Optimized scheduling of battery storage and appliances for demand response

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Abstract

The desire to increase the use of renewable energies, reducing the environmental impacts of energy use, has the potential to create stability problems to the electric grid. As part of the solution, demand response programs may play an important role by providing part of the flexibility needed to adapt the now variable supply to the variable demand. However, not all types of consumers have a natural capability to offer significant load change, namely residential consumers, even if considering their aggregation. However, the use of battery storage combined with the management of loads and eventual self-generation devices may provide enough flexibility to give small consumers a possible role in supporting the grid.

The objective of the work here described was to optimize the scheduling of user appliances and battery storage charging and discharging to respond to real-time price schemes and the eventual availability of self-generation, while limiting the discomfort for the consumer. An analysis was made of two possible real-time price schemes, one following the actual variations of the Iberian wholesale market, still strongly dominated by thermal power plants, and another inversely following the variation of renewable generation in Portugal.

The results show that, although with present conditions only the maximization of the usage of self-generation may justify this type of control, a future power system dominated by variable renewable generation will probably lead to many situations in which load flexibility can be paid enough money to make this kind of system cost-effective.

Introduction

The management of a Power System, balancing supply and demand is one of the most challenging issues. Nowadays climate change, energy security, and limited fossil fuel resources are driving the grid to increasingly integrate renewable energy sources (RES) such as photovoltaic panels (PV) and wind turbines (WT) into the modern power grid, considering also the improvement of costs.

The International Energy Agency (IEA) published the World Energy Outlook in 2013, where an important increase in the share of variable RES in total electricity generation is predicted, growing from 6.9 % in 2011 to 23.1 % before 2035 inside the EU (International Energy Agency, 2013). The relevance of buildings in the global total final energy consumption of the world is also reported to represent about 32 %, corresponding to 40 % in terms of primary energy in most IEA countries, and 65 % of the total electric consumption (International Energy Agency, 2013). Moreover, according to the Eurostat[1] statistics reported in 2018, households are the second most relevant category in terms of final usage of energy in the EU, accounting for 26.1 % of the total consumption.

However, the growth of zero-carbon renewable based generation, variable by nature, will present major challenges to the operation of transmission and distribution networks in terms of voltage/frequency control and power flow management (Lyons et al., 2010). This requires the adoption of new technologies, as smart metering and communication systems, to help matching the availability of supply to the demand of consum-

1. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview#Final_energy_consumption

ers, ensuring electricity security, affordability and efficiency (Khan and Khan, 2013).

Under these circumstances, the concept of Demand Response (DR) has been seen as a possible source of flexibility, consisting in inducing the demand-side to change their normal consumption profiles through dynamic changes of price over time or incentive payments, according to the needs of the power electric system (Federal Energy Regulatory Commission, 2012).

Electrical energy storage (EES) systems are another important solution increasingly used besides DR to supply the flexibility needed for variable renewable energy applications, leading to the recognition by the European Commission as one of the crucial technologies for the future smart grid, able to support the grid with different services, as frequency control or price arbitrage and as well the capability of contributing peak shaving and energy cost reduction (Kousksou et al., 2014; Yao et al., 2016). EES also allows maintaining the same comfort and consumption patterns, if properly managed, while improving the integration of RES, e.g., by storing excess production (Zhao et al., 2015).

This paper presents a household energy cost minimization through a mixed integer non-linear programming (MINLP) model designed for scheduling appliances and battery operations inside a house context, where the energy supply comes from a PV panel and grid connection, but without the capability of selling energy back to the grid. The work is based on the approaches followed by Setlhaolo and Xia (2015) and Yahia and Pradhan (2018) which aimed to optimize the operation of a set of appliances under time of use (TOU) tariff rates, without considering differences related to seasonality, one of them also considering the presence of battery storage. The model is applied to a case study representing a single household, but in this case considering a real-time price scheme (RTP), different solar conditions and willingness to different levels of discomfort.

The remainder of this text is structured as follows. The following section presents a brief literature review referring the concept of Demand-Response, the operation of Home Energy Management Systems, the role of energy storage and a list of related works regarding the optimization of demand response and storage systems. The third section presents the proposed methodology, summarizing the implemented optimization model. The fourth section describes the case study, including the definition of two real-time-price datasets, one based on the actual Iberian wholesale market, and another on the availability of renewable generation. The fifth section presents the results of the model and, finally the last section presents conclusions.

Literature review

DEMAND RESPONSE

The Federal Energy Regulatory Commission (2012) defines DR as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower or higher electricity use at times of high or low wholesale market prices or when system reliability is jeopardized".

The original objective of DR was to make the load follow the generation in order to make the system more efficient economically, aiming to avoid having too much idle grid capacity or having to start expensive generation, but its goals were extended to deal with variable generation (U.S. Department of Energy, 2006).

DR is one of the main strategies to be promoted in order to guarantee security and supply of the grid and can be divided by the way in which consumption shifting is stimulated: incentive-based and price-based. Incentive-based DR consist in motivating the customers through incentives or rebates, which are based on the needed electricity usage change calculated a priori and offered by the local operator. In this type of DR, customers may be subject to financial penalties if they fail to participate or reach the load change required, usually a reduction (Zhang and Li, 2012).

An example of incentive-based is the direct load control (DLC) of air-conditioners (ACs) within the residential sector, directly making possible to change the thermostat temperature set-point or to manipulate on-off cycles during peak times. Many other different typologies are available as curtailable load, which consists in discounts for reducing the load during contingences periods, and demand bidding or buy back, where customers offer bids to curtail according to wholesale electricity market.

On the other hand, a price-based DR can be implemented as a manual control of loads if made by customers or an automatic control if it's entrusted to Energy Management Systems, in response to time-varying prices as time-of-use rates (TOU), critical peak pricing (CPP), inclined block rating, and real-time pricing (RTP) (Zhang and Li, 2012). These solutions leave up to the customers to reduce usage of energy-intensive appliances during periods of high prices or shift usage to a different time, such as waiting for the use of high consumption appliances until the peak period is over.

The efficiency of a rate is larger, the shorter is the updating period (Q. Zhang and Li 2012). According to that, TOU being a pre-determined solution varying only in the long term or seasonally cannot help further to reduce the demand, in particular when the system is under shortage of capacity. RTP schemes, which are more dynamic with price updating periods of one hour or less, can come to aid and better reflect these issues, effectively strengthening the link between wholesale and retail markets (Faruqui and Sergici, 2010; Federal Energy Regulatory Commission, 2012).

To have an adequate response time to RTP, the rates are usually given a day-ahead or some hours ahead, so the customer can act and make the needed adjustment according to the prices previously communicated (Barbose et al., 2004). According to Borenstein (2005), RTP represent a greater reflection of the marginal costs of supply, becoming economically attractive, and allowing more benefits for both the utilities and customers, as peak load reduction and greater bill savings, with TOU rates obtaining only 8 % to 29 % of the benefits of RTP.

HOME ENERGY MANAGEMENT SYSTEMS

Smart home appliances are very important to get the most of energy management systems in residential houses, (Zhao et al., 2013). Some existing home appliances can be made "smart" with the addition of remotely controlled switches and even sensors and controlling microprocessors, but there are already smart appliances being produced, like refrigerators which allow users to interact through a tablet or mobile phone (Zhao et al., 2013).

Home Energy Management System (HEMS) are important tools to perform the control, scheduling and optimization of the electricity usage, including various in-home appliances, applying different algorithms and models usable, depending on load types and requirements of DR programs available. A HEMS is a fundamental piece in the role of achieving automated house DR programs, as customers cannot be always monitoring and acting when needed as it would be required to implement DR manually. An effective HEMS should provide the needed DR operations with the least impact on customer lifestyle. A possible methodology to evaluate the impact of the deployment of such systems was proposed by Miguel et al. (2014).

Such a system placed in a residential home should be able to communicate with the appliances and utilities, receive prices information and then manage and reduce the power consumption according to an optimal scheduling of appliances (Shareef et al., 2018). Specified set of requirements expressed by the individual customer would be take into account for the operations and optimizations, in order to maximize the quality of service. The main controller device can be implemented around smart meters, taking profit of the measuring capabilities as well as the capabilities of communicating with the utilities (Lee et al., 2011).

A typical HEMS is composed by a personal computer or a single-board computer, a smart meter connected with wired or wireless communication devices in order to coordinate, receive and send data from utility to the appliances of the smart house and an in-home display for visual communication with the user (Shareef et al., 2018). Depending on the power architecture in smart home and objectives need to be met, different HEMS can be developed to ensure the optimal energy utilization and optimal energy sustainability (Yao et al., 2016).

ENERGY STORAGE

Energy storage systems have a fundamental role to fully integrate renewable energy sources, due to their variable nature, frequently not aligned with the typical demand, implying lack of availability at certain times of the day and excessive availability in others. With EES it is possible and profitable to supply a system with 100% RES, even on off-grid systems (Zhao et al., 2015). EES can stabilize the power grid with a high penetration level of RES and so facilitate them to become completely reliable as a primary source of energy (Díaz-González et al., 2012).

The growth of capacity in EES coupled with a large amount of application opportunities led to a rapid development of EES technologies. Different benefits can be obtained in terms of environment and supply security thanks to the RES expansion accompanied by the peak shaving of demand profile. This reduced the need to resort to conventional thermoelectric generators to compensate supply and demand variations (Zheng et al., 2018). Some manufacturers started to promote electricity storage for individual homes, e.g. Tesla Powerwall® batteries, and the use of electric vehicles' (EV) batteries for this purpose has been also suggested as a way to improve system flexibility and supporting local peak power and energy demand (Zheng et al., 2018).

The energy demand of a typical residential consumer includes different types of loads: inelastic, as lighting, TV, computers, refrigerators and cooking appliances which have the highest priority, being considered essential for the user's comfort, and elastic loads that can be easily rescheduled thanks to higher flexibility and/or lower importance. Typically, HEMS control the later type, to avoid conflicting with the user comfort levels, but this reduces the amount of flexibility to offer. In this context, energy storage systems can act as a tool to transform any kind of load on a controllable load, acting as an uninterruptible power supply (UPS). With a properly sized battery, the demand of a whole house could be traded as a flexible load with minimum nuisance to the users (Bayram and Ustun, 2017).

RELATED WORKS

A wide range of research has focused scheduling problems in HEMS. Nirmalya Roy et al. (2006) showed that an intelligent algorithm integrated into the HEMS and based on the game theory was able to improve the comfort level while reducing the energy consumption, thanks to the tracking of the activities. Yu et al. (2013) proposed a hybrid genetic particle swarm optimization to schedule the energy consumption of appliances in HEMS with the integration of RESs. Boynuegri et al., (2013) presented an algorithm based on the battery state of charge level and RES, while using multiple tariffs, being able to integrate them for a scheduling of the appliances and demand reduction. Z. Zhao et al. (2013) proposed a generic algorithm (GA) to optimize the operation of a HEMS in the presence of RTP and inclined block rate, in order to reduce electricity cost and the peak-to-average-ratio (PAR) factor, being PAR an indicator of instability of the grid. Terci Flores et al. (2016) presented another GA based work for the residential sector presents a model for energy optimization considering the presence of distributed generation, time-differentiated prices, and preference of loads. Nguyen, Song, and Han (2015) proposed a management of appliances energy consumption in the residential sector, considering RTP and distributed energy sources, using fractional programming. Di Somma et al. (2018) developed a stochastic programming model for the optimal scheduling of distributed energy resources, aiming to reduce energy cost and CO_2 emission, satisfying time-varying user demand in the meanwhile. Ma et al. (2016) categorized the different appliances and considered the uncertainties related to different kind of loads, when aiming to minimize costs, using a day-ahead pricing scheme (Ma et al., 2016). Another study using day-ahead prices use a hybrid technique named teaching-learning genetic optimization to solve the optimization problem of reducing electricity cost at minimum user discomfort (Manzoor et al., 2017). Rasouli et al. (2019) compared two different methodologies, a mixed-integer linear programming (MILP) model and a metaheuristic (genetic algorithm) to use on a HEMS, aiming to integrate energy resources under dynamic tariffs. Gonçalves et al. (2019) proposed a model considering two types of power cost scenarios.

Methodological proposal

The configuration of the system to study is shown in Figure 1, where a household is supplied by its own PV generation system and by the main grid, and there is a battery system which can be charged and discharged when necessary. The main objective is the energy cost reduction of the household. The household is considered to be participating in a DR load scheduling program with RTP scheme, meaning that inside a certain time window chosen by the user the appliances can be rescheduled to profit from the variations in RTP.

Following the works developed by Setlhaolo and Xia (2015) and Yahia and Pradhan (2018) an algorithm is developed that can be implemented by the controller of the system. The algorithm intends to minimize the cost to the user while keeping in consideration the discomfort in which the user can incur. This implies considering the characteristics of the appliances, the PV panel system and BS system, as well as the parameters decided by the user. Based on the day-ahead data regarding user parameters, solar forecasts and prices, the algorithm is implemented to obtain the optimal scheduling of the individual components, as for example the optimal period for charging and discharging the BS system, in order to obtain the higher benefits.

All the components of the system are subjected to certain constraints, as keeping the state of charge of the battery inside a certain range or respecting dependences and forced sequences regarding the operation of appliances, making the problem a Mixed Integer Non-Linear Programming (MINLP) problem.

The main grid is considered to be only an energy supplier component, thus excluding the possibility of being able to receive or to value the energy produced in excess or at advantageous times to the supplier. This possibility is excluded, as we intend to develop a model that strictly optimizes the use of the battery inside the home, excluding the possibility of further stressing it to obtain further small savings at the expense of greater degradation, and assuming the current trend towards self-supply.

To achieve the objectives, a function of minimization of the different day-ahead costs is implemented. The function aims to minimize the cost of the power purchased to the grid ($Cost_{Grid}$) and the cost of the weighted scheduling inconveniences ($Cost_{I}$). $Cost_{Grid}$ is in turn composed by the cost of supplying the appliances in the house ($Cost_{Household}$) directly from the grid, the net cost of charging the battery ($Cost_{BS}$) to which the cost saved due to the PV panel power produced ($Cost_{PV}$) is subtracted.

The optimal scheduling is based on user preferences, which are the desired use of each appliance (start and stop time) and a time window within which it is possible to operate the appliance. This time window represents the flexibility for operating the appliance and the wider the appliance operating time window, the greater will be the flexibility.

A MINLP mathematical model is described in Box 1 in order to handle this problem, assuming data series with $T/\Delta t$ values, for a study period T and Δt a fraction of the time unit.

In order to evaluate the developed model, different scenarios for using a battery unit and a DR program were implemented, with and without the consideration of a PV panel, in order to analyse if the usefulness of storage depends on the existence of self-generation. Multiple different values of δ were used in order to see whether the higher willingness to accept discomfort significantly affect the cost reduction. The model was also applied to periods of the year, where the availability of different solar radiation and different types of loads conditionate the choices, in addition to the relative different prices, reflecting the changing availability of all renewable sources in different months.

The model is a day-ahead optimization model, which means that it is based on different parameters and forecasts made for the following day, namely for the PV power production, the

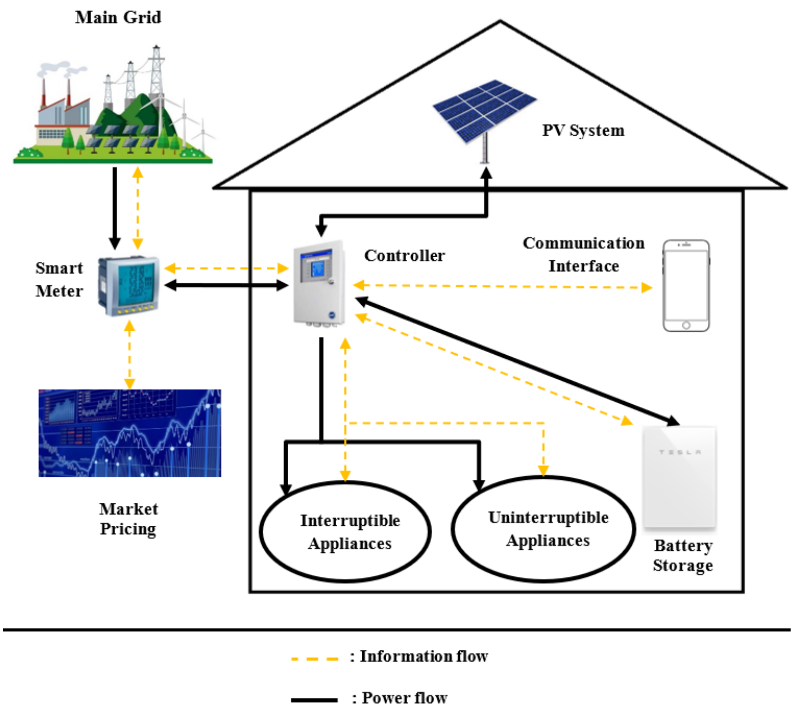

Figure 1. Configuration of the studied system.

Box 1. A MINLP mathematical model assuming data series with T/Dt values, for a study period T and Dt a fraction of the time unit.

$\textbf{Minimize}[\text{Cost}_{Grid} + \text{Cost}_I]$	
$\text{Cost}_{GRID} = \sum_{t=1}^{T} RTP(t) \times P_{Grid}(t) \times \Delta t$	$RTP(t)$: energy price at the instant t.
$\text{Cost}_I = \delta \times \text{RTP}(t) \times I(t) \times \Delta t$	δ is the relative importance assigned to the inconveniences
$P_{Grid}(t) = P_{\text{Household}}(t) - P_{PV}(t) + P_{BS}(t)$	$P_{BS}(t)$: Net Battery demand power
$P_{BS}(t) = P_{BS,Ch}(t) - P_{BS,Dis}(t)$	"Ch": charging; "Dis": discharging
$P_{\text{Household}}(t) = P_{Unc}(t) + \sum_{i=1}^{N_a} P_i(t) \times OT_i^{opt}$	$P_{Unc}(t)$: power of uncontrollable loads; $P_i(t)$: Rated power of appliances
$I(t) = \sum_{t=1}^{T}\sum_{i=1}^{N_a}\left(OT_i^{\text{user}}(t) - OT_i^{\text{opt}}(t)\right)^2$	I: Inconvenience factor
$OT_i^{opt}(t) = \begin{cases} 1 \text{ , if appliance } i \text{ is on at instant } t \\ 0 \text{ , if appliance } i \text{ is off at instant } t \end{cases}$	$OT_i^{opt}(t)$: Optimized schedule of appliance i
$P_{PV}(t) = \frac{G_a^t}{G_{a,0}} \times \left\{P_{Max,0}^M + \alpha_{P_{max}} \times \left(T_a^t + G_a^t \times \frac{\text{NOCT} - 20}{800} - T_{M,0}\right)\right\}$	$P_{PV}(t)$: Power generated at PV panel; G_a^t: Instantaneous irradiation; $G_{a,0}$: Standard irradiation; $\alpha_{P_{max}}$: temperature coefficient; T_a^t : temperature; $T_{M,0}$: temperature at standard conditions; NOCT: Normal operating temperature.
$P_{\text{Household}}(t) \leq P_{\text{Demand}}^{\max}$	$P_{\text{Demand}}^{\max}$: Maximum demand at any time.
$P_{Grid}(t) \geq 0$	Constraint to assure self-supply
$\sum_{s_i}^{e_i} OT_i^{opt}(t) \geq D_i + k_i$	D_i: Appliance i cycle duration; k_i: Time adjustment flexibility parameter
$D_i + k_i \leq (e_i - s_i)$	e_i: end of cycle of appliance i; s_i: start of cycle of appliance i
$OT_i^{opt}(t) \leq 1 - X_i(t)$	$X_i(t) \in \{0,1\}$: indicator of uninterrupted operation: 1 = cycle completed at time t.
$OT_i^{opt}(t-1) - OT_i^{opt}(t) \leq X_i(t)$	$\forall\, t \geq 2$
$X_i(t-1) \leq X_i(t)$	$\forall\, t \geq 2$
$X_i(e_i) \geq X_i(e_i + 1)$	Allows more than 1 cycle per appliance
$OT_{i=\text{Clothes dryer}}^{\text{opt}}(t) \leq X_{i=\text{Washing machine}}(t)$	Constrains dryer to the WM operation
$X_{i=2^{\text{nd}}\text{part}}(t) = X_{i=1^{\text{st}}\text{ part}}\left(t - D_{i=2^{nd}\text{ part}}\right)$	$\forall\, t \geq D_{i=2^{nd}\, part}$; for breakable cycles
$SoC_{BS}(t) = SoC_{BS}(t-1) + \frac{\left(\eta_{Ch} \times P_{BS,Ch}(t) - P_{BS,Dis}(t)/\eta_{Dis}\right) \times \Delta t}{E_{tot}}$	$SoC_{BS}(t)$: state of charge; η_{Ch}: efficiency of charging; η_{Dis}: efficiency of discharging; E_{tot}: Total energy storage capability
$SoC_{min} \leq SoC(t) \leq SoC_{max}$	SoC_{min} and SoC_{max}: Assumed limits for SoC
$0 \leq P_{BS,Ch}(t) \leq P_{BS,Ch}^{\text{limit}}$	$P_{BS,Ch}^{\text{limit}}$: Imposed limit for charging power
$0 \leq P_{BS,Dis}(t) \leq P_{BS,Disch}^{\text{limit}}$	$P_{BS,Disch}^{\text{limit}}$: Imposed limit for discharging P.
$P_{BS,Ch}(t) \times P_{BS,Dis}(t) = 0$	

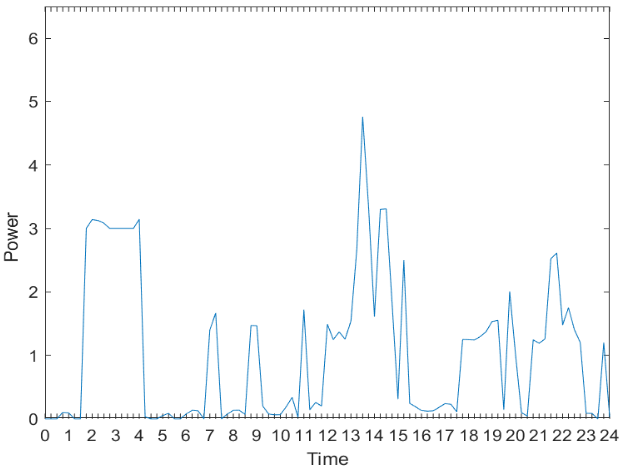

Figure 2. Initial load profile.

precision of which may affect the result. The mismatch between the forecast and the real production is satisfied by purchasing the missing amount from the grid or injecting the excess production in the grid without a reward for it, thus representing a worst-case scenario. As a result, there will be a potential difference between the amount of expected savings calculated a day-ahead and the real amount of savings obtained.

The evaluation of results focusses:

- The amount of expected savings obtainable, according to the different characteristics of the scenarios.
- The amount of participation of the BS system to produce savings.
- The possible order of magnitude of the disparity between expected savings and real savings.
- The analysis of the sensitivity of results to the variation of δ values.
- The factors which appear to exert a strong influence on the performance of the algorithm.

Case study

For the PV forecasts, the house to control is considered located in Leiria, Portugal. The system is connected to the grid and contains a PV power plant, a HEMS which manages the household energy flow and the BS unit scheduling to better reduce the energy demand cost. Moreover, the consumer participates in a real time price-based demand response program implemented by the electricity supplier.

The usage of the BS unit is explored considering the seasonality of PV power generation and of the price variation, as well as different values for a parameter (δ) representing the allowed inconvenience. It also taken in consideration different maximum values of demand limit, in order to evaluate the changes occurring for this limitation.

The different components of data were defined based on datasets of house load demands, of appliance load profiles, PV and other renewable generation data, and wholesale market hourly electric prices.

HOUSEHOLD APPLIANCES

Being a generic case, with the aim of testing the optimization model, the set of appliances was defined based on a monitoring study conducted in the Netherlands (Uttama Nambi et al., 2015). In addition, some commonly used appliance consumption profiles were obtained from measurement campaigns in Portugal to which the authors had access.

The appliances were divided in two categories of usage: uninterruptible and interruptible, the former mandating the completion of any started cycle without interruption, and the latter allowing the operation to be interrupted, on the condition that the total duration of the cycle is respected. The category of interruptible appliances included the air conditioner and the car charger, due to the possibility of interrupting the operation cycle without noticeable differences in the perception of the user. The same could have been done for electric water heaters with hot water storage, which profit from thermal inertia. However, for simplicity reasons, the water heater demand was considered instantaneous.

Figure 2 depicts the reference load profile of the household assuming the load profile which was used for all the experiments for simplification reasons, even if the load profiles of certain loads, as AC, are for sure not the same during the whole year.

SELF GENERATION AND STORAGE

The household was considered to have its own renewable power production system based on solar PV panels, using the silicon crystalline technology, with a peak power of 3 kW. The system characteristics were defined assuming the default characteristics of PVGIS[2] for Leiria, namely 34 ° slope, 9 ° azimuth and system losses of 14 %. The generation time-series was obtained from PVGIS. The difference between two consecutive days was used as an estimate of the possible mismatch between forecasts and actual generation.

The battery considered assumed the data values for the Tesla Powerwall 2, according to the available technical specifications. However, the Depth-of-Discharge (DoD) used for the model was limited to a maximum of 80 %, below the maximum specified by Tesla, to reduce the degradation of the battery, following recommendations regarding the impact in the lifetime of batteries (Wu et al., 2017).

RTP DATASETS

In the absence of existing RTP schemes for residential customers in Portugal, the price values datasets used to assess the developed model were created from two different hypothesis, one based on the Iberian wholesale market of 2019 and one based on the renewable energy availability in Portugal in the same year. The second model intends to forcefully represent the dependence of future RTPs on renewable energy production, due to the expected greater expansion of RES in the country, following the European target for the whole electricity production to be covered by renewable sources in 2050 (RNC2050, 2019). The current market price already accounts in part for the RES variability, but it is still smoothed by the significant share of thermal-based energy generation. As the current objective of

2. https://ec.europa.eu/jrc/en/pvgis

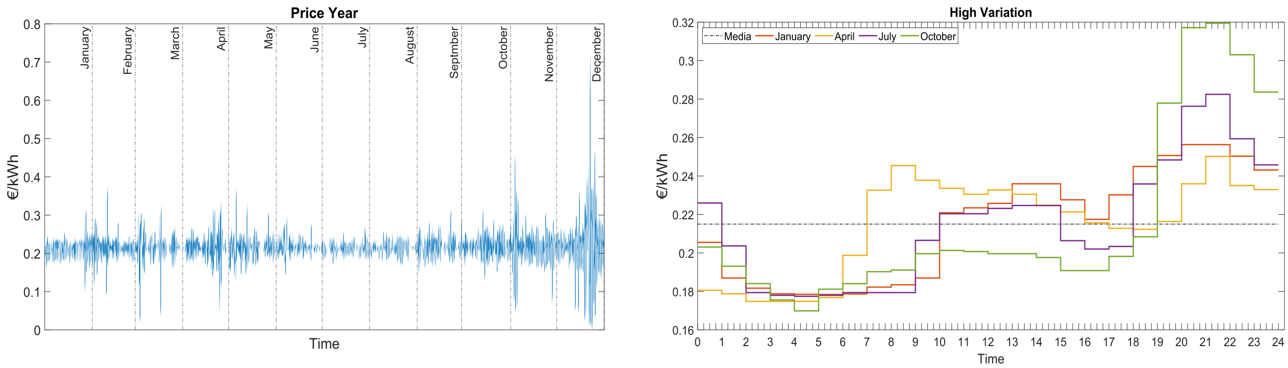

Figure 3. Hypothetical RTP based on the MIBEL wholesale prices (€/kWh). a) Whole year; b) Selected days.

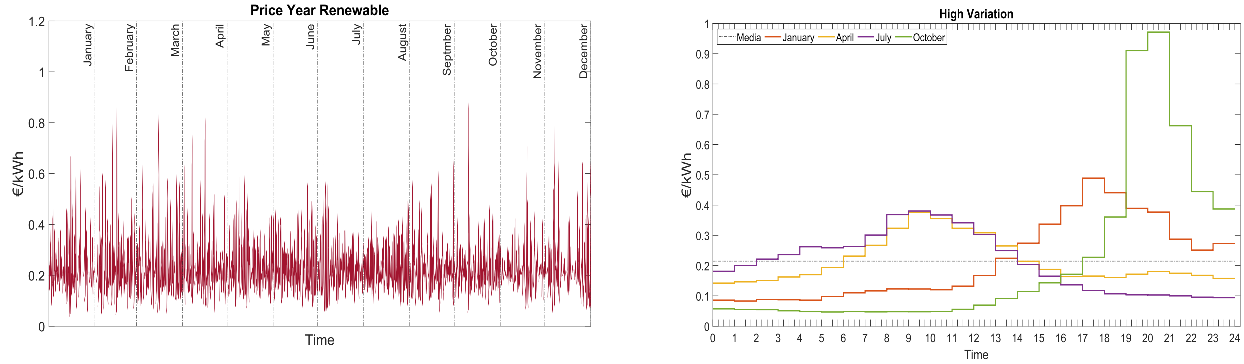

Figure 4. Hypothetical RTP based on the availability of RES (€/kWh). a) Whole year; b) Selected days.

DR is to allow for an increased integration of renewables, the true value of the system proposed must be assessed with RTP that more accurately reflect what would be the electricity generation cost dynamics in such a situation.

The first model was obtained by scaling data collected from the Iberian Electricity Market Operator[3] (OMIE), the operator of the market where electrical companies in Portugal and Spain perform trade, so that the average price equals the average price to residential consumers, €0.2150/kWh, including taxes, according to EUROSTAT[4] (Figure 3).

The second was created based on data provided by the Portuguese System Operator (REN) regarding renewable energy production[5], scaling the inverse of the hourly solar and wind energy also to the average price to residential consumers (Figure 4).

As the model implemented relies on daily operations, a few days were selected to represent the most relevant cases, namely RTP daily profiles relatively flat and daily profiles with significant variations. Examples of the choices for the first dataset are depicted in Figure 3b), while for the second choices are shown in Figure 4b), the second case resulting in much larger variations, reaching close to €1/kWh at the evening in October.

3. https://www.omie.es/en/file-access-list#Day-ahead%20MarketPrices?parent=Day-ahead%20Market

4. https://www.dgeg.gov.pt/pt/estatistica/energia/precos-de-energia/precos-de-eletricidade-e-gas-natural/

5. https://www.mercado.ren.pt/EN/Electr/MarketInfo/Gen/Pages/default.aspx

Application of the optimization model

The proposed MINLP model was solved on a PC with a 1.99 GHz Intel Core i7-8550U CPU of 8th Generation with 16 GB of RAM, running under Windows 10, with MATLAB R2020 through the OPTI toolbox.

The execution time averages to 7.5 seconds, with a minimum of 5.6 and a maximum of 13.5. The time normally increases for higher values of inconvenience allowed, defined through a low value for δ, due to a larger number of combinations.

The model was applied to example days with high and low variation of prices, in both datasets, for the months of January, April, July and October, with and without considering the existence of the PC panel, in a total of 32 cases. Results show that, with the exception of the case without the contribution of the PV panel when considering the RTP dataset that reflects the current wholesale market variations, all the remaining cases result in significant savings, reaching a maximum of 88 % for a day of high variation in prices in October, when considering the RTP dataset following the availability of renewable sources, and in almost all cases it is possible to achieve almost maximum savings without assuming significant inconveniences.

The contribution of the battery to the savings is in almost all cases quite significant, from a minimum of 31 % to a maximum of 91 % on the cases with PV. The contribution of load shifting could also be nonetheless relevant, reaching 31 % of the savings on the case without PV, in October, for the RES based RTP.

Figure 5 shows the optimal scheduling obtained for a day in January, when considering PV and the RES based RTP scheme, and assuming no elasticity for loads. It is visible the use of the grid mostly for charging the battery and supplying the evening load, and the use of the battery to also benefit from the excess PV production during the day, in order to supply the load during the remaining time.

In this case, the scheduled operation resulted in the grid directly supplying only 30 % of the load, 26 % coming directly from the PV panel and the remaining 44 % from the battery, 39 % of which charged by the PV panel and 61 % by the grid during low price hours.

Conclusions

The need for decarbonizing the electricity production sector led to the rapid expansion of renewable energy production, but the electricity generated by these primary sources is extremely dependent on their fluctuations, therefore implying difficult constraints to the power system. The daily significant variations of the solar and wind-based generation as well as the deep seasonal variations of hydropower create a significant variability of the supply which adds to the natural variability of the demand, increasing the complexity of finding the essential instantaneous balance which is an absolute requirement for the operation of the power system.

Therefore, new solutions are required to grant the reliability to the power system it usually had when the availability of supply could be accurately planned. The future power system needs sources of flexibility to be able to match demand and supply and energy storage systems and demand-response programs are being developed with such ambition.

The main objective of this work was to implement an optimization procedure, based on day-ahead forecasts of real-time prices and solar generation, to schedule the use of appliances and battery management actions, analysing a possible result of a DR scheme in which a residential customer would participate using not only the ability to shift the usage of appliances, but also energy storage and energy self-generation abilities. To analyse the magnitude of the results for different possible real time price schemes, two different hypotheses were used to generate hourly prices which a residential user could be subject to, one using the actual Iberian wholesale market as a source of variation, the other using the availability of RES. Both schemes produced a wide range of different situations, from a flatter daily profile of prices to a highly variable daily profile, the latter stressing the importance of such HEMS to control demand shifting for residential customers. The situation was analysed with and without the contribution of self-generation obtained from a PV production system, considering also its variability according to simulation data.

Although not intending to make general conclusions from a single case, the results allow for some comments. As an example, the application of an RTP scheme based on the current variations in price observed in the Iberian wholesale market led only to small profits when not considering the PV generation, but increased significantly when considering a small PV production, and then reached significant cost savings (circa 70 %) in periods of high solar generation. However, when applying a RTP scheme based on the fluctuations of RES, which produced much higher variations in price, the results improved considerably, reaching cost savings as high as 85 %.

In detail the model shows that to obtain an interesting quantity of savings, sufficient to be advantageous against the inconvenience cost, a significant magnitude of price difference or a high quantity of solar energy production are needed. With a small PV production, when the price profile becomes more variable during the day due to relative higher and lower maximum and minimum peaks, the expected savings increase significantly, only requiring a small increase in the level of discomfort, as in fact the inconvenience cost tends to decrease. In addition, if the solar production becomes high, the savings reach maximum values with a high participation of the battery.

The second model of RTP implemented shows the true relevance of DR and EES, producing meaningful savings even without PV production. This case represents the objectives for

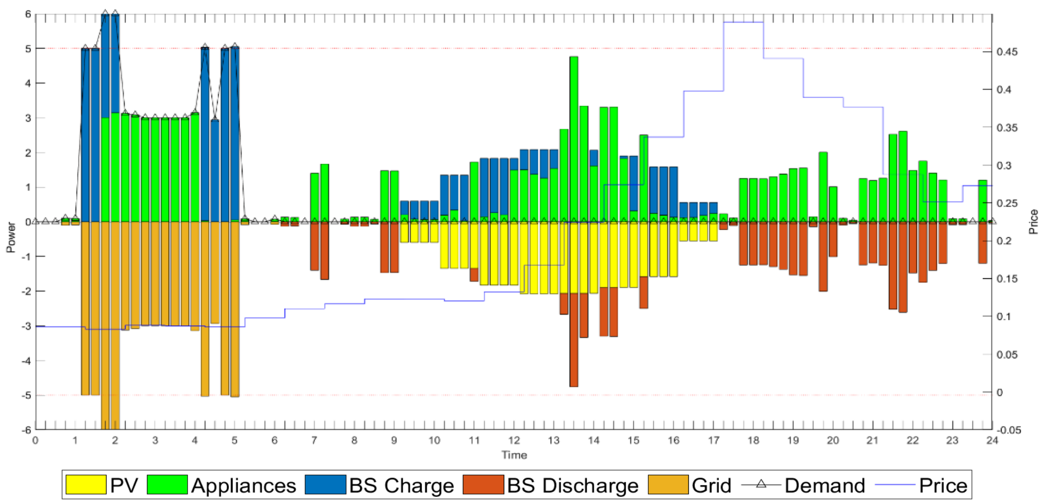

Figure 5. Optimal schedule for January, with PV and the RES based RTP.

this type of HEMS as a way to create flexibility to cope with the higher variation of supply costs following the scarcity or abundance of supply. But, with additional PV generation, the obtained value is even higher in the perspective of the individual customer, allowing for the maximization of the use of such an investment. As an example, there is a case in the month of October when a sudden variation of RES availability leads to price variation from a very low value to a peak, to which the optimization model responded with an adequate scheduling of the battery, making this event a noticeable source of income instead of a possible cause of energy bill increase.

To conclude, it is assumed that the present work had some limitations, namely regarding the modelling of appliances which were simplified. Future works on this subject should aim for improvements, e.g.:

- To implement thermal models for requiring appliances, as for example the electric water heater with a water tank, in order to better represent the role of thermal inertia. The same concept can be done for the air conditioner, controlling the room temperature in relation with the settings of the user. These solutions should permit a more realistic model of the consumptions.
- To use a dynamic model for the EV battery charging, considering also the possibility of using also this battery as part of the house flexibility sources.
- To improve the control of the charging/discharging cycles in order to minimize battery degradation.

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