicability of the techniques traditionally proposed. In this research area, we addressed these problems by proposing a novel algorithm, designed for HEM systems, to predict individual household devices consumption and usage based on power meter sensors and stochastic models.

With reference to energy optimization models, the present work considers and addresses several limitations of the traditional solutions proposed in the literature. First of all, the whole house environment, including loads, generators, and ESSs, together with market energy prices have been realistically modeled and taken into account. In addition, a parallel analysis between users' and grid's benefits provided by the HEM architecture is carried out, as well as a comparative study between single- and multi-user (i.e., cooperative) approaches in managing electric energy resources.

Conclusion

Traditionally, electric power systems have been managed by adjusting the production of large power plants according to end-users' demand. These power plants, typically connected to the transmission network, were also used to supply the needed ancillary services. The revolution of Smart Grids, with the increasing penetration of (intermittent and uncontrollable) DG and the need for a more efficient power system, requires a much more active role of users in the system management. The aim is to make their electricity consumption adjustable according to RESs fluctuations and changes in the system requirements, hence allowing an improvement of the network efficiency and reliability. To achieve these goals, within the house framework, the local generation has to be properly coordinated with loads and, in perspective, ESSs have to be used to reach a further degree of flexibility. However, the development of new instruments based on ICT that can support end-users in these new tasks is essential for stimulating their participation and for enabling the interaction with the retailers and system operators.

In this paper, a new framework that includes tools for the monitoring and management of home energy systems is presented. Solutions that can simplify the configuration and management tasks of users through the profiling of their habits in using home appliances, the accurate estimation of the locally produced energy and the support in the decisions on system optimization, are developed. The framework allows the cooperation among users in order to improve the overall efficiency and to limit the flexibility required to residential customers in using energy.

The proposed tools are tested on realistic instances based on the Italian electricity market, but that can be considered representative of several similar scenarios in western countries. Results obtained in the tests confirmed the benefits achievable with the optimization driven by electric energy dynamic prices, even if due to current low electricity prices, the direct economic savings are not probably sufficient to stimulate domestic users toward a more efficient and sustainable electric energy consumption. Results also showed that remarkable improvements can be achieved with cooperation among users, thus confirming that services for the coordination of the demand of groups of users can guarantee a huge improvement of the electric system performance.

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