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Near real time load shifting control for residential electricity prosumers under designed and market indexed pricing models ☆

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HIGHLIGHTS

- Design of an energy management system for residential electricity prosumers.
- Both designed and market indexed pricing models are considered.
- Optimal load-shifting, self consumption and automated demand side management.
- Simulation of relevant scenarios which will characterize future residential nodes.

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ABSTRACT

This paper presents an event driven model predictive control approach for a local energy management system, enabling residential consumers to the automated participation in demand side management (DSM) programs. We consider a household equipped with smart appliances, a storage unit, electric vehicles and photovoltaic micro-generation. Resources are coordinated according to the needs of maximizing self-consumption and minimizing the cost of energy consumption, in a contractual scenario characterized by designed or market indexed pricing models, with DSM options. The control action (appliances' start times, the storage charging profile and the IEC 61851 compliant charging profile of the electric vehicles) is updated every time an event triggers the controller, such as a user request, a price/volume signal or the notification of a new forecast of micro-generation from the photovoltaic unit. The control framework is flexible enough to meet the real dynamics of a household and short-term grid requirements, while taking into account user preferences, contractual and technical constraints. A proper set of simulations validates the proposed approach.

1. Introduction

The future electricity grid will feature rapid integration of distributed and renewable energy sources (RES) as a priority for a sustainable growth of the industrialized countries [1]. The implications of such a trend are widely being investigated and the availability of negative and positive balancing power is commonly recognized as a basic requirement in order to mitigate the effects of RES volatility on grid stability and reliability [2,3]. Depending on the size and placement of distributed generators from consumption, the balancing task can be performed at different levels, according to the basic principle "the smaller the distance between RES and consumption, the higher the benefit for the grid." As a matter of fact, when talking about micro-generation at residential level, a local energy management system (EMS) matching generation with consumption appears as a meaningful and cost-effective technological solution both in the consumer and distribution system operators (DSOs) perspective. Further, when considering larger amounts of energy, extended control architectures implementing automated demand side management (DSM) strategies and several forms of storage devices installed along the distribution lines are complementary, clean and cost

Abbreviations: DAP, day ahead pricing; DER, distributed energy resources; DSM, demand side management; DSO, distribution system operator; EMS, energy management system; EV, electric vehicle; MILP, mixed integer linear programming; MPC, model predictive control; PV, photovoltaic; RES, renewable energy sources; RTP, real time pricing; SHC, smart home controller; ToU, time of use; UP, user preference; V2G, vehicle to grid; VPT, virtual power threshold.

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Nomenclature

T	discretization time step
ct	first time step of problem definition
ch	last time step of problem definition
dt	departure time of the electric vehicle (EV)
$\tilde{C}$	pricing parameter
C	electricity tariff
P^*	estimate of power from non-plannable loads
P^{pln}	estimate of power from planned loads
P^{pv}	estimate of micro-generated power
VPT	virtual power threshold
M	set of appliances to be planned
S_m	first possible start-time interval for the mth plannable appliance (set by the user)
E_m	last allowed end-time interval for the mth plannable appliance (set by the user)
N_m	duration of the mth plannable program
$\overline{P}_m$	mean consumption of the mth plannable appliance
$\hat{P}_m$	peak consumption of the mth plannable appliance
u_{mk}	Boolean control variable related to the activation of the mth appliance
x	state of charge of the electric energy storage
ξ^{st}	efficiency coefficient of the storage
ΔP^{st}	charging/discharging rate of the storage
u_k^{st}	Boolean control variable related to storage charging operations at kth time interval
v_k^{st}	Boolean control variable related to storage discharging operations at kth time interval
y	state of charge of the EV
ξ^{ev}	efficiency coefficient of the EV
ΔP^{ev}	maximum charging/discharging rate of the EV
u_k^{ev}	semi-continuous control variable related to EV charging operations at kth time interval
v_k^{ev}	semi-continuous control variable related to EV discharging operations at kth time interval
st, ev, pv	superscripts referred to, respectively, the electricity storage, the EV and the photovoltaic panel
max, min, 0	superscripts referred to, respectively, a maximum and minimum allowed value, and an initial value

competitive technologies in the balancing markets with respect to legacy generation, as they can reduce the reliance on expensive and pollutant power plants taken in stand by hot mode for the most of time. In the real case, characterized by a combination of small and medium size generating units from RES, a local energy management system working at residential level is the key element enabling the consumer to optimally benefit from the energy produced inside the dwelling and to participate in DSM programs in an automated way, then enlarging his/her level of responsiveness and the related economic benefit in reaction to proper signals [4,5]. Such a system is also promising with respect to the objective of minimizing the cost related to the energy that exceeds the local production from the micro-generation, in a scenario characterized by a time varying electricity tariff. Indeed the recognition of electricity product differentiation as a meaningful concept for the improvement of grid operation [6] has resulted in the possibility for consumers to choose among several pricing schemes characterized by different risk levels, based on their flexibility in electricity usage [7]; the higher the tariff variability during the day, and day by day, the higher the risk transfer from the retailer to the consumer [8], the higher the need of help for the consumer in order to optimize energy consumption [9]. Starting from designed tariffs such as the time of use (ToU) scheme, characterized every day by the same two or three fares (off-peak, on-peak and sometimes mid-peak [10]), the variability increases considering market indexed schemes such as day ahead pricing (DAP), where the hourly tariff is known on a day ahead basis, and real time pricing (RTP), where the cost of energy is updated during the day [11]. It is straightforward to look at ToU and DAP as basic forms of DSM; however, the implementation of the rigorous DSM concept, as defined in [12], requires the exchange of intra-day price/volume signals as additional feature, as a result of a trading in the balancing markets established in order to meet short-term requirements of the grid. As a matter of fact, RTP can be seen as a tariff scheme including DSM features. In the light of above, it is clear that a residential energy management system has to be able to manage loads taking into account information known in advance, and to react to real-time user needs and DSM signals, which implies the solution of a real time load shifting problem.

In this paper we establish an event driven model predictive control (MPC) approach for a local energy management system designed to optimally manage the resources of residential electricity prosumers, considering a dwelling equipped with a photovoltaic (PV) panel, a storage unit, smart household appliances and an electric vehicle (EV) with back-feeding capability. This paper provides the natural extension of the work presented in [13], which detailed the basic load-shifting control rationale of an EMS targeted for passive electricity consumers. The innovative contribution of the present paper regards the inclusion of the micro-generation unit, the electricity storage, and the EV into the EMS problem formulation, thus considering a reference scenario focused on electricity prosumers. Moreover, operation of devices is here coordinated according to different optimization criteria, such as cost minimization under ToU, DAP and RTP models, self-consumption maximization and automated overload avoiding. These objectives are met by dynamically assigning appliances start times, and optimally controlling the charging process of the storage unit and the EV. Our approach assures the respect of user preferences in the use of electric energy, and has the flexibility needed to meet the dynamics of real life in a household.

The remainder of the paper is organized as follows. In Section 2 the state of the art is discussed along with the proposed innovations. In Section 3 the system architecture is described. In Section 4 the control system is presented from a functional point of view. In Section 5 the mathematical formulation of the load shifting problem is given. Section 6 is dedicated to the presentation and discussion of simulation results. Finally, in Section 7 the conclusions are drawn.

2. State of the art and proposed innovation

Load management has received increasing attention from academics and industries during the last decade. Industry has been the driving sector, and the first one for which pioneer DSM programs have been deployed [14–16]. Even if load shifting criteria are strictly connected there to the productive process under control, the idea of re-optimizing arises as a way to manage disturbances and inaccurate system modeling. The same approach sounds reasonable also when thinking about load control in the residential sector, which is being faced at different scales with different granularity levels of control.

A first class of problems are those trying to solve the load shifting problem taking a single household as reference domain. First guidelines about how a local EMS should work can be dated well before the arise of the smart grid concept [17,18] and recently prototypal implementations have emerged (see e.g. [19], based on stochastic dynamic programming). Several approaches have been studied in this research area. In [9] the authors propose an EMS aimed at minimizing costs while keeping under control the waiting time for operation of the appliances. The authors correctly argue that EMSs acting in a RTP environment require price prediction capabilities. However, integration of storage unit and EVs is only envisaged, while integration of micro-generation is not treated. Another interesting approach is presented in [20], where a load scheduling system based on artificial neural networks is considered. The appliances self-organize in a distributed way and then a coordinator corrects their outputs in order to provide a feasible schedule and enhancing micro-generation self-consumption for the next day. The approach cannot be used in a real time framework, since the user must provide a list with the appliances to be executed within the next 24 h. Moreover, non-deferrable loads are not explicitly taken into account in problem formalization: these drawbacks are rather recurring in the relevant literature. Also genetic algorithm techniques have been applied. For example, in [21], though presenting only an illustrative formulation, the authors show how the local EMS can be designed to optimize the size and cyclic operation of battery storage, minimizing the impact of aging and replacement costs. Local EMSs have been also investigated using the concept of *utility function* from micro-economy [22,23]. A significant aspect of the optimization-based approach in [22] is related to the possibility to work in a RTP framework; possible drawbacks regard: (i) the need of knowing in advance the exact daily energy demand, which is a very sensitive data when referred to a single consumer, and (ii) the provided output, which consists of a hourly energy allocation, without any indication about how controlling single loads on a higher temporal resolution, in order to match the given allocation. In [23] the authors present a Markov decision process formulation. They apply Q-learning techniques to find policies minimizing a balance of financial costs and dis-utility deriving from long waiting times. Among the drawbacks, we mention parameters and utility functions selection, the impossibility to strictly control appliances execution times and prevent overload and, most of all, the fact that the approach works only for loads whose power profile can be modulated (only the overall amount of energy required by the appliance is taken into account, not its power profile).

Utility functions are largely used also for a relevant class of problems that considers the allocation of energy to a cluster of consumers served by an energy supplier, by maximizing the social welfare through distributed optimization. They were first applied to the energy procurement problem at transmission level [24]. A similar problem is discussed in [25] for the allocation to small consumers on a day ahead basis, then not capturing intra-day dynamics of consumption; in [26] the same approach is used for intra-day allocation, but time correlations in consumption are neglected. A significant step forward is given in the series of works [27–29], where the day ahead capacity procurement and the real time demand response problems in presence of RES uncertainty are jointly formalized and coordinated over the two timescales. Differently from most of the works in this category, where each utility function is associated with a single consumer, in these works a utility function together with a specific set of constraints model a single appliance, then introducing a deeper granularity in the load shifting control; however as in [23], a strong assumption is made regarding the ability of appliances to adapt their demand within a continuous power interval and without power correlations among phases, which is not true in practice for EVs with vehicle to grid (V2G) capabilities and above all for typical white household appliances such as dish-washers and washing machines. In this sense, household appliances manufacturers recommend a specific power profile for each appliance program and allow minor deviations such as temporarily suspensions at the end of specific phases. Finally, the authors consider the need of real time load shifting only as a consequence of RES realization at delivery time; conversely other events such as the dynamics of consumer requests and short term grid needs require a real time control framework: we remark the need of controlling loads on a event basis to be in line with real life. As far as specifically concerns electromobility, there are several ongoing research projects working on the topic of EV charging, such as *e-DASH* [30], *Green eMotion* [31] and *Mobincity* [32], which supports this work. A lot of works in literature deal with the charging control of EV *clusters* (e.g. [33,34]). Some contributions are becoming to appear also in relation to the residential sector [35,36]. However, none of the EV control strategies we found in literature explicitly consider the limitations on the charging control imposed by the international standard IEC 61851 [37].

Our work extends the contributions aforementioned for local EMS working in the home domain, overcoming the highlighted drawbacks and taking motivation also from the works here mentioned on load shifting control through dynamic allocation of energy to consumers. The characterizing aspects and the innovations of this work are:

(1) The controller is event driven. The control action is updated in response to events from the environment, such as: user requests for the execution of an appliance program, EV charging requests, notification of DSM volume/price signals, updates of micro-generation power forecasts, RTP notifications and overload warnings. That allows to take into account real dynamics of the household.
(2) The controller works based on *time varying signals*. The controller is able to work in a highly dynamical scenario in which the tariff is periodically announced by the retailer, the contractual power threshold may be temporally changed by the DSO, peak and average load profiles associated to smart appliances programs vary according to the environmental conditions and short-term forecasts from the micro-generation unit are frequently updated.
(3) The controller *interacts with the market*. The controller calculates the *minimum rebate* which a qualified market actor has to give to the consumer for positive reaction to DSM volume signals, and the cost/saving resulting from reaction to price signals.
(4) The user is made completely *aware* about energy consumption and related cost. Through preferences expressed when asking for each load running, the user can decide how much the EMS could affect his daily life. That regards both the execution of plannable loads within the time boundaries specified by the user, and also the satisfaction of the user preferences related to the EV charging requests (i.e. duration of the charging process and desired final state of charge of the EV).
(5) The exploitation of the micro-generation unit is maximized. The controller maximizes self-consumption through proper load shifting and proper control of the EV and storage charging/discharging processes, always respecting technical constraints and user preferences related to the execution of appliances' programs and the EV recharging.
(6) The integration of EV charging process in the problem, including back-feeding capability and the limitations on control action imposed by the international standard IEC 61851.

To the best knowledge of the authors, no other work on residential EMSs deals with efficient integration of smart appliances, storage, EVs and micro-generation, in different contractual scenarios and always respecting user preferences and habits.

3. System architecture modeling

The system architecture (Fig. 1) consists of a home area network of sensors (a smart meter and smart plugs to connect legacy appliances), smart devices (smart appliances, an electricity storage, EVs) and a computing unit (the smart home controller (SHC)). The architecture is in line with the ones developed in the Italian project *E-Cube* [13] and the FP7 project *ADDRESS* [38], which are reference projects, respectively, in Italy and in Europe, in the field of *active demand*. In the following, a description is given for each device making part of the architecture, also mentioning data on the expected cost of the device. In this regard, valuable data can be found also in [39].

3.1. Smart home controller

The SHC is a software module responsible for the solution of the load shifting control problem discussed in this paper. In the *E-Cube* project, the SHC is hosted by a residential Internet gateway, which acts as a central node providing connectivity among the smart devices inside the household and with the actors outside the household. In particular, from one side, the gateway manages (through wireless ZigBee connection [40]) data acquisition from the smart meter, the smart plugs and the smart appliances, and sends the control signals computed by the SHC to the storage, the EV, the smart appliances and the smart plugs. On the other side, the gateway features an Internet connection that can be used to connect with upper level actors (the retailer, the DSO, etc.) and receive DSM signals notification (from the DSO or a community energy management system [25]), tariff updates (from the retailer or a community energy management system in case of dynamic pricing schemes) and photovoltaic forecasts updates. Suitable residential gateways will be available on the market at a cost not exceeding 50 €. The cost is characterized by a decreasing trend due to the traditional electronics employed. We highlight that the architecture depicted in Fig. 1 refers to the particular business model addressed in *E-Cube*, where the Internet gateway is property of a service provider (a telecommunication operator in the specific case) and acts as a platform for the convergence of multiple services, including the SHC module but also, e.g., provisioning of entertainment contents, Internet connection, etc. All the interactions with the outer actors possibly involved in the energy management problem (i.e. the DSO, the retailer, etc.) are through the Internet link offered by the gateway. As a matter of fact, as specified also next, in the *E-Cube* scenario there is no need to communicate with the fiscal meter (property of the DSO) of the household since a non-fiscal meter is deployed to the purpose of gathering aggregated consumption data. Other business models are possible as well, for example the case in which the leading business actor is the DSO, and the EMS is hosted directly by the smart meter (see also the next discussion in Section 3.6). Finally, the minimum functional requirements for the SHC module are as follows:

(1) The SHC has to maximize self-consumption of power from the micro-generation plant.
(2) The SHC has to minimize the costs related to energy consumption.
(3) The SHC has to satisfy the user preferences while avoiding overloads.
(4) The SHC has to be able to perform near-real time computation and notification of decisions to the user.
(5) The SHC must efficiently manage the storage and the EV, taking into account battery aging and losses.
(6) The SHC has to be able to compute the minimum rebate in case of DSM signals.

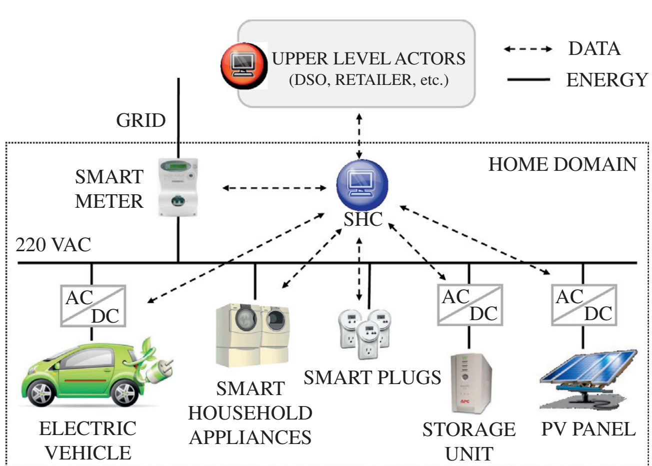

Fig. 1. The system architecture.

3.2. Household appliances

Household appliances can be classified according to their load-shifting flexibility and degree of smartness in data processing and interaction with the user [13]. We recall here the basic distinction between *plannable* and *non-plannable* loads. Plannable loads are those loads whose start time can be chosen by the SHC according to proper optimality criteria: the user prepares the appliance to run and then, instead of starting the appliance, specifies the first possible start time (denoted by S_m, where subscript m identifies the appliance) and the last allowed termination time (E_m). The couple (S_m, E_m) is the so called user preference (UP). Based on environmental variables (e.g. temperature, humidity, pressure, etc.) and the program selected, the smart appliance calculates an estimate of the program's duration N_m and program's mean and peak power profiles (time series $\overline{P}_m$ and $\widehat{P}_m$). The user preference, N_m, $\overline{P}_m$ and $\widehat{P}_m$ are sent to the SHC as an input for the control problem: we call this a "R event" (request event). The user is free to modify previously submitted requests at his/her free convenience, meaning that he/she may ask the SHC to anticipate, defer or cancel the execution of previously planned loads (we call this an "U event" – update event). Furthermore, the user may even override the system by deciding to immediately start an appliance, regardless of whether it was previously planned by the SHC or not (we call this an "O event" – override event).

Non-plannable loads (i.e. loads whose start time cannot be decided by the SHC) are taken into account for calculating an estimate of the power available for plannable (smart appliances) and controllable (storage, EV) household devices. Such a threshold is built based on the concept of virtual power threshold (VPT) – defined in [13] as the difference between the contractual power threshold and the estimated consumption from not plannable loads – and taking also into account the forecast of the power from micro-generation and the power discharged from the storage and the EV. Prototypes of smart household appliances are available at a cost of about 1000 € (in case of a washing-machine). Once on the market, the price will be comparable to that of premium household appliances.

3.3. Electric energy storage

We assume the storage batteries absorb and supply energy at a fixed rate ΔP^{st}. Due to losses, we assume that a portion $\xi^{st}\Delta P^{st}T$ of the energy exchanged during the time period T is lost in the conversion process. $\xi^{st} \in (0,1)$ is the efficiency factor. Let $x[k]$ denote the state of charge at the end of the generic kth time interval, then the discrete-time dynamics of the storage state of charge is

$$x[k] = x[k-1] + \Delta P^{st} T\{(1-\xi^{st})u_k^{st} - (1+\xi^{st})v_k^{st}\} \tag{1}$$

where T is the discretization time step, u_k^{st} and v_k^{st} are Boolean control variables associated, respectively, with the charging and discharging phase ($u_k^{st} = 1$ if and only if the storage is commanded to absorb energy during the kth time interval; whereas $v_k^{st} = 1$ if and only if the storage is commanded to discharge at k). We further considered the following technical parameters: power input/output $\Delta P^{st} = 1$ kW, efficiency factor $\xi^{st} = 0.02$, minimum allowed state of charge $x^{min} = 1$ kW h and maximum allowed state of charge $x^{max} = 6$ kW h. We considered a cost of 190 €/KW h (Lithium-ion batteries), with an estimated life of 5000 load cycles at 80% depth of discharge. These data have been obtained based on projections to 2020 [41] and will be used to derive a proper value for the depreciation term to be included in the formulation in order to account for battery wear. Finally, it is necessary that the storage state of charge can be measured, in order to recover from model uncertainties affecting (1).

3.4. Electric vehicle

The EV is modeled similarly to the storage, with the addition of proper constraints imposed by the user and the charging process. The user sets the departure time dt and the desired final level of charge y^{des}. A charging request including this data is called an “EV event”. Similarly to (1), the EV dynamics is given by

$$y[k] = y[k-1] + \Delta P^{ev} T\{(1-\xi^{ev})u_k^{ev} - (1+\xi^{ev})v_k^{ev}\} \tag{2}$$

where $y[k]$ is the state of charge at the end of the generic time interval. According to standard IEC 61851, the charging power is a semi-continuous variable: beyond the standby mode, the current has to be limited between a positive lower bound and an upper bound. If ΔP^{ev} denotes the maximum allowed charging power, then $u_k^{ev} \in \{0\} \cup [\alpha, 1]$, with $\alpha > 0$ denoting the minimum allowed charging rate. It is assumed that V2G power is modeled in the same way (i.e. v_k^{ev} is assumed semi-continuous, with $v_k^{ev} \in \{0\} \cup [\alpha, 1]$). The following technical parameters have been considered: $\Delta P^{ev} = 3.3$ kW, $\alpha\Delta P^{ev} = 1$ kW, efficiency coefficient $\xi^{ev} = 0.02$, minimum allowed state of charge $y^{min} = 2$ kW h and maximum allowed state of charge $y^{max} = 17$ kW h. In order to derive a depreciation factor to account for the wear of the battery pack, we further considered a cost of 280 €/kW h for Lithium-ion batteries (a projection over 2020 [42]), with an estimated life of 192000 km and an average consumption of 0.21 Kw h/km. Like for the storage, current market values (around 500–600 €/kW h) are still in general not compatible with cost-efficient deployment of storage devices in the context of residential energy management systems.

Like for the storage, we assume that the EV state of charge can be measured. If that is not the case, at least the initial value of the state of charge must be known (it can be read by the driver on the EV dashboard and submitted to the SHC together with the user preferences on charging). As a matter of fact, starting from the initial value, the evolution of the state of charge in the future can be assessed via detailed non-linear *simulation* models [43].

3.5. Micro-generation

We deal here with photovoltaic micro-generation. We assume that power forecasts [44] are available at each time of problem formulation. To this end, we consider the possibility that the forecast (time sequence denoted with P^{pv}) is periodically updated during the day, through proper notifications to the SHC, which we call “F events”. Depending on the adopted forecasting technique, the F event may be notified by a specialized sensor belonging to the household domain, or by an external actor via the Internet connection of the residential gateway. We highlight that the proposed control scheme contributes to increasing the return on PV investments, being self-consumption maximization one of its objectives.

3.6. Smart meter and smart plugs

The smart meter provides the SHC with aggregated consumption data for the day-ahead computation of the VPT and real-time notifications of overload warnings, which we call “W events”. As specified above, in the *E-Cube* project the SHC does not communicate with the DSO-owned fiscal meter, but rather with a non-fiscal smart meter (which we call in the following “commercial” meter) installed on purpose immediately downstream of the fiscal meter (for simplicity, in Fig.1 only the commercial smart meter has been depicted, leaving out of the picture the fiscal meter, which in *E-Cube* has no direct role). As discussed in [39], another possibility (which requires the direct involvement of the DSO into the business model) is the roll-out by the DSOs of new fiscal smart meters with enhanced communication capabilities (a solution which would imply no installation costs for the user). As a matter of fact, as mentioned by the authors in [39], some currently available models of smart meters are already equipped with network interface cards (the electronic component of the smart meter that takes care of communication with the outer environment) already provided with both a wide area network transceiver (to communicate with the DSO for automated meter reading) and a home area network transceiver (to communicate with the home devices, including the SHC). In this case, the data on aggregated consumption would be provided to the SHC directly by the fiscal smart meter, as well as the communication with the DSO (in Fig. 1, the smart meter depicted would be precisely the fiscal smart meter, and there would be no need to install an additional commercial meter). Furthermore, considering a business case centered on the DSO, it would be also reasonable to expect (as discussed in [39]) that the energy management module would be hosted directly by the smart meter. In that case, the SHC module depicted in Fig.1 would collapse onto the (fiscal) smart meter, which would thus become the central element of the home area network, for both control and communication tasks. However, once again we remark that the architectural choices depend on the selected business model, and, to the best of the knowledge of the authors, there is still not a comprehensive view on the matter. The reader is addressed to [39] for a discussion on current and future smart meter technologies, relevant standards, supported functionalities, communication capabilities, costs assessment, etc. Finally, in case the link between the smart meter and the SHC is not present (due to the missing of a commercial meter and the impossibility of establishing a connection with the fiscal meter), the following considerations apply: (i) the estimation of the VPT could still be done by processing historical consumption patterns in case they can be received through the gateway from the DSO (which acquires them via automatic meter reading); (ii) it is not possible to detect overloads in real time; however, given the fact that the VPT is computed based on a conservative estimate of the aggregated consumption from non-plannable loads (see [13], Section 5), and also considered the capability of the fiscal meter to sustain temporary overloads, it can be concluded that, thanks to the proposed approach, the incidence of overload events is smaller than in the non-automated case.

Smart plugs are provided both with metering functions and control capabilities: they provide local consumption data (used to estimate the incidence of non-plannable loads) and they are capable of interrupting supply of energy (this functionality can be deployed to respond to overload warnings). Prototypes of smart-plugs are available at a cost of about 110 €, with a significantly (9% per year) decreasing cost-trend. We highlight that the basic version of the algorithm described in this paper does not require the installation of smart plugs (they are mostly needed in order to develop fine overload-avoiding strategies, while a good estimate of non-plannable loads consumption can be obtained also through the proper elaboration of the measurements coming from the smart meter and the smart appliances [13]). Concluding, the combined action of the smart meter, smart appliances and proper estimation algorithms, together with the introduction of strategically placed smart plugs, is considered the optimal solution for effective and viable monitoring of the domestic environment [39].

3.7. Aggregator

In case the household is part of an energy community, an aggregator may be considered at the interface between the SHC and the market/DSO [38]. It is in charge of generating DSM signals for the SHC in the form of price/volume signals, based on balancing market trading or specific DSO paybacks. We call "DSM event" the notification of a DSM signal to the SHC. Further, in case of RTP, we assume that the aggregator notifies the tariff to the SHC on a hourly ahead basis. Even though such a notification can be technically seen as a price signal, for the sake of clearness we call it a "P event".

3.8. Notes on deriving costs and benefits

The migration to energy management architectures will be a gradual process. We designed the architecture based on components that either are in place in today's households, or are close to the market and will be present in houses of the future (gateways, EVs, smart appliances, smart plugs and residential storages). Furthermore, the architecture is modular (i.e. it can work with a subset of devices) and can be built incrementally, following the process of household renovation. Naturally, current implementations are characterized by high prototypal costs. However, studies [38] indicate that the value generated for users (in the form of economic saving) and DSOs (through DSM for grid support, distributed energy resources (DER) integration, etc.) is expected in the future to outbalance costs, which will decrease significantly due to the advancement of technologies (especially with respect to storage devices).

4. SHC working logic

The control system is designed with the aim of optimally reacting to events (Fig. 2). Each time an event triggers the SHC, the SHC verifies the set of loads for which a request exists, and the boundary conditions in terms of user preferences, energy tariff C, current VPT, micro-generation power P^{pv} and planned power from previous iterations P^{pln}. Then it retrieves the current state of charge of the storage and the EVs currently in the home domain and solves a discrete time open loop optimal control problem. The outputs of the problem are the control signals to the storage and the EV, and the best times to run the smart appliances. Event after event, control is updated (by solving the updated control problem) in order to "follow" optimality, thus optimizing consumptions. We call this mechanism *event driven MPC*, to distinguish it from traditional MPC concept [45].

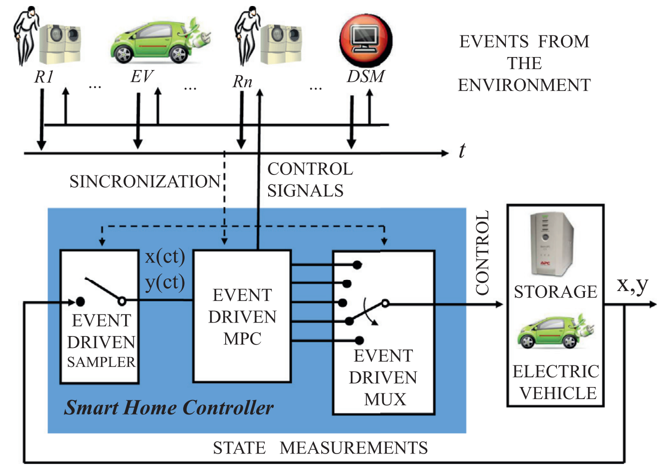

Fig. 2. Working logic of the control system.

The user is always free to interact with the SHC to submit new requests, update previously expressed preferences or even override the system by, e.g., forcing the execution of an appliance scheduled by the SHC for future times. In particular, in case the user updates previously submitted preferences, the SHC reacts by simply performing an iteration of the control problem in which the updated user preferences are considered. As a result, the schedule of the previously planned devices is consequently updated. In case of an override event instead (e.g. a user willing to immediately start an appliance), the appliance in question communicates to the SHC the expected load profile characterizing the requested program, and the SHC performs an iteration of the control problem in which the specified load profile is added to the power curve P^{pln} of planned loads already started. Also, even if not explicitly considered in this paper, appliances already running at the moment of computing may be temporarily suspended after specific phases, only in case of DSM events (this is suggested by the appliances manufacturers for avoiding service degradation and guaranteeing flexibility during emergency operation of the grid).

All the user requests are preliminary examined (i.e. before computation) by the SHC in order to verify that they are correctly formatted. However, that is not sufficient to guarantee that a particular user request can be satisfied according to the specified user preferences (for example that, in case of EV charging, the final desired state of charge will be reached). That depends on the current state of the household environment (i.e. the loads running at the time of the request, etc.). Nonetheless, a definitive notification can be given by the SHC to the user after solving the load shifting problem (see Table 1). If the problem is infeasible, the SHC notifies the user and may also suggest, in case of EV charging for example, the minimum additional time required to reach the desired final state of charge.

Table 1
Events, related actors and notifications.

Event	Actor generating the event	Notification to the actor
R event	User	Appliance start time, cost
EV event	User	Cost
F event	Forecasting operator	Not applicable (NA)
W event	Smart meter	NA
DSM event	Aggregator	Minimum rebate
P event	Aggregator	NA
U event	User	Update outcome
O event	User	Override outcome

Finally, we highlight that, prior to computation, the SHC updates the current state of the household domain by performing the following updating tasks:

- It acquires the current state of charge of the EV (in case a charging session is active in that moment).
- It acquires the current state of charge of the storage.
- It verifies which of the plannable loads scheduled in the previous iterations have started and which instead have not started yet (the latter can be re-scheduled in the forthcoming iteration).
- It updates the value of vector P^{pln}, which represents the aggregated load consumption of all the plannable loads that have already started and that cannot be re-scheduled anymore by the SHC. The knowledge of vector P^{pln} allows the SHC to avoid to plan a new load in a temporal interval in which a previously planned load is currently working (to be precise, the overlap could be allowed by the SHC if it does not lead to overload and it is deemed convenient).

Furthermore, depending on the event triggering the controller, the SHC updates also other relevant quantities, such as: the tariff (price event), the forecast on PV production (forecast event), the power threshold (DSM event, volume signal), the set of loads to be scheduled (request event and EV event). So doing, the model considers the temporal correlations between iterations, in the sense that decisions taken in past iterations are taken into account when solving the current iteration of the problem.

5. Mathematical formulation

This section details the optimal control problem based on mixed integer linear programming (MILP) that the SHC solves each time it is triggered by an event. The problem is set up in a discrete-time framework (T is the time step). The temporal interval of problem definition goes from the time instant when the SHC is triggered (called ct – current time), to the time instant denoted by ch (control horizon), which, in general, varies depending on the chosen length of the control window ($ch - ct$). In particular, the control window can be chosen *fixed* iteration after iteration (i.e. *sliding control window* approach) or, as for the simulations in this paper, the value of ch can be fixed instead, so that the problem is defined up to a specified time instant (as in the case the problem is defined on a daily basis). In any case, ch has to be chosen such that it "covers" all the user requests (including both requests to run smart appliances and requests for EV charging).

The formulation given below is based on the relevant assumption that the price paid for the energy injected into the grid (say C^{sell}) is always smaller than any value of the energy tariff (i.e. $C^{sell} \leqslant \min_k\{C_k\}$, being C_k the electricity tariff). The assumption is nowadays generally confirmed by the electricity market data and consistent with the objective of minimizing RES injections into the grid. As a matter of fact, the following considerations apply under the above assumption: (i) it is always more convenient for the user to self-consume the energy generated by the PV panel, rather than selling it to the grid; (ii) it is always more convenient to self-consume the energy discharged from the storage or the EV, rather than injecting it into the grid. As a result, the given problem formulation leads to self consumption maximization and does not need to optimize the energy exchanges with the grid (since the optimal strategy is always to maximize self-consumption, and the energy injections into the grid can be computed consequently once the amount of self-consumed energy is known). Furthermore, the assumption makes possible to derive a linear formulation for the cost minimization problem treated here (which is relevant for the purpose of practical implementation). As a further logical step in the SHC problem, in future works a (non-linear) extension of the formulation presented here will be given in order to optimize the energy trades with the grid (which is necessary only in case the assumption does not hold). Finally, a second assumption, taken only for ease of discussion, is that only one EV per time is being recharged.

5.1. Objective function

The objective function J to be minimized has an economic meaning and is written to capture: (i) the *cost* due to devices' activation, (ii) the *saving* coming from self-consumption and (iii) the *value* given by the additional energy possibly stored at the end of the control horizon with respect to the beginning.

The objective function J is therefore given by

$$\begin{aligned} J = & \sum_{m\in M}\sum_{k=S_m^*}^{E_m-N_m+1}\left\{\sum_{i=k}^{k+N_m-1}\overline{P}_m[i-k+1]TC[i]\right\}u_{mk} + \sum_{k=ct}^{ch}\Delta P^{st}TC[k] \\ & \times(u_k^{st}-v_k^{st}) + \sum_{k=ct}^{ch}\Delta P^{st}TD^{st}(u_k^{st}+v_k^{st}) + \sum_{k=ct}^{dt}\Delta P^{ev}TC[k](u_k^{ev} \\ & - v_k^{ev}) + \sum_{k=ct}^{dt}\Delta P^{ev}TD^{ev}(u_k^{ev}+v_k^{ev}) - \sum_{k=ct}^{ch}\max\{P^{pv}[k] \\ & - P^*[k],0\}TC[k]v_k^{pv} - \widetilde{C}\sum_{k=ct}^{ch}\Delta P^{st}T\{(1-\xi^{st})u_k^{st}-(1+\xi^{st})v_k^{st}\} \end{aligned} \quad (3)$$

The first term of J is related to the cost of energy consumption resulting from the execution of plannable loads to be scheduled by the SHC. The binary decision variable u_{mk} is equal to one if and only if the mth plannable load is scheduled for starting at the beginning of the kth time interval. The term $\sum_{i=k}^{k+N_m-1}\overline{P}_m[i-k+1]TC[i]u_{mk}$ is the resulting cost in case the appliance starts at k. The parameter S_m^*, defined as $S_m^* = \max\{S_m, ct\}$, identifies the first feasible start time for the mth appliance, which is different from the first possible start time S_m specified by the user upon request. In particular, in the case of new user requests S_m^* is equal to S_m while, in case of appliances already scheduled in the past but not already started at ct – i.e. the appliances to be rescheduled – it may happen that $S_m \leqslant ct$, and therefore $S_m^* = ct$ should be chosen as the first feasible start time for the appliance. Therefore, the start time k of the mth appliance can be chosen (see the summation over index k) in the interval $[S_m^*, E_m - N_m + 1]$, always respecting temporal user preferences. Finally, the total cost related to all the plannable appliances is obtained by summing over index m.

The second and third terms of J are related to the control of the charging and discharging cycles of the storage. The Boolean control variable u_k^{st} (v_k^{st}) is equal to one if and only if the storage recharges (discharges) during the kth time interval. Variables u_k^{st} and v_k^{st} are equal to zero in standby mode. The term $\Delta P^{st}TC[k](u_k^{st}-v_k^{st})$ accounts for the cost or saving related to the energy charged or discharged by the storage at k. The term $\Delta P^{st}TD^{st}(u_k^{st}+v_k^{st})$ is instead a *depreciation* term that accounts for the economic cost (i.e. loss of life) associated to wear of the storage deriving from the charging or discharging operations at k.

The fourth and fifth terms of the objective function are related to the control of the EV. Variables u_k^{ev} and v_k^{ev} are semi-continuous in this case (see Section 5.2.1). ΔP^{ev} is the maximum allowed charging/discharging power. D^{ev} is the EV depreciation factor. D^{ev} is the average depreciation per kW h charged or discharged by the EV. Parameters D^{st} and D^{ev} are technology dependent and can be computed based on the cost of the related device and its expected life [21]. The introduction of the depreciation terms is such that the devices are activated only in case the deriving economic benefits outbalance the expected costs coming from wear.

The sixth term of the objective function is related to the saving coming from self-consumption of energy. The term $\max\{P^{pv}[k] - P^{*}[k], 0\}$ indicates the amount of micro-generation power available for controlled devices. The real variable $v_k^{pv} \in [0, 1]$ is needed to take into account the amount of micro-generation power actually consumed by controlled household devices (see also constraint (12) below).

The last term in (3) is an estimate of the value associated with the energy accumulated in the storage at the end of the control problem (i.e. at *ch*). That amount of energy has an associated value in the sense that it allows the storage to be discharged in a future time, leading to savings. The fact that such a value is associated to future (i.e. beyond the current control horizon *ch*) operations of the storage makes possible to implement different pricing strategies, that is, different choices for the cost parameter $\widetilde{C}$ are possible. A conservative strategy (adopted in the simulations below) would be to set $\widetilde{C}$ to, e.g., the minimum value of the energy tariff observed in the past. Other more balanced strategies are possible as well, like setting $\widetilde{C}$ to a future expected value of the tariff (if known), or to a moving average of the tariff observed in the past. Notice that a similar term can be included also for the EV, but for the sake of simplicity we avoid doing that here.

Finally, in (3) all the economic terms relevant to the problems have been included. Other *secondary optimization terms* (with no direct associated economic meaning) can be included in (3) in order to refine the optimization model, as explained in Section 5.4.

5.2. Constraints

A number of technical and economic constraints must be considered in order to obtain a meaningful formulation.

5.2.1. Constraints on variables' nature

The problem includes binary, semi-continuous and continuous variables

$$\begin{aligned} &u_{mk} \in \{0, 1\}, \quad u_k^{st} \in \{0, 1\}, \quad v_k^{st} \in \{0, 1\} \\ &u_k^{ev} \in 0 \cup [\alpha, 1], \quad v_k^{ev} \in \{0\} \cup [\alpha, 1], \quad v_k^{pv} \in [0, 1] \end{aligned} \tag{4}$$

5.2.2. Overload avoiding

A constraint must be put in order to prevent overloads

$$\begin{aligned} &\sum_{m \in M_k} \left\{ \sum_{i=\max\{S_m, k-N_m+1\}}^{\min\{k, E_m-N_m+1\}} \widehat{P}_m[k-i] u_{mi} \right\} + P^{pln}[k] + \Delta P^{st}(u_k^{st} - v_k^{st}) \\ &\quad + \Delta P^{ev}(u_k^{ev} - v_k^{ev}) - P^{pv}[k] \leqslant VPT[k] \quad \forall k \in [ct, ch] \end{aligned} \tag{5}$$

M_k represents the set of plannable loads *possibly* active in the *k*th time interval: $M_k = \{m \in M : S_m \leqslant k \leqslant E_m\}$. The term $P^{pln}[k]$ refers to the power of plannable appliances started in previous iterations and possibly still active after *ct*. The introduction of such a term prevents any "interference" or "overlap" between loads planned in the past and still active at *ct*, and loads to be planned in the current iteration of the problem. Looking at (5), and recalling the definition of *VPT* given in [13] (i.e. the difference of the contractual power threshold and the forecast aggregated power consumption from non-plannable loads), it is clear that the quantity $VPT + P^{pv}[k] + \Delta P^{ev} v_k^{ev} + \Delta P^{st} v_k^{st}$ defines the threshold on the power that can be *absorbed* by the smart appliances, the storage and the EV. Note that, since $P^{pv}[k]$ and $VPT[k]$ are conservative *estimates* [13], in very rare circumstances it might happen that an overload state is reached even if (5) is satisfied. In such cases, the SHC issues an overload warning, and a series of countermeasures can be taken, including the forced activation of the storage unit and, in case that is not enough, the prioritized shedding of loads [13].

5.2.3. Constraints on devices activation

Only one start time per plannable load can be selected

$$\sum_{k=S_m^*}^{E_m-N_m+1} u_{mk} = 1, \quad m \in M \tag{6}$$

This is not related with the possibility of interrupting plannable loads. If we assume that appliances can be suspended only once, then suspension can be simply handled by conceptually dividing the program into two sub-programs: one which is rigid, and a second one, which is the suspended portion of the program, which can be seen as a new plannable program subject to particular "user preferences" (the maximum allowed interruption period). If programs can be suspended more than once, then new decision variables and proper constraints have to be included in the formulation.

A second constraint is on the storage: only one mode (charging/discharging/standby) per time interval can be selected

$$u_k^{st} + v_k^{st} \leqslant 1 \quad \forall k \in [ct, ch] \tag{7}$$

A similar constraint holds for the EV. However, since control variables in this case are not Boolean, it is not sufficient to pose $u_k^{ev} + v_k^{ev} \leqslant 1$ at the generic *k*th time interval. Instead, we pose

$$I(u_k^{ev}) + I(v_k^{ev}) \leqslant 1 \quad \forall k \in [ct, dt] \tag{8}$$

where with little abuse of notation, we denote with $I(u_k^{ev})$ and $I(v_k^{ev})$ two Boolean variables equal to one if, respectively, u_k^{ev} and v_k^{ev} are greater than zero. We force that by imposing $I(u_k^{ev}) \geqslant u_k^{ev}$ and $I(v_k^{ev}) \geqslant v_k^{ev}$.

5.2.4. State constraints

The constraint on storage capacity is $x^{min} \leqslant x[k] \leqslant x^{max}$ $\forall k \in [ct, ch]$, where $x[k]$ is the state of charge at the end of the *k*th time interval. The state of charge $x[k]$ can be expanded by writing the explicit solution of the dynamics (1). The following constraint is obtained

$$\begin{aligned} x^{min} &\leqslant x^0 + \Delta P^{st} T \left\{ \sum_{k=ct}^{i} (1 - \xi^{st}) u_k^{st} - \sum_{k=ct}^{i} (1 + \xi^{st}) v_k^{st} \right\} \\ &\leqslant x^{max} \quad \forall i \in [ct, ch] \end{aligned} \tag{9}$$

where x^0 is the storage initial state of charge at *ct*. The reader can derive a similar constraint for the EV.

Further, the final state of charge of the storage has to be equal or greater than a reference value x^{ref} (to prevent the economic saving coming from mere storage discharging)

$$x^0 + \Delta P^{st} T \left\{ \sum_{k=ct}^{ch} (1 - \xi^{st}) u_k^{st} - \sum_{k=ct}^{ch} (1 + \xi^{st}) v_k^{st} \right\} \geqslant x^{ref} \tag{10}$$

Instead, the constraint on the final state of charge of the EV is simply related to the EV user preferences (desired final state of charge y^{des})

$$y^0 + \Delta P^{ev} T \left\{ \sum_{k=ct}^{dt} (1 - \xi^{ev}) u_k^{ev} - \sum_{k=ct}^{dt} (1 + \xi^{ev}) v_k^{ev} \right\} \geqslant y^{des} \tag{11}$$

5.2.5. Constraints on distributed energy resources

A constraint must be put in order to ensure that the savings reported in the objective function (3) really occur, in the sense that the incoming energy from the storage, the EV and the micro-generation is actually absorbed by the controllable devices. We pose

$$\begin{aligned} &\Delta P^{st} v_k^{st} + \Delta P^{ev} v_k^{ev} + \max\{P^{pv}[k] - P^{*}[k], 0\} v_k^{pv} \\ &\quad \leqslant \sum_{m \in M_k} \left\{ \sum_{i=\max\{S_m, k-N_m+1\}}^{\min\{k, E_m-N_m+1\}} \overline{P}_m[k-i] u_{mi} \right\} + \Delta P^{st} u_k^{st} + \Delta P^{ev} u_k^{ev} \\ &\quad + P^{pln}[k] \quad \forall k \in [ct, dt] \end{aligned} \tag{12}$$

in order to ensure that the power accounted by the saving terms in the objective function (3) is always less or equal than the power consumed by the household (i.e. the power which determines a saving is really self-consumed by the household devices). The reader can derive a similar constraint for $k \in [dt+1, ch]$ (in which EV terms have to be neglected). Constraint (12) plays a fundamental role in maximizing self-consumption, as it encourages the residential node in always behaving as a passive node, a behavior which is highly beneficial to the grid and will be probably rewarded in the future by the distribution system operator. We take $\overline{P}_m$ as a good estimate of the lower energy consumption profile of the appliance: the constraint must be conservative.

5.3. Overall problem definition

The generic iteration of the SHC energy management problem can be summarized as follows.

SHC event driven optimal control problem. *For a given trigger time ct, an electricity tariff C (estimated or known, depending on the tariff scheme), a virtual power threshold sequence VPT, a planned power sequence P^{pln} from previous SHC iterations, an estimate of non-plannable power P^*, a forecast of micro-generated power P^{pv}, a storage unit, an EV charging request characterized by desired departure time dt and desired final state of charge y^{des}, a set M of user requests with related average and peak power time sequences $(\overline{P}, \widehat{P})$ and UPs intervals (S_m, E_m), minimize J subject to the constraints discussed in Section 5.2.*

Hence, the control problem is based on MILP [46].

5.4. Model refinements

The formulation given above includes all the objective function terms and all the constraints which are necessary for achieving feasible and cost-efficient solutions under the taken assumptions. In particular, the given formulation highlights the concept of the SHC as a mean to generate value both for the user (through rationale usage of electric energy) and the DSO/grid (through implementation of DSM programs). Some model refinements can be considered when moving to the practical implementation phase. As a matter of fact, the problem given in Section 5.3 is characterized, in general, by many solutions. Hence, "secondary" terms in the objective function can be introduced in order to choose optimal solutions which match particular criteria. For example, solutions can be preferred in which, being the costs equal, the appliances finish the job earlier, or the EV is recharged faster. That can be achieved by adding to the objective function (3) the following terms

$$\sum_{m\in M}\sum_{k=S_m^*}^{E_m-N_m+1}\alpha(k-S_m^*)u_{mk} + \sum_{k=ct}^{ch}\beta(k-ct)\Delta P^{st}T(u_k^{st}+v_k^{st}) + \sum_{k=ct}^{dt}\gamma(k-ct)\Delta P^{ev}T(u_k^{ev}+v_k^{ev}) \tag{13}$$

where α, β and γ are parameters small enough not to "interfere" with the terms in (3) (i.e. several orders of magnitude smaller than the terms of C). The terms $\alpha(k-S_m)$, $\beta(k-ct)$ and $\gamma(k-ct)$ are therefore fictitious costs linearly increasing with time. They have the effect of selecting the optimal solution characterized by early activation of devices.

6. Simulation results

We present three simulation studies. The first one is related to normal operation of the system in case the tariff over all the control horizon is known in advance. We refer to DAP (but the approach works also for more "static" designed tariffs, such as flat rates and ToU tariffs). The second simulation case deals with reaction to DSM signals, and the concept of minimum rebate for acceptance of DSM signals is introduced. The third simulation deals with RTP.

The details on the specific load profiles considered for the simulations are reported in Table 2 (load profiles from ID 1 to ID 6 have been provided by the appliances manufacturer Electrolux s.p.a., while the consumption profiles of the programs ID 7 and ID 8 have been built based on information from the respective manufacturers [47,48]). The tariff used in the simulation is based on the Italian PUN ("prezzo unico nazionale") tariff (Fig. 3a) [49], which results from day ahead trading. Measured PV power curves were used (Fig. 3b) [50], while the estimate of non-plannable power was taken from [13]. Simulations span over one day (i.e. we choose a fixed control horizon), from 05:00 to 05:00 of the following day. This choice (05:00 AM) derives from the consideration that such an hour (or a close time) can be considered as the time in which all the requests related to the previous day (including night-time EV charging) have been satisfied and no new ones for the coming day are pending. The time step T is equal to five minutes.

Simulations have been performed on an INTEL® Core i5-3230 M CPU, 2.40 GHz, 8 GB RAM computer, running the MS WINDOWS® 8 64-bit operating system. The simulation environment has been built in MATLAB® R2011b. The MILP problem defined in Section 5.3 has been solved by calling from MATLAB® the *cplexmilp* function, made available by the CPLEX® for MATLAB® feature of the IBM® ILOG® CPLEX® Optimizer (version 12.5). The CPLEX® for MATLAB® module allows a user to define optimization problems and solve them within MATLAB® (via the *cplexmilp* function in this case).

6.1. Normal operations – DAP scheme

We simulate the reaction of the SHC to the sequence of events reported in the first row of Table 3. The events' trigger times are reported in the second row of the table, while the third and the fourth rows report the time boundaries related to the simulated events. Three EV charging requests have been simulated: EV1 demands for 5 kW h, EV2 demands for 3 kW h and EV3 for 11 kW h. For ease of exposition, the F event simply consists in a notification of a 50% reduction in the forecast PV power generated in the time interval indicated in Table 3. Given these events, three different scenarios have been simulated: (i) *non-automated scenario*, in which the storage is not considered, loads are immediately started by the user and the EV charging is uncontrolled and starts at maximum power as soon as the EV is plugged; (ii) *pure load-shifting scenario*, in which the storage is again not considered but the SHC optimizes the EV charging process and the choice of the appliances' start times, and (iii) *fully automated scenario*, in which the smart appliances, the storage and the EVs are managed (including storage and EV discharging) according to the control strategy presented in this paper. The appliances' start times computed by the SHC in the fully automated scenario are reported in the third block of the table. In the fourth block of the table, c denotes the total cost obtained in the non-automated scenario, while c_{op} and c_{op}^s denote, respectively, the cost in the pure load-shifting scenario and the cost in the fully automated scenario. The rows below c_{op} and c_{op}^s report the savings achieved, respectively, in the pure load-shifting scenario and in the fully automated scenario, with respect to the non-automated scenario.

Fig. 4 reports the outcome of SHC control after event R5. The line in red represents the threshold on the power available for the controllable devices (as said in Section 5.2.2, it is computed as $VPT + P^{pv}[k] + \Delta P^{ev}v_k^{ev} + \Delta P^{st}v_k^{st}$). The power consumption profiles of the appliances, of the storage and the EV are represented as colored bars. The bars of loads active at the same time are

Table 2
Load specifications, including: appliance, load ID, number of phases of the selected program, duration of each phase, mean power consumption and peak power consumption of the program.

Appliance	*ID*	Phases	Δt (min)	$\bar{P}$ (kW)	$\hat{P}$ (kW)
Washing mach. 40 °C	1	6	[5,10,15,5,5,10]	[0.02,2.0,0.02,0.02,0.02,0.05]	[0.15,2.1,0.15, 0.15,0.2,0.55]
Dryer	2	1	[105]	[2.4]	[2.7]
Washing mach. 60 °C	3	7	[5,25,20,5,10,10,20]	[0.04,2.0,0.3,0.06,0.06,0.06,0.08]	[0.2,2.1,2.1,0.2,0.3,0.3,0.5]
Dishwasher Normal	4	6	[15,30,10,5,20,50]	[0.07,1.4,0.1,0.07,2.0,0.01]	[0.1,2.1,1.2,0.1,2.2,0.02]
Washing mach. 95 °C	5	8	[25,5,60,20,10,10,10,20]	[0.3,0.05,2.1,0.1,0.1,0.1,0.1,0.3]	[2.1,0.3,2.2,0.2,0.6,0.8,0.8,1.1]
Dishwasher E8	6	6	[20,15,35,10,20,50]	[0.07,2,0.07,0.07,1.8,0.01]	[0.1,2.1,0.1,0.25,2.3,0.02]
Water heater	7	1	[140]	[1.2]	[1.2]
Oven	8	1	[40]	[2.1]	[2.1]

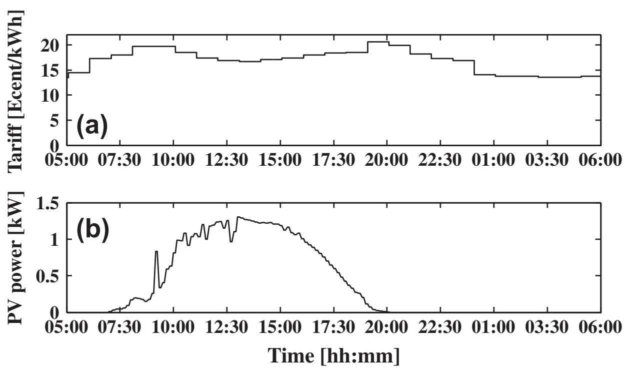

Fig. 3. PUN tariff (a) and PV power curve (b) used in the simulations.

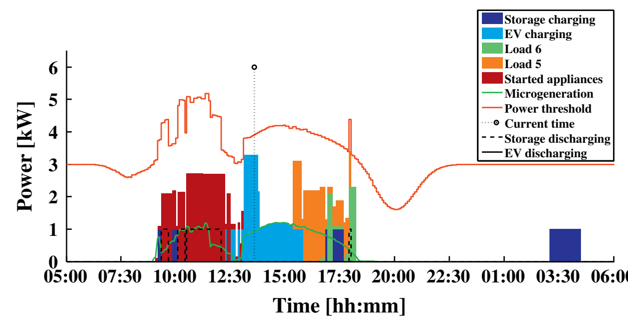

Fig. 4. Normal operation: aggregated power profile after event R5.

superimposed, in order to easily visualize overload conditions. The curve in green represents the power from micro-generation, while the dashed line represents power discharged by the storage. The dotted vertical line denotes the current time (bars referring to appliances started before the current time are colored the same way). The analysis of Fig. 4 is explicative of how optimal energy management is achieved. First of all, loads and EV charging are shifted as far as possible under the PV curve in order to maximize self-consumption. The portion of load exceeding the PV curve is then managed through proper load shifting and storage discharge control. It can be noticed for example that the EV charging power tracks the PV curve during large part of the charging session, while most of the additional energy needed to satisfy the user charging request is taken by charging at maximum power during the tariff valley between 13:00 and 14:00. The storage also recharges under the PV curve and releases power to feed the other load exceeding the PV curve (see the dashed line representing storage discharging before 12:30). Storage discharging can be also implemented to prevent overloads (notice the activation of the storage around 18:00). From the figure, it can be seen also that the energy previously discharged is then planned to be recovered by the storage during night-time, taking advantage of the low tariff. Fig. 5 displays the final planning (the one after event EV3). All the UPs are always respected and the threshold on power is never violated (thanks to proper load shifting and, around 19:30, thanks also to the contribution of storage and EV discharging). It can be seen that convenient overnight EV charging is selected. The control action exerted by the SHC is evident when considering the final planning obtained in the non-automated scenario (see Fig. 6). It is evident in that case

Table 3
Simulation scenario setup (rows 1–4) and results (rows 5–19) in case of normal operations.

Event ID	Start	R1	R2	R3	F	EV 1	R4	R5	U EV1	R6	EV 2	R7	O R7	R8	R9	EV 3
Trigger time	05:00	08:00	08:20	08:40	09:00	12:00	13:00	13:30	14:00	15:00	17:00	19:00	19:00	20:00	20:30	21:00
Start time	NA	08:00	08:20	08:40	11:30	12:00	13:00	14:00	14:00	15:00	17:00	19:00	19:00	20:00	20:30	21:00
End time	NA	13:00	13:20	13:40	13:00	16:00	19:00	18:00	15:00	20:00	21:00	21:00	NA	23:00	23:30	05:00
Load ID	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan	Plan
Load 1	NA	10:10	10:10	09:00	12:05	12:10	12:10	12:10	12:10	12:10	12:10	12:10	12:10	12:10	12:10	12:10
Load 4	NA	NA	10:55	09:10	09:00	09:00	09:00	09:00	09:00	09:00	09:00	09:00	09:00	09:00	09:00	09:00
Load 2	NA	NA	NA	10:55	10:25	10:25	10:25	10:25	10:25	10:25	10:25	10:25	10:25	10:25	10:25	10:25
Load 6	NA	NA	NA	NA	NA	NA	15:55	16:30	15:55	15:50	15:50	15:50	15:50	15:50	15:50	15:50
Load 5	NA	NA	NA	NA	NA	NA	NA	15:15	14:30	14:30	14:30	14:30	14:30	14:30	14:30	14:30
Load 7	NA	NA	NA	NA	NA	NA	NA	NA	NA	15:55	15:55	15:55	15:55	15:55	15:55	15:55
Load 8	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	20:20	19:00	19:00	19:00	19:00
Load 3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	21:25	20:45	20:45
Load 4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	21:20	21:20
c (€cent)	−164.3	−157.5	−131.2	−67.7	−58.4	23	39.1	72.7	72.7	111.9	165.7	194.6	194.6	213.9	240.3	428.7
c_{op} (€cent)	−164.3	−159.8	−141.4	−80.2	−65.2	0.04	17.5	54.8	57.3	101.6	157.8	185.8	186.7	204.4	230.2	383.9
Saving (%)	0	1.4	7.7	18.4	11.5	99.8	55.1	24.6	21.1	9.2	4.7	4.5	4	4.4	4.2	10.4
c^s_{op} (€cent)	−172.2	−168.5	−152.5	−97.7	−83.6	−10.1	8.9	46.8	49.7	93.7	150.2	177.3	178.1	195.7	221.6	376.2
Saving (%)	4.8	6.9	16.2	44.4	43.1	143.7	77.1	35.5	31.6	16.2	9.4	8.8	8.4	8.5	7.7	12.2

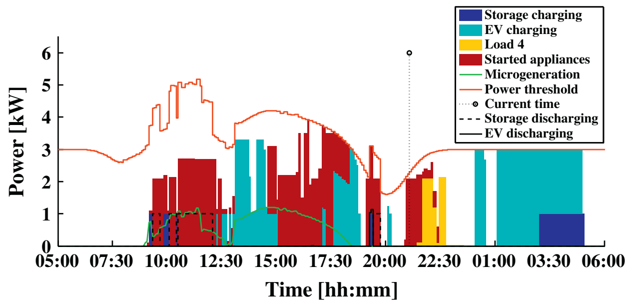

Fig. 5. Normal operation: final aggregated power profile (after event EV3).

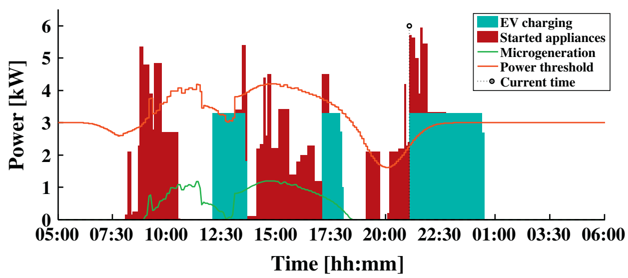

Fig. 6. Final planning in the non-automated scenario, obtained by ignoring the overload constraint during simulation (i.e. the planning is not feasible in practice due to overloads).

that the user requests cannot be satisfied due to overloads (in that regard, notice that the values of c in Table 3 have been computed by neglecting the overload constraint, since they correspond to load configurations that may be non-feasible in practice due to overloads).

A more detailed analysis can be carried out by examining Table 3, which reports the evolution of the appliances' start times and the evolution of the total cost event after event. In particular, for each load (specified by the "Load ID" in the first column), the corresponding row of the table reports the evolution of the load's start time as computed by the SHC after the events specified in the first row of the table, so that the last column of the table reports the final start times (the ones computed after event EV3). It is seen that, whenever necessary, the SHC updates the start times of the previously planned loads in order to manage the new events. It is also interesting to examine the evolution of the costs event after event, as the number of loads managed by the SHC increases. The SHC initializes itself at 05:00, when it has no loads to manage. The revenues (negative costs) computed after the first iteration (i.e. at 05:00) come from the expected future injection of PV power into the grid. In the fully automated scenario the revenue is higher because the storage is planned to absorb part of the energy from the PV plant. It is seen that it is always $c \geqslant c_{op} > c^s_{op}$, but it can be noticed that the difference between c^s_{op} and c_{op} tends to be small after the SHC has managed a large number of loads (compare the values at the end of the table). The difference is great instead in case of mildly loaded scenarios, especially when the aggregated energy of the scheduled loads is comparable to the cumulative PV energy. As a matter of fact, in that case the storage can be loaded under the PV curve and can be used by the SHC to feed the portion of the loads that cannot be shifted under the PV curve. As a result, costs are negative or close to zero (see Table 3, from event R3 to event R4). Besides R and EV events, the table reports also a forecast event (visible also in the above figures), an update event (U EV1 – at 14:00 the user anticipates the termination of the charging session from 16:00 to 15:00) and an override event (O R7 – at 19:00 the user ignores the start time suggested by the SHC for load 8 and forces the SHC to start the load immediately).

Fig. 7 displays the storage control evolution at three different times of the day. The portion of control lying at the left of the line of current time is the control *actuated* in the past; the portion at the right is the *planned* control sequence. As commented before, at early hours the storage is planned to absorb energy from micro-generation. Then, as the number of appliances to be served increases, the storage tends to discharge to feed them and then recovers energy in periods characterized by a convenient tariff. The state evolution corresponding to the control sequences in Fig. 7 is depicted in Fig.8. Note that at the end of the control horizon the storage recovers the initial state of charge (saving does not come from mere discharging). Fig. 9 reports the final state and control evolution related to EV2 charging request, which is fulfilled on time.

In the above simulation we did not impose any time out to the solver (i.e. either the algorithm converged to an optimum, or it reached an incumbent sufficiently close to the optimum [46]). The average computational time was 3.83 s, while the maximum waiting time was 15.3 s. Also, excellent approximate solutions could be achieved by imposing a time out to the solver. For example, after imposing a time out of 5 s, the average optimality gap [46] was only 2.12%. Performances can be improved by designing problem-tailored solution algorithms, able to exploit the particular structure of the problem. This is one of the research lines we are currently developing.

6.2. Demand side management

The SHC enables the household to join "active demand programs" [38], through automatic rescheduling of planned loads and updating of storage and EV control sequences. To test the

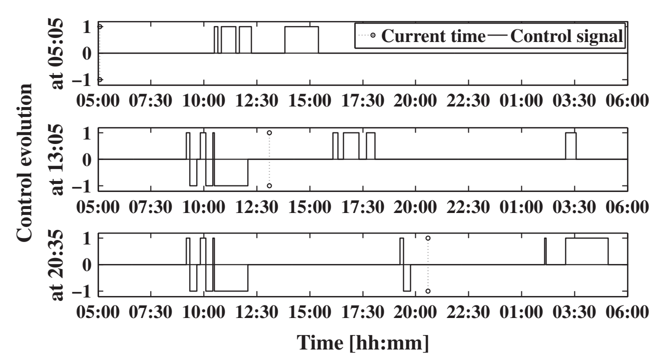

Fig. 7. Storage control evolution ($u_k^{st} - v_k^{st}\ \forall \in [ct, ch]$) at three different times of the day (notice how control is updated iteration after iteration).

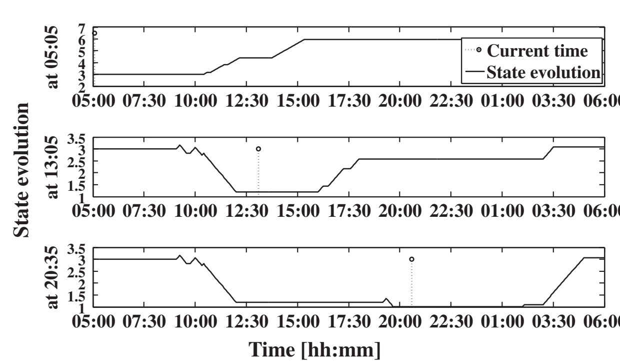

Fig. 8. Storage state evolution (in [kW h]) at three different times of the day.

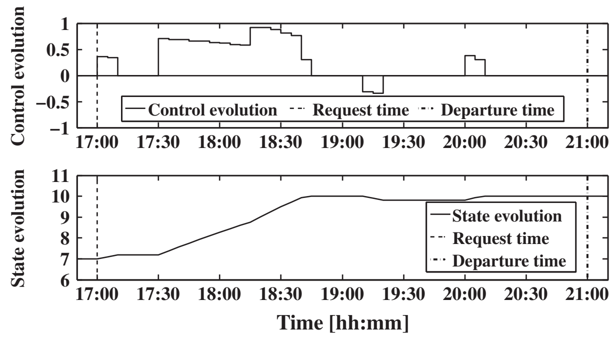

Fig. 9. Final control evolution ($u_k^{ev} - v_k^{ev}\ \forall k \in [ct, dt]$) and state evolution (in [kW h]) for EV2.

strength of the proposed approach, we keep the same simulation scenario as above and simulate SHC reaction to a DSM volume signal notified at 16:00 and demanding for a 1 kW reduction of the contractual power threshold between 17:00 and 19:00 (a congested period, see Fig. 5). Fig. 10 displays the final outcome, while the details of the simulation are presented in Table 4. In particular, the last column of the table presents the final planning of the appliances, which is equal to that in Table 3 since, in this case, the DSM signal is managed by the SHC by properly controlling the storage and the EV, while the loads working at DSM time cannot be rescheduled since they have already started when the DSM is notified (see the second column of Table 4). The contribution of storage discharging is therefore relevant for avoiding overload, as it can be seen from Fig. 10 (notice the storage discharging immediately after the volume reduction).

Table 4 also reports the costs obtained in the pure load-shifting scenario (c_{op}^{dsm}) and the ones obtained in the fully automated

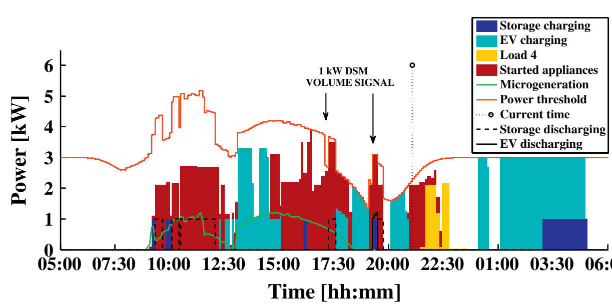

Fig. 10. Aggregated power profile after the DSM event.

Table 4
Simulations results: DSM operations.

Event ID	DSM	EV 2	R7	O R7	R8	R9	EV 3
Trigger time	16:00	17:00	19:00	19:00	20:00	20:30	21:00
Start time	17:00	17:00	19:00	19:00	20:00	20:30	21:00
End time	19:00	21:00	21:00	NA	23:00	23:30	05:00
Load ID	Plan	Plan	Plan	Plan	Plan	Plan	Plan
Load 1	12:10	12:10	12:10	12:10	12:10	12:10	12:10
Load 4	09:00	09:00	09:00	09:00	09:00	09:00	09:00
Load 2	10:25	10:25	10:25	10:25	10:25	10:25	10:25
Load 6	15:50	15:50	15:50	15:50	15:50	15:50	15:50
Load 5	14:30	14:30	14:30	14:30	14:30	14:30	14:30
Load 7	15:55	15:55	15:55	15:55	15:55	15:55	15:55
Load 8	NA	NA	20:20	19:00	19:00	19:00	19:00
Load 3	NA	NA	NA	NA	21:25	20:45	20:45
Load 4	NA	NA	NA	NA	NA	21:20	21:20
c_{op}^{dsm} (€cent)	101.6	158.9	186.8	187.7	205.4	231.2	384.9
$c_{op}^{dsm,s}$ (€cent)	93.1	151.1	180	180.1	197.9	223.7	378.2

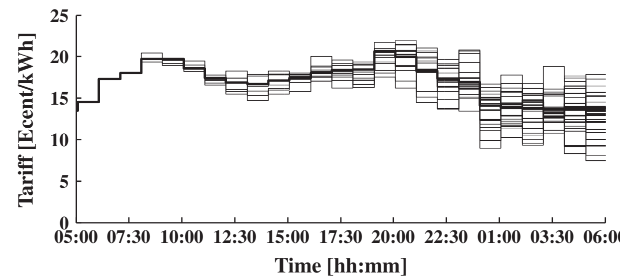

Fig. 11. Estimates of the electricity tariff (the thickest line is the final tariff).

Table 5
Comparison of the final start times obtained in the DAP and the RTP scenarios.

Load ID	1	4	2	6	5	7	8	3	4
Start time DAP	12:10	09:00	10:25	15:50	14:30	15:55	19:00	20:45	21:20
Start time RTP	12:05	09:00	10:25	13:30	15:10	16:00	19:00	20:45	21:20

scenario ($c_{op}^{dsm,s}$). Comparing Table 4 with Table 3 it is seen that costs have raised. The analysis of such kind of data provides a rationale for the computation of the *minimum rebate* that a qualified market actor has to provide to the user for positive acceptance of the DSM program. The rebate should further take into account and remunerate at least the investment cost in household equipment and a remuneration to the user for any discomfort deriving from the participation in the DSM program.

6.3. Real time pricing

In this subsection we consider a RTP scheme in which the tariff is notified on a hourly basis, one hour in advance. The scenario considered is the fully automated one. In particular, we keep the same sequence of events of Section 6.1, *simulating* also hourly price notifications and tariff prediction updates. The SHC in this case works based on estimates of the tariff. In particular, we emulate two properties of efficient price predictors: the first one requires the expected value of the price estimate to be equal to the actual value of the tariff. Secondly, the variance of the estimate is assumed to be increasing in time and small for short prediction horizons.

Let us regard the PUN displayed in Fig. 3a as the actual tariff resulting from RTP (known only at the end of the simulation). Then we can emulate the two properties above by ‘‘artificially’’ generating the tariff predictions starting from the PUN in Fig. 3a and superposing to it a uniformly distributed random sequence with zero mean and a support size linearly growing from zero (corresponding to a price *notification*) to a maximum value $\hat{c}$ at the end of the prediction horizon. We took $\hat{c} = 7$ €cent/kW h for a 24 h ahead prediction (a challenging value: the average energy component of the tariff in the simulation days is 7.0822 €cent/kW h). Some of the resulting simulated price predictions are reported in Fig. 11. Thin lines refer to predictions in the early hours of the day (notice they are not accurate). Thicker lines refer to predictions obtained later in the day. The thickest line represents the final tariff. Table 5 reports the outcome of RTP simulations. The final cost is 377.4 €cent, compared to 376.2 €cent obtained in the case of DAP. The difference is negligible, in spite of the great variability of simulated tariff predictions.

7. Conclusions and future work

This work has discussed a control framework for the optimal energy management of a household equipped with smart appliances, smart plugs, a smart meter, a storage unit, a local micro-generation plant and an EV point of recharge. The problem has been addressed both from a *user perspective* (satisfaction of UPs, costs minimization and maximization of self-consumption), but also enabling the interaction with upper-level market or grid actors. Event driven MPC provides the flexibility and robustness needed in a dynamical context characterized by the interaction with the user, uncertainty and time-varying signals. Several developments are currently being investigated, including the analysis of the theoretical properties of the control approach, the investigation of DSM strategies acting on a significant number of SHCs and the introduction of the SHC concept in micro-grids and energy communities. Other major future works will regard the investigation on minimum software and hardware requirements for the unit hosting the SHC module (an issue which is strictly related to the task of developing efficient and tailored solution algorithms) and a comprehensive and detailed cost-benefit analysis of the proposed residential energy management system, performed using approaches like the ones presented in [51,52] to generate highly realistic sequences of events.

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