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OPTIMIZING THE USE OF ENERGY STORAGE AS A DEMAND RESPONSE TOOL

Master degree in Electrical and Electronic Engineering

Energy and Automation

Luca Zampighi

Leiria, December of 2020

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Dissertation under the supervision of Professor Luís Miguel Pires Neves

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Originality and Copyright

Dedicated to

my parents Monica and Luciano,

my brother, Marco,

and my beloved grandparents,

Siria, Eliano, Fiorella and Giorgio.

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Abstract

The renewable energies expansion over last years, due to the need to bring electricity production towards ever higher levels of green production and the increase of the demand, have brought further stability problems to the main grid. The handling of the integration of these alternative sources and the optimization of the electricity grid have given high attention on the role of demand response program as a key part for the target. The combination of battery storage units with real-time prices is part of the research effort that aims to reduce the instability of the grid and the energy costs of the users.

Literature shows good potential for the control strategies as the relative wide range of technologies developed recently for the scope, even if for the residential customers usually the potential is constrained by the limited controllable loads and their significant share of consumption. However, the aspect of user comfort is not always fully considered leading to less realistic conclusions.

The objective of the work described in the dissertation was then to obtain a reduction in residential energy costs through the optimal scheduling of user appliances supported by the use of battery storage, under a real-time price scheme, while limiting the discomfort for the customer.

Although the first results of applying a real time pricing scheme based on the current variations in price observed in the Iberian wholesale market led only to small profits when not considering additional self-generation, they increased significantly if a small photovoltaic based production is considered, and reached significant cost savings (circa 70%) in periods of high solar generation. But, when applying a real time price following the fluctuations of the renewable energy supply, which produced much higher variations in price, the results improved considerably, reaching cost savings as high as 85%.

The implemented model shows the true relevance of Demand Response and Energy Storage, producing meaningful savings if the supply costs change with the availability of renewable energy supply. With self-generation, the obtained value is even higher in the perspective of the individual customer, maximizing the cost-effectiveness of such investment.

Keywords: Demand-Response, Battery-Storage, Real-Time-Pricing, Inconvenience.

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List of Abbreviations and Acronyms

AC	Air Conditioner
BS	Battery Storage
CPP	Critical Peak Pricing
DA	Day-Ahead
DLC	Direct Load Control
DOD	Depth of Discharge
DR	Demand Response
EES	Electrical Energy Storage
EV	Electric Vehicle
GA	Genetic Algorithm
HEMS	Home Energy Management System
HVAC	Heating, Ventilation and Air Conditioning
IEA	International Energy Agency
IOT	Internet of Things
MINLP	Mixed Integer Non-Linear Programming
OMIE	Iberian Electricity Market Operator
PAR	Peak to Average Ratio
PFC	Primary Frequency Control
PHS	Pumped Hydroelectricity Storage
PV	Photovoltaic
RES	Renewable Energy Source
RTP	Real-Time Pricing
SCES	Supercapacitor Energy Storage
SG	Smart Grid
SMES	Superconducting Magnetic Energy Storage
SOC	State of Charge
TES	Thermal Energy Storage
TOU	Time of Use
V2G	Vehicle to Grid
WT	Wind Turbines

1. 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, accounting for 26.1% of the total consumption. In terms of CO_2, buildings are also responsible for 36% of the EU CO_2 emissions. Another important information is that one of the major drivers for increased emissions from the electricity sector is the rising peak demand, which is often met by fossil fuel generation (International Energy Agency 2013; I. Khan 2019). The climate also interferes with the residential demand, which is highly correlated with the seasonal variation of weather. As an example, in Texas the hot temperatures are estimated to cause half of the summer peak demand (Bandyopadhyay et al. 2020; Yongxiu He et al. 2012).

The peak demand increase is typically met by peak generators, which often are old, inefficient and polluting generation units powered by diesel or coal. Moreover, peak demand also creates the need for extra infrastructure, which is not used for most of the year, and can lead to an overall increase in electricity production cost (Liu et al. 2013; Stenner et al. 2017).

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

The U.S. Environmental Protection Agency (2011) stated that the electricity generation sector represents 32% of total emissions in the U.S. and around 42% globally (Ummel 2012). According to that, many steps towards decarbonizing the power grid have been brought forward, with a result of declining emission over the last few years as a consequence of significant investments in renewable sources of energy and energy managements (Bayram and Ustun 2017).

As a result, the current trend aims a more sustainable solution compatible with the decarbonization of the electricity generation, favouring investments in renewable sources (Bayram and Ustun 2017).

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 consumers, ensuring electricity security, affordability and efficiency (R. H. Khan and Khan 2013). These technologies can be found in the definition of smart grid (SG): an electric grid able to manage electricity in a smart way, both from the point of view of generation and of consumers, the latter playing a fundamental role (Bayram and Ustun 2017; Siano 2014).

Under these circumstances, the concept of Demand Response (DR) has become quite important as a possible source of flexibility, consisting in inducing the demand-side to change their normal consumption profiles through 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 them to be recognized 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, Shen, and Lim 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 (H. Zhao et al. 2015).

However, while some charging and discharging operations may appear to bring immediate benefits, they may be outweighed by negative impacts on battery lifetime which may have to be taken in consideration in a viability study (Lyons et al. 2015).

This dissertation 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 (Setlhaolo and Xia 2015; Yahia and Pradhan 2018). In our work, the implementation is made scheduling the battery system under a real time price (RTP) scheme, also including a PV power production in self-consumption mode, not allowing selling back energy to the grid. The model is applied to a case study representing a single household, based on a similar study in the Netherlands, considering a RTP price scheme, different solar conditions and willingness to different levels of discomfort (Uttama Nambi, Reyes Lua, and Prasad 2015).

The remainder of this text is structured as follows. The following chapter describes Demand Response implementations, as well as the necessary technologies, including Electrical Energy Storage. Chapter 3 describes the methodology adopted for the development of the work, defining the optimization model, the definition of credible price time-series to represent real-time prices which a residential customer could be subject to if such a tariff scheme was available in Portugal, and also the way how to assess the benefits produced. Chapter 4 exposes the case study with relative's technical data and combinations of scenarios, and chapter 5 presents the analyses and discussions of the obtained results. Finally, chapter 6 presents some conclusions and possible future works for the improvement of the model.

2. State of the art

This chapter starts by reviewing the concept of DR, then it explores technologies that may help to assure the flexibility needed to match a variable supply to a variable demand, such as Home Energy Management System (HEMS) and Battery Storage (BS) system, while in the penultimate section are addressed the possible problems related to DR and finally, the problem under study is presented, together with the main references that inspired and contributed to the realization of this work.

2.1. Demand Response

The DR is defined 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" (Federal Energy Regulatory Commission 2012).

The objective of DR is to make the load to follow generation to make the system more efficient economically, using DR programs in order to avoid having too much idle grid capacity or having to start expensive generation, but that is seen differently now with variable generation (U.S. Department of Energy 2006).

As a way to show the relevance of such tools, domestic electricity low voltage networks are the major factors leading towards peak demand in UK which contributes to 20% of the totality of electricity bills (Department of Energy & Climate Change 2010)

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 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 (Q. 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 appliances, in response to time-varying prices: real-time pricing (RTP), critical peak pricing(CPP), time-of-use rates (TOU), inclined block rating and day-ahead (DA) pricing (Q. 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.

In a smart-grid environment, the concept of controllable loads as DR is used to realize strategies of matching and coordinate the RES generation with Heating, Ventilation and Air Conditioning (HVAC) loads (Arabali et al. 2013).

DR benefits can be outlined as follow:

- Bill savings:
    - For participants: agreeing to modify load usually translates in relevant electricity bill savings or an incentive payment.
    - For other customers: lower system costs due to an increased economic efficiency lead to lower general market prices.
- Reliability: the probability of system failures leading to high financial costs and other inconveniences is reduced.
- Improved choice: customers are able to choose different options based on their needs.
- Security of the system: the grid and consequently system operators are endowed with more flexibility tools to meet contingencies.

2.1.1. Price-based DR

Since the first price-based DR programs were released in the US, most of the population was wary of using them due to the high costs and long duration of the peak periods, until they were redesigned in the early 2000s due to several blackouts (Faruqui and Sergici 2010). With increased acceptance, the first programs began to take hold favouring a decrease in loads during peak hours, as observed in California by the Electric Power Research Institute, without significantly increasing demand during off-peak hours (Faruqui and Sergici 2010).

The TOU electricity price consists in rates having different unit prices for the energy usage during blocks of time and can reflect the time-varying costs of supply. Typically the rates are pre-determined for several months or even years, with differences on the peak and off-peak prices and also seasonal pricing (Q. Zhang and Li 2012). The TOU rates can provide greater efficiency and benefits, as social welfare and valley filling, than common flat rates (H. Aalami, Yousefi, and Parsa Moghadam 2008; Celebi and Fuller 2007)

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 in day-ahead or some hours ahead, so the customer can act and make the needed adjustment according to the prices previously communicated (Barbose, Goldman, and Neenan 2004).

Representing RTP a greater reflection of the marginal costs of supply, makes them more economically attractive 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 (Borenstein 2005).

As an alternative dynamic pricing scheme, CPP rates are a combination of TOU and RTP, which can be triggered for a limit number of day or hours per year to cope with system contingencies or high prices of power. Customers participating in CPP schemes usually receives discounts on off-CPP periods (Wolak 2007). A review of several programs in North

America found that critical peak prices are more effective to reduce the peak demand than time-of-use rates, due to the higher CPP values gap for the on-peak prices values to off-peak than for TOU rates (Newsham and Bowker 2010).

Dynamic pricing is found to effectively encourage to shift the residential peak away from the time of overall peak load to concentrate the electricity demand within low price hours, but with the possible adverse impact to obtain a higher residential peak(Burkhardt, Gillingham, and Kopalle 2019).

2.1.2. Incentive-based DR

“Incentive-based demand response programs represent contractual arrangements designed by policymakers, grid operators, load-serving entities (utilities and retail electricity suppliers) to elicit demand reductions from customers at critical times called program “events”. These programs give participating customers incentives to reduce their load that are separate from their retail electricity rate. The incentives may be in the form of explicit bill credits or payments for pre-contracted or measured load reductions.” (U.S. Department of Energy 2006)

In exchange for specific benefits, customers typically perform load reductions during critical events and are penalized if they do not comply. This type of DR can be invoked in different cases, like during local or regional grid congestions, operational reliability requirements and local or system extreme temperature events (Mohagheghi et al. 2010). The demand reduction is either required for system reliability or for periods with prices too high. This kind of tools contributed with about 90% of the peak load reduction up to 2013 in the U.S. (Zhong, Xie, and Xia 2013).

DLC programs are typically the ones where the utility is allowed to directly shut down customer’s appliances with a short time of previous notification in order to handle system or local contingencies. Mainly these programs are first offered to small and residential customers as the typical short-term interruptions of loads will not affect largely the impact of the quality of the services, namely is using air conditioners and water heaters which profit from thermal inertia (Federal Energy Regulatory Commission 2012). DLC programs are commonly used for reducing the system peak, but are also functional for mitigating high electricity prices or managing demand charges (U.S. Department of Energy 2006).

A curtailable load program implies a solution where the customers obtain a rate discount or bill credit for agreeing to reduce load during contingencies. Normally these programs are made for large and industrial customers which sign up contracts specifying details, as the maximum duration and number of interruptions, payments and penalties for non-compliance (Q. Zhang and Li 2012). Curtailable load programs produce benefits in terms of system reliability, providing non-spinning reserve, emergency reserve and reducing the generation investment (Goel, Aparna, and Wang 2007).

Demand bidding programs consist in enabling the demand side to actively participate in the electricity market by offering customers the opportunity to have economic rewards for changing the pattern of consumption through bidding. For industrial and large customer, the participation is direct, while for small customers this usually requires a third party usually called an aggregator, which establishes some business agreement with individual customers and bids their aggregated load flexibility (Rassenti, Smith, and Wilson 2003).

2.2. Technologies for demand flexibility

A communication infrastructure is the foundation for the success of the developing smart grid DR (R. H. Khan and Khan 2013). The Internet of Things (IoT) emerges as a potential efficient solution for the energy management due to the interactive characteristics, which facilitate the perception, aggregation, interaction and visualization, thanks to the real-time exchange of information as RTP (Yao, Shen, and Lim 2016).

This concept is widely recognized as the base of the strategic implementation for the mitigation of urban problematics and the increase of the city efficiency toward the realization of smart cities (Carli, Dotoli, and Pellegrino 2017).

The smart city, illustrated in Figure 2.1, is one of the results of multiple optimizations where different sectors are involved. The home appliances management is a big slice of the smart city due to the fact that households are major sources of consumption. Moreover, another important candidate for energy management and optimization is the transportation sector, including public transport and personal vehicles, where smart parking and congestion control may represent important contributions to reduce the energy consumption as well as CO_2 emissions. (Ejaz et al. 2017)

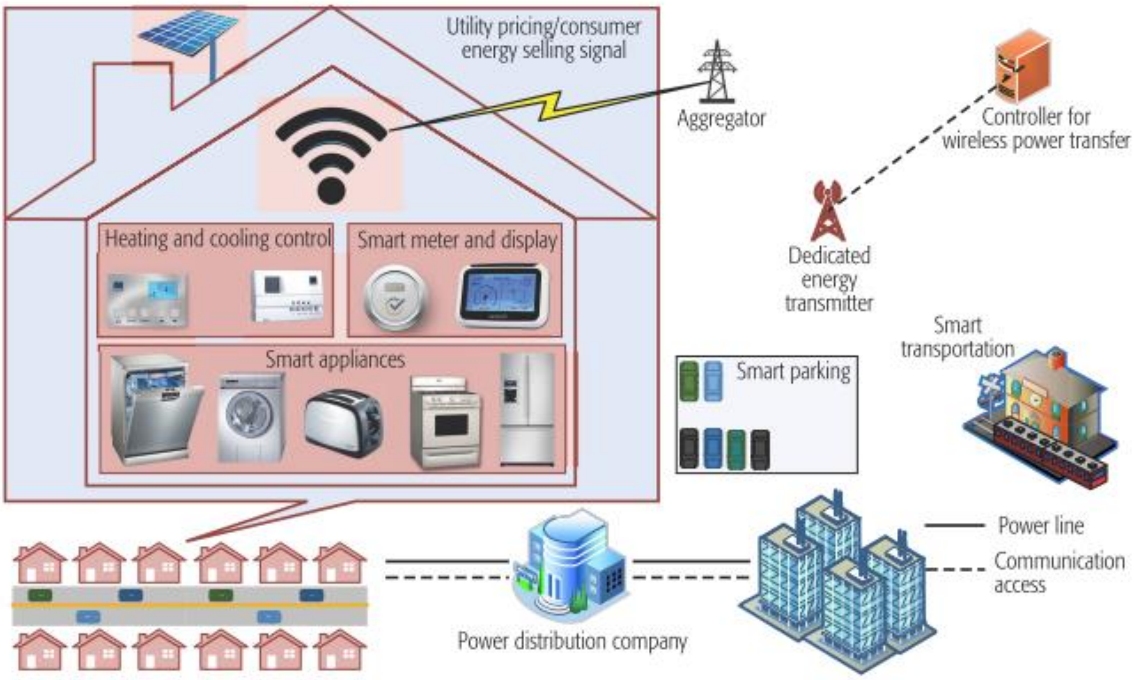

Figure 2.1 – Smart city illustration (Ejaz et al. 2017).

Smart home appliances are very important to get the most of energy management systems in residential houses, (Z. Zhao et al. 2013). Some existing home appliances can be made “smart” with the addition of remote 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 (Z. Zhao et al. 2013).

2.2.1. Energy Management System

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.

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 in 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).

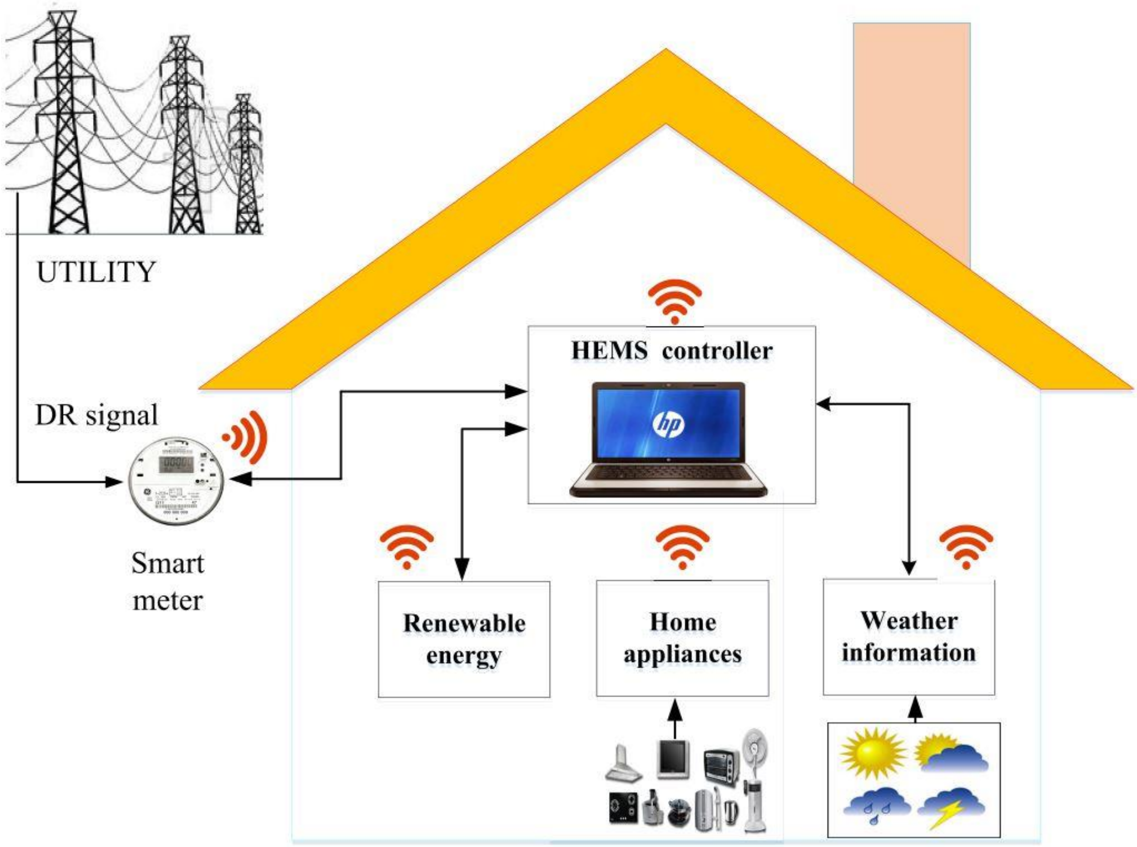

Figure 2.2 – Illustration of a HEMS (Shareef et al. 2018).

A typical HEMS, in Figure 2.2, is composed by a personal computer (PC), 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). To assure required levels of comfort, the system should use weather information as indoor and outdoor temperatures. The communication makes use of available communication protocols such as Wi-Fi, ZigBee, Bluetooth, and KNX. Moreover, HEMS usually also connect to self-generation units such as PV, BES, and WT. (Shareef et al. 2018)

HEMS also allow the development and design of intelligent controllers using smartphones, in order to facilitate interaction with the customer, which can control and monitor appliances through mobile applications[2].

A wide range of research has focused scheduling problems in HEMS. 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.

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, Shen, and Lim 2016)

Nirmalya Roy, Abhishek Roy, and Das (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. Another work using ZigBee communication system, in Turkey, presented another algorithm based on the battery state of charge level and RES, while using multiple tariff, being able to integrate them for a scheduling of the appliances and demand reduction (Boynuegri et al. 2013). The DR allows also to participate in real-time management by adopting battery charging and PV system (Zhou et al. 2014).

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. 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 (Terci Flores et al. 2016). 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.

The categorization of the different appliances and the consideration of the uncertainties related to different kind of loads is tackle for the reduction of costs, using day-ahead pricing

[2] https://www.geappliances.com/

scheme (J. 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).

2.2.2. Energy storage

The main goal of DR is to reduce the electricity generation cost and optimizing the grid by matching the demand pattern to the generation availability. For this goal, the costumer can manage part of the energy demand controlling 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 easier rescheduled thanks to higher flexibility and lower importance. There are also controllable/adjustable loads like the electric vehicle charging or air conditioning systems that can be controlled according to the network conditions, within an allowable comfort range. In this context the energy storage systems can act as tool that may transform any kind of load on a controllable load, acting as an UPS. With a battery properly sized on the power of the household, the whole house could continue to operate for a given time without nuisance to the users while selling the total power to the grid at the same time on DR scheme. (Bayram and Ustun 2017)

To fully integrate renewable energy sources, energy storage systems have a fundamental role due to the variable nature of the resources, not always 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 (H. 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).

Storage technologies, with distributed generation, along with intelligent management will reduce short-term effects (e.g., voltage spikes, dips, and surges) which in turn involve the reduction of the mean service interruption duration, increasing also energy security standard by reducing losses and congestions on transmission lines (Bayram and Ustun 2017).

In Hemsby, England, an EES system installed has clearly demonstrated how the capability of an EES system can in practice contribute to local distribution network operation by peak-shaving, voltage control and levelling out the fluctuations of power close to RESs (Lyons et al. 2015).

Izadkhast, Garcia-Gonzalez, and Frías (2015). simulated the participation of a large number of EVs on primary frequency control (PFC), obtaining a relevant improvement of the minimum transient frequency and on the frequency recovery duration, reducing it in several minutes. The relation between the number of EVs in PFC and the outcomes is visible in Table 2.1.

Table 2.1 – EVs impact in frequency regulation (Rehman and Riaz 2017).

N° of EVs	Max frequency Oscillations (Hz)	Quasi-stationary frequency value (Hz)
0	49.31	49.82
100	49.55	49.98
200	49.67	50 ± 200mHz

EES is also important for the improvement of network management for islanded networks, e.g., accelerating black starts (Lyons et al. 2015).

Different studies have reviewed the technological aspects of EES (Aneke and Wang 2016; Díaz-González et al. 2012). Some have thoroughly investigated operational features of pumped hydroelectricity storage (PHS) technology (T. Ma, Yang, and Lu 2014; Zheng, Meinrenken, and Lackner 2015). Others payed attention to compressed air energy storage (CAES) (Karellas and Tzouganatos 2014). The different technologies of batteries also stimulated specific reviews (Alotto, Guarnieri, and Moro 2014; Zheng, Meinrenken, and Lackner 2015). Flywheel energy storage are reported by (Sebastián and Peña Alzola 2012), while superconducting magnetic energy storage (SMES) and supercapacitor energy storage (SCES) are discussed in (H. Chen et al. 2009; Zakeri and Syri 2015; Zheng, Meinrenken, and Lackner 2015).

The EES can be grouped by level efficiency according to (H. Chen et al. 2009) - Figure 2.3:

- High efficiency: Li-on battery, supercapacitor, flywheel and SMES have cycle efficiency greater than 90%.
- Medium efficiency: batteries, excluding Li-on, PHS, CAES and normal capacitor vary in the range between 60% and 90%.
- Low efficiency: comprehending technology with an efficiency lower than 60% and is the case of thermal energy storages (TES), solar fuel, fuel cell, hydrogen and cryogenic cells.

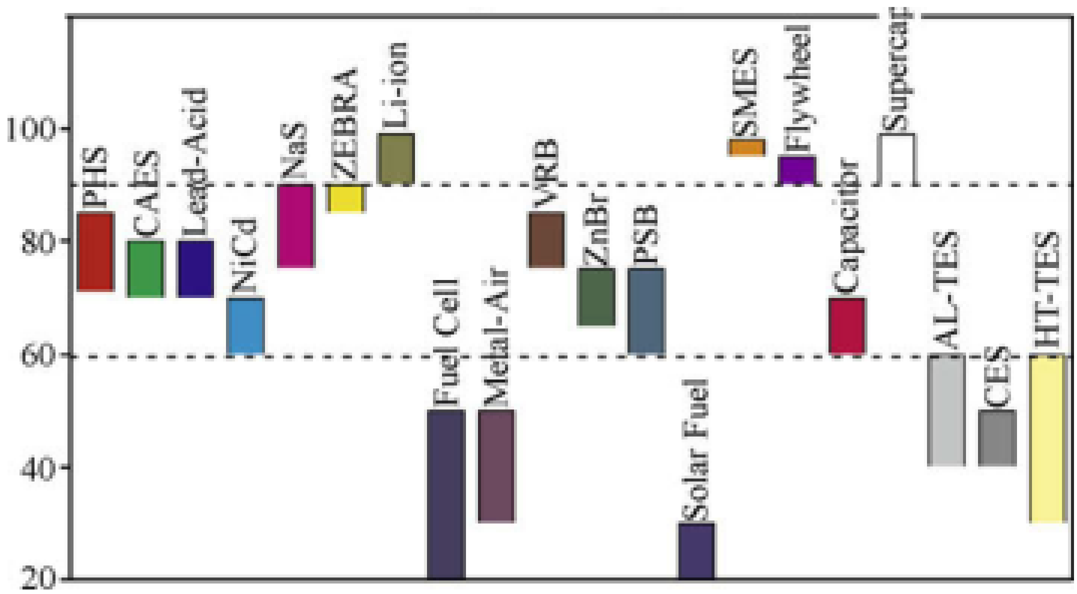

Figure 2.3 – Cycle efficiency of EES technologies (H. Chen et al. 2009).

In Figure 2.4 EES are instead divided according to discharging time and power rating, in addition to efficiency division (Aneke and Wang 2016).

The trade-off between capital cost and roundtrip efficiency is a detail that must be underlined, because technologies with low capital cost but high round trip efficiency are competitive with others having high efficiency and high capital costs (H. Chen et al. 2009).

The lifecycle is another topic which is relevant to analyse due to the deterioration of certain parts of batteries, including flow batteries and fuel cell, when compared to SMES or capacitors which are very high (Zakeri and Syri 2015).

From the technical point of view, batteries have shorter installation time and are able to provide fast response times, being typically placed close to the generation or load centers (Lazard 2016).

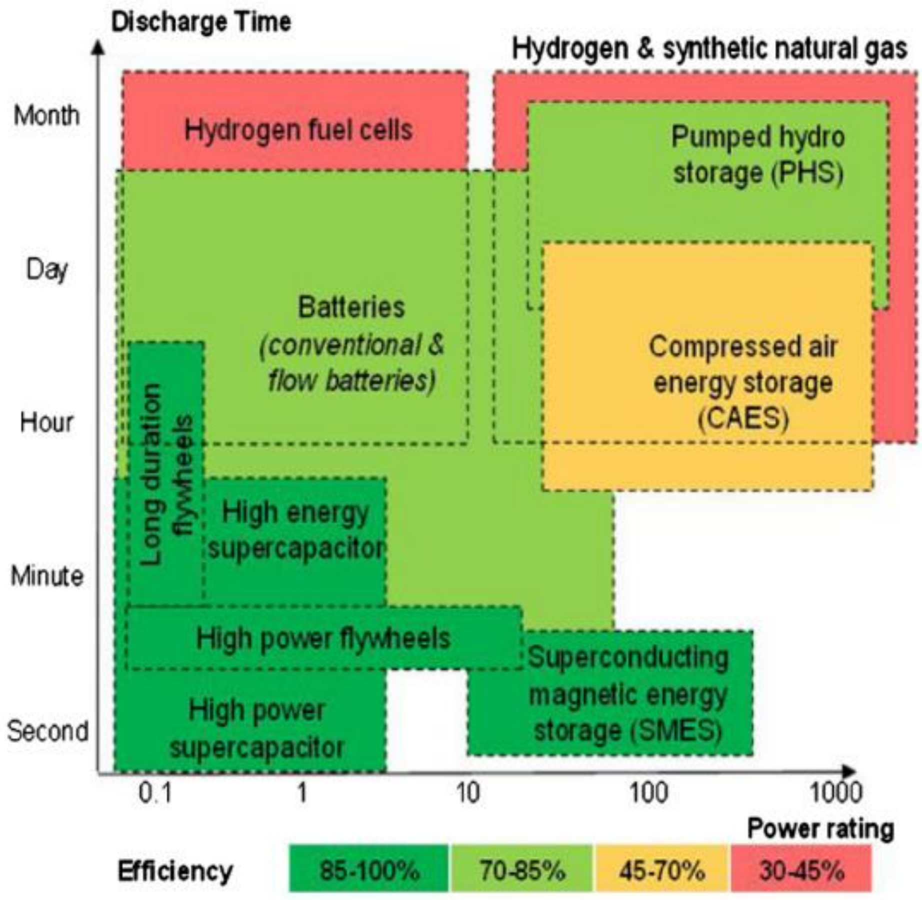

Figure 2.4 – EES technologies classification by discharge time and power rating (Aneke and Wang 2016).

2.2.2.1. Small scale commercial solutions

For residential applications, lithium-ion and lead-acid technologies are the main technologies used in recent years, with the former now dominating the market with nearly 100% of share since 2017. The reasons are attributable to the drastic decrease of average prices, falling over 50% between 2013 and 2018, higher energy efficiencies and longer lifetimes. (Figgener et al. 2020)

Two of the most developed commercial solutions in recent years are Tesla Powerwall and sonnenBatterie.

Tesla Powerwall[3], in Figure 2.5, is a rechargeable lithium-ion battery for residential or light commercial use, suitable for solar self-production storage and partial or whole backup, in the event of a power outage. It is easily electrically interfaced with any building and is simple to install. The Tesla Powerwall is available in a single capacity size of 14 kWh, where the maximum usable energy is restricted to 13.5 kWh.

The batteries can be placed inside or outside thanks to the high resistance to atmospheric agents, low noise level (< 40 dB) and wide range of operating temperatures: between -20°C and 50°C.

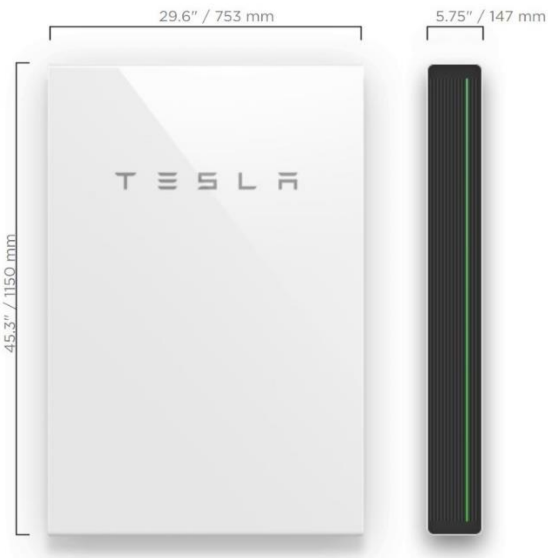

Figure 2.5 – Tesla Powerwall 2.

[3] https://www.tesla.com/powerwall

The second model, depicted in Figure 2.6 with different sizes, is the lithium iron phosphate (LiFePO4) battery of the Sonnen[4] company, which is available in three solutions: sonnenBatterie "eco", "hybrid" and "pro".

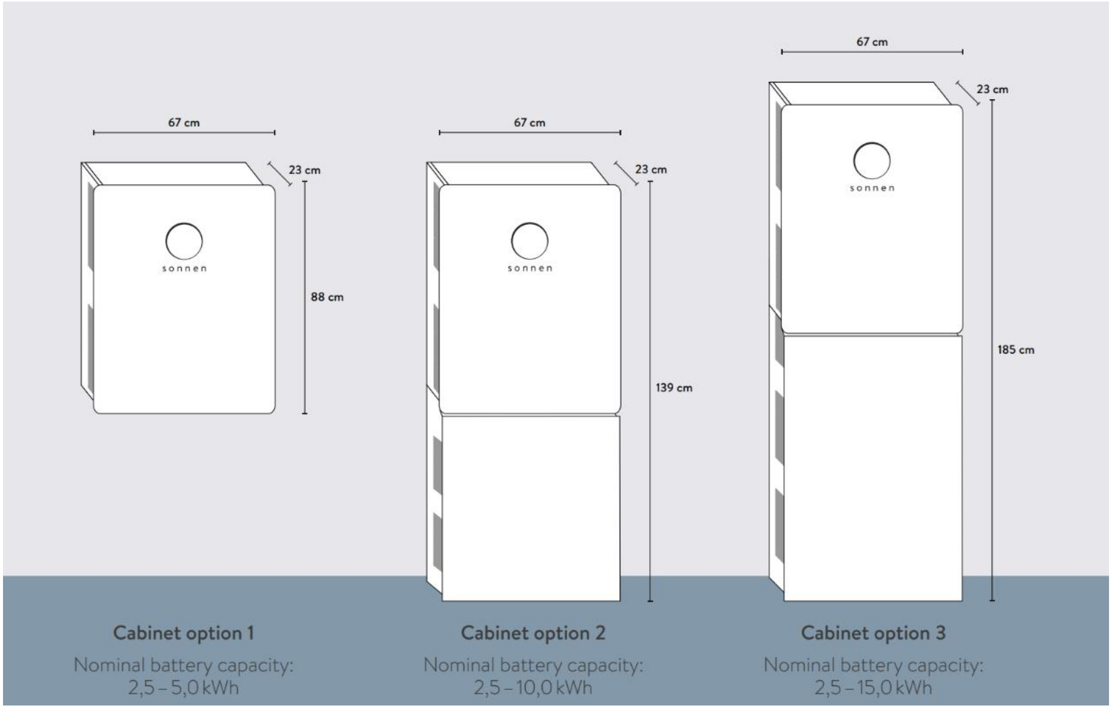

Figure 2.6 – The three cabinet options to expand the battery capacity of Sonnen battery.

The "eco" and "hybrid" battery are both suitable for customers who want a great flexibility with the difference that the first can be interfaced with a mini wind turbine, micro co-generation unit, a fuel cell or an already existent PV system, having their own inverter, while the second also include the inverter.

While the above referred models are adequate for single-family homes, the "pro" model can be a solution for multiple-family buildings or small commercial companies, as it allows combining three single batteries to form a larger capacity unit as in Figure 2.7. This one, due to the increased capacity, operates also with larger PV systems. All the options have a range of capacity between 5 kWh and 15 kWh, expandable in steps of 2.5 kWh.

[4] https://sonnengroup.com/sonnenbatterie/

Figure 2.7 – Sonnen battery “pro”.

An interesting topic to be noticed for the owners of sonnenBatterie is that the company organizes a novel service, the sonnenCommunity, allowing customers to that the excess of their production for the benefit of other members and for the public grid. The community is already available in Germany, Austria, Switzerland and Italy, where for every kilowatt hour shared, a financial compensation is given.

2.2.2.2. EV as Distributed Storage

The positive effects of EVs depend strongly on the load management regime applied. If no load management is used, the electricity system will not be able to easily include large numbers of EVs. Thus, implementing a suitable load management regime for EVs is crucial to successfully introducing large numbers of EVs into the system (Bellekom et al. 2012).

The plug-in electric vehicle (PEV) can be seen as one of the distributed energy storage technologies more deployed, and thanks to the complementary nature of their fuel tank, they create lower range anxiety and may offer a relevant capability in terms of primary frequency control (PFC) both in island and grid connected systems (Baboli, Moghaddam, and Fallahi n.d.; Pillai and Bak-Jensen 2010).

The use of the energy stored in EVs to occasionally supply the grid during high price/contingency hours is known as the “vehicle to grid system” (V2G), in opposition to the normal grid-to-vehicle (G2V) that represent the charging.

The EV owner has the possibility to charge his car batteries whether at home or at his workplace, or in a parking station in which fast chargers are available. A significant presence of EVs can consequently help the grid management, contributing to decrease marginal costs. EVs batteries may typically recharge during situations that present a stimulus for it, like an excessive availability of RES eventually reflected by low energy prices, which in the future may not occur at night as is common nowadays, e.g. in a scenario of high PV share. The impact of a large scale deployment of EVs in an electric grid and the eventual new peak demands is the theme of many studies (Y. He, Venkatesh, and Guan 2012).

The existence of aggregators to manage a large set of EVs can enhance the possibilities to support the electric grid as usually EVs' owners cannot access directly the electricity market as supply bidders due to their small size. An EV aggregator is defined as an entity that controls the charge of the batteries of several connected EVs, thus being able to benefit the grid with a wide controllable source or load to be used as a supplementary service (Rehman and Riaz 2017).

EVs, as other traditional cars are only used for 10 percent of their lifetime, meaning that they could be used for serving the grid for a large portion of time. Parking areas and parking lots could then be used as an aggregated EES, providing services to the grid as an extra service that could be traded in exchange for parking permits. (Fachechi et al. 2015)

Some sceptics claim that V2G is too expensive to be worthy and that exist easier solutions to store energy and support the power grid for electricity supply. However, many studies have shown that V2G is technically and economically promising and feasible (University of Delaware 2019).

2.2.2.3. Degradation of batteries

The battery energy storage system, concerning all storage technologies explained, have been one of those to have attracted the most interest in electrical networks and which is growing rapidly (Y. Zhang et al. 2017).

Several parameters define how a battery is and should be used, such as, charging-discharging state, depth of discharge (DoD), efficiency, initial energy state of charge (SoC) and nominal power-capacity (Alotto, Guarnieri, and Moro 2014; C. Chen, Xiong, and Shen 2018; H. He, Xiong, and Peng 2016). These parameters significantly impact on the life-cycle and lifetime of the battery system (Lyons et al. 2015).

Lifetime prediction models have therefore been the subject of many studies, being also different within technologies (Sauer and Wenzl 2008; Shi et al. 2018). Typically, the manufacturers give two metrics of lifetime: calendar lifetime, which is due to parasitic reactions gradually affecting materials whether they are used or not, and cycling lifetime, which is associated to the degradation due to reactions of active materials with electrolytes (Shi et al. 2018).

Being the SoC value variating throughout the day and the peak intensity changing stochastically each day, the charge and discharge event are not always carried out completely to full cycles adding further complexities because for most storage technologies, lifetime depends on the number and depth of each (dis-)charge cycle (Zheng, Meinrenken, and Lackner 2015).

As a way to specify the cycling lifetime of a battery, a fixed amount of energy that can be cycled through a battery has been specified, being demonstrated that it is an effective way to quantify the degradation of the lifetime at standard operating conditions, i.e. not exceeding η_{DoD} and rated P_{max} at standard temperature and conditions (Sauer and Wenzl 2008). Another study analysing a specific type of Li-ion battery, showed that the energy that could be cycled throughout the battery's life was statistically independent of the SoC in each cycle (Peterson, Apt, and Whitacre 2010). However, other studies have proved that SoC, temperature, charge and discharge rate may affect the total energy cycled throughout the whole life, achieving higher energy performances when avoiding full cycles (Guena and Leblanc 2006; J. Wang et al. 2011). Furthermore, the design of the impact of the initial energy SoC of the batteries operation and the correlation between initial energy and depth of discharge are aspects which have not been well studied or rarely investigated (Hemmati 2018).

A comparison for different EES with parameter details, as η_{DoD}, charge and discharge efficiency and total-energy-throughput per one kWh of effective capacity are provided in Figure 2.8 (Zheng, Meinrenken, and Lackner 2015).

		Lifetime available full cycles n	Healthy depth of discharge η_{DoD} (%)	(Dis-)charge efficiency $\eta_{in} = \eta_{out}$ (%)
Flywheel		30,000	88	90
Conventional batteries	Metal air	800	100	64
	Lead-acid (Pb-acid)	2350	75	84
	Nickel–cadmium (NiCd)	2000	75	83
Advanced batteries	Lithium-ion (Li-ion)	5500	80	89
	Sodium sulfur (NaS)	3250	80	86
	Sodium nickel chloride (NaNiCl ZEBRA)	2500	80	90
Flow batteries	Zinc bromine (ZnBr)	6000	100	78
	Vanadium redox (VRB)	10,000	100	82
	Nickel zinc (NiZn)	7000	90	85
	Zinc manganese dioxide ($ZnMnO_2$)	4000	90	85
Super capacitor		5E+07	100	93
Compressed air energy storage (CAES)		12,500	70	70
Pumped hydro storage (PHS)		35,000	100	85
Superconducting magnetic energy storage (SMES)		55,000	100	93

Figure 2.8 – Lifetime cycle comparison of EES systems (Zheng, Meinrenken, and Lackner 2015).

2.2.2.4. Economics of storage

The use of EES to store energy in periods of excessive availability of supply resources/low demand to be used in periods of low availability/high demand, contribute to reduce the need for building of extra power capacity. Some practical examples of economic benefits can be seen in cases of high share of nuclear power, where EES are used to stabilize the production capacity avoiding the partial load operation or undesirable shut downs, offering more economical production. Generation units are not the only resources to be constrained during peak hours, as also the transmission and distribution grids are subject to capacity limits. Their traditional design for one-way operation frequently imply that they must be oversized to address the occasional peak hours. Therefore, EES can also reduce the risk of consequent overload of transmission and distribution networks and reduce the large costs of management and reliability services of the grid (Zakeri and Syri 2015).

Two studies give an idea of how storage can bring economic benefits. The first, in Nevada (USA), indicate how aggregation of distributed storage could improve savings of $2–8/month per customer and avoid over 140 MW of extra generating capacity in Nevada and over 4.5 GW in the entire US (Burger et al. 2017).

The second, performed in the New York State under TOU tariff for an average household of the state, shows that a central coordination of distributed energy resources (DERs) could yield significant financial incentives as profits from 4.3% to 24% of the annual cost without storage and DR (Zheng et al. 2018).

A study where the EES system is installed at customer side, but the operation choices are shared between customer and the network operator with a fixed or dynamic sharing, can provide flexibility and benefits for both side, as investments reduction and bill savings (Z. Wang et al. 2013).

2.3. Aggregators

As already stated, an aggregator usually acts on behalf of a group of distinct small agents (i.e. consumers, producers, prosumers), as an intermediary between the represented group and the other power system participants (Ikäheimo, Evens, and Kärkkäinen 2010).

Niesten and Alkemade (2016) suggest that aggregation creates significant values only when implemented for large scales. In contrast, others concluded that even relatively small aggregations, in response to aggregation signals can provide a substantial and significant service to the electricity system (Calvillo et al. 2016; Zheng et al. 2018).

A case study performed for New York State, aiming to verify the economic and environmental effectiveness of the coordinated control, shows that profits can be 43% higher than those achieved under the distributed control strategy. Moreover, the aggregated scheme also provide larger positive impacts by alleviating state-level of NO_x, SO_2 and CO_2 emissions resulting from electricity generation (Zheng et al. 2018).

2.4. Possible problems caused by DR

The bigger problems regarding DR are identified to be related with inconveniences and changes in the lifestyle, influenced also by the frequent changes of peoples' routines, i.e. room temperature violation for those thermostatic programs using the temperature as a control variable (Pipattanasomporn, Kuzlu, and Rahman 2012).

Gelazanskas and Gamage (2014) suggest that the rapid development and diffusion of DR programs and residential batteries, such as Tesla Powerwall and sonnenBatterie, have increased the challenges for a proper control of the power system. A work, conducted by the Columbia University, have shown that these EES used to shift loads from peak to off-peak hours were resulting in a new stress for the grid in the night time (off-peak period). The stress is due to the rigid TOU tariff system, which favours charging the storage devices during the low-price periods, and that if not coordinated can overlap periods where there is still high demand, thus causing negative effects for the grid. (Zheng 2015). These new peaks would probably also imply environmental impacts, due to the need to resort to fast thermal generation with consequent impacts on NO_x, SO_2 and CO_2 emissions (H. Ma et al. 2012). A RTP scheme may eventually avoid such problems as in principle the price would change according to the new grid conditions.

Nevertheless, there are also concerns regarding the privacy over the critical information supplied by participating customers (Gong et al. 2016).

2.5.Problem formulation

The configuration of the system to study is shown in Figure 2.9, 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.

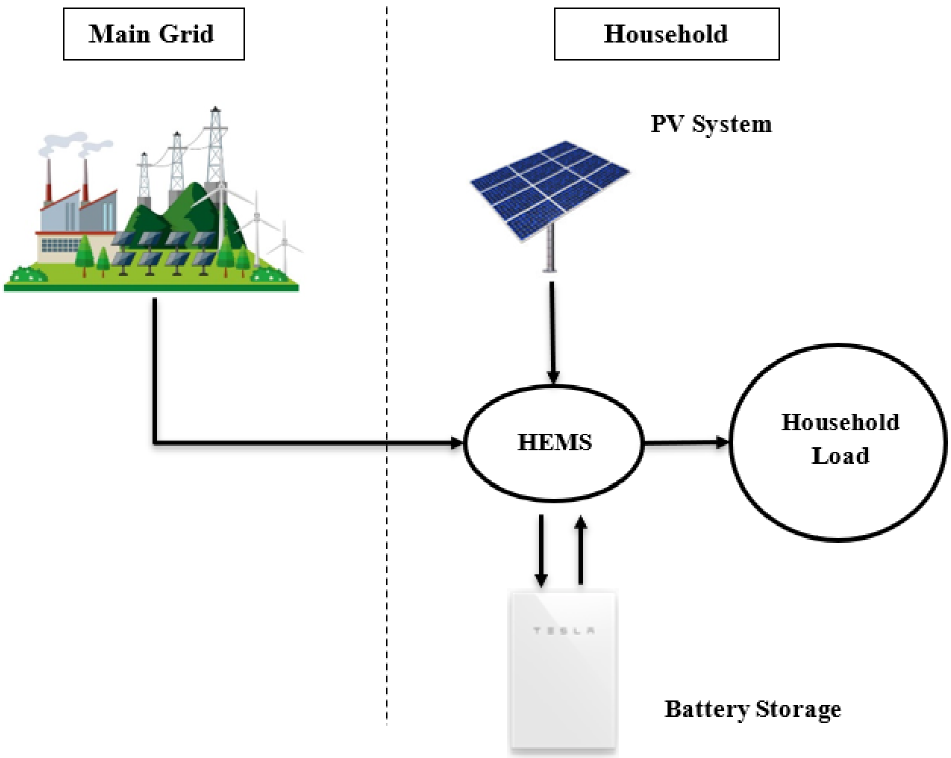

Figure 2.9 – Schematic configuration of the system.

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 payed by 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.

3. Methodology

The day-ahead optimal schedule of domestic appliances and battery operations are the main objective behind which the cost minimization strategy is formulated for a single household, where the inconveniences of an optimal appliance scheduling are taken into account and also minimized.

The methodology is developed for the case depicted in Figure 2.9 consisting in a household grid where the energy demand, optimally scheduled by a HEMS, is satisfied by a non-dispatchable PV power plant, a BS energy system and by the main electricity grid. 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, as mostly already developed by other studies (Nikmehr, Najafi-Ravadanegh, and Khodaei 2017; Wu et al. 2017).

To achieve the objectives, a function of minimization of the different day-ahead costs is implemented. The function consists in the minimization of the cost of power purchased to the grid ($\mathrm{Cost_{Grid}}$) and the cost of the weighted scheduling inconveniences ($\mathrm{Cost_{I}}$), where $\mathrm{Cost_{Grid}}$ is in turn composed by the cost of supplying the appliances of the house ($\mathrm{Cost_{Household}}$), the net cost of using the battery ($\mathrm{Cost_{BS}}$) to which the cost saved due to the PV panel power produced ($\mathrm{Cost_{PV}}$) 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 below in order to handle this problem, with a sampling time ($\Delta\mathrm{t}$) and a study period (T). The variables, indices and parameters used are summarized in Table 3.1.

3.1. Optimization structure and models

This section describes the details of the MINLP model, which is solved using the OPTimization Interface[5] (OPTI) Toolbox, a free MATLAB toolbox for constructing and solving linear, nonlinear, continuous and discrete optimization problems. Inside OPTI are executable many solvers as SCIP (Solving Constraint Integer Programs) which is a fast-non-commercial solver available through academic license used for the work.

The solver permits the resolution of problems in the following form:

$$\textbf{min}\ \mathrm{f(x), s.t.} \begin{cases} \mathrm{Ax \leq b\ (Linear\ Inequalities)} \\ \mathrm{A_{eq}x = b_{eq}\ (Linear\ Equalities)} \\ \mathrm{l_b \leq x \leq u_b\ (Decision\ Variable\ Bounds)} \\ \mathrm{c(x) \leq d\ (Nonlinear\ Inequalities)} \\ \mathrm{c_{eq} = d_{eq}\ (Nonlinear\ Inequalities)} \\ \mathrm{x_i \in \mathbb{Z}\ (Integer\ Constraints)} \\ \mathrm{x_j \in \{0,1\}\ (Binary\ Constraints)} \end{cases}$$

where, f(x) is a scalar function containing the nonlinear objective function subjected to the listed constraints above.

The variables and symbols of the model are listed in the following Table 3.1.

Table 3.1 – Variables of the model.

Notation	Description
Indices	
$\boldsymbol{i}$	Index of appliance of the house. $i = 1, \dots, N_a$, where N_a is the number of appliances.
$\boldsymbol{t}$	Index of time. $t = 1, \dots, (T/\Delta t)$, where T is the horizon study period.
Parameters	
$\boldsymbol{G_{a,0}}$	Irradiation of sun at the standard condition
$\boldsymbol{G_a(t)}$	Instantaneous irradiation of the PV panel.
$\boldsymbol{P^M_{Max,0}}$	Maximum power producible by the PV module.
$\boldsymbol{T_{M,0}}$	Temperature of the PV module at standard conditions.

[5] https://inverseproblem.co.nz/OPTI/index.php/Main/HomePage

$T_a(t)$	PV module instantaneous temperature.
$Cost_{BS}$	Cost associated to charging and discharging of battery energy.
$Cost_{Grid}$	Cost associated to the energy purchased by the main grid.
$Cost_{Household}$	Cost associated to the appliance's consumption of the house.
$Cost_{PV}$	Cost associated to the PV panel generation.
D_i	Duration of cycle of work of application *i*.
E_{Tot}	Total energy capacity of the battery system.
N_a	Number of appliances.
$OT_i^{user}(t)$	A binary parameter representing the preferred operating time of the appliances chosen by the user. 1 means the user would like to use in that time the appliance, 0 otherwise.
$P_{BS,Ch}(t)$	Power of the battery while charging.
$P_{BS,Ch}^{limit}$	Limit value of power allowable to be charged at any time.
$P_{BS,Dis}(t)$	Power of the battery while discharging.
$P_{BS,Dis}^{limit}$	Limit value of power allowable to be discharged at any time.
$P_{BS}(t)$	Power of battery storage system.
P_{Demand}^{max}	Maximum value of power for the demand part any time.
$P_{Grid}(t)$	Power of the main grid.
$P_{Household}(t)$	Power of the whole appliances of the household.
$P_{Load}(t)$	Total load power of the household.
$P_{PV}(t)$	Output power of the PV panel.
$P_{Supply}(t)$	Total supply power of the household.
$P_i(t)$	Rated power of appliances.
$P_{Unc}(t)$	Power not controllable (plugs and appliance not schedulable).
SoC_{Ini}	Initial value of the State of Charge of the battery.
SoC_{max}	Maximum value of State of Charge of the battery to be respected.
SoC_{min}	Minimum value of State of Charge of the battery to be respected.

e_i^{opt}	Optimal ending time of appliance *i*.
e_i^{user}	Ending time of appliance *i* set by the user
k_i	Flexibility parameter to adjust the appliance running time.
s_i^{opt}	Optimal starting time of appliance *i*.
s_i^{user}	Starting time of appliance *i* set by the user.
$\alpha_{P_{max}}$	PV temperature coefficient.
η_{Ch}	Battery storage efficiency of charge.
η_{Dis}	Battery storage efficiency of discharge.
Δt	Sampling time.
DoD	Depth of Discharge of the battery system.
$NOCT$	Normal Operating Cell Temperature.
T	Horizon study period.
$RTP(t)$	Real time price scheme.
$SoC(t)$	State of Charge of the battery.
δ	A weighting parameter stating the relative importance of the scheduling inconvenience.
Decision Variables	
$OT_i^{opt}(t)$	A binary variable representing the optimal operating time of the appliances that have been determined. 1 represent the optimal schedule of the appliance, 0 otherwise.
I	Inconvenience factor.
Auxiliary Variables	
$X_i(t)$	A binary indicator function to guarantee uninterrupted operation, which equals 1 if the operation of appliance **i** is already completed during time slot t and zero otherwise.

3.1.1. Objective function

The objective function is therefore the following:

$$\boldsymbol{Minimize}[Cost_{Grid} + Cost_{I}] \tag{1}$$

Where $\mathrm{Cost_{Grid}}$ can be seen as the sum of the different part composing the grid:

$$Cost_{Grid} = Cost_{Household} + Cost_{BS} + Cost_{PV} \tag{2}$$

In detail in equation (3), the cost of the grid is given by the amount of energy purchased by the main grid in each time step $\Delta\mathrm{t}$, times the related price signal of that period $\mathrm{RTP(t)}$:

$$Cost_{GRID} = \sum_{t=1}^{T} RTP(t) \times P_{Grid}(t) \times \Delta t \qquad \forall\, t \tag{3}$$

The component $\mathrm{P_{Grid}(t)}$ is subject to the household power equilibrium (4) in order to support the load, which is composed by a positive part related to the household appliances consume and the charging of the BS unit and a negative part given by the PV panels production and the discharging of the BS unit which are going to support and reduce the amount purchased.

$$P_{Grid}(t) = P_{Household}(t) - P_{PV}(t) + P_{BS}(t) \qquad \forall\, t \tag{4}$$

3.1.2. Household

The household cost in equation (5) is due to the electrical load profile of the user.

$$Cost_{Household} = \sum_{t=1}^{T} RTP(t) \times P_{Household}(t) \times \Delta t \qquad \forall\, t \tag{5}$$

The electrical load (6) is therefore composed by an uncontrollable part, given by the appliances that cannot be schedule, and a second one consisting in the DR component which allow the modelling of the load, where the control variable OT_i^{opt} is the optimal schedule.

$$P_{Household}(t) = P_{Unc}(t) + \sum_{i=1}^{N_a} P_i(t) \times OT_i^{opt} \qquad \forall\, t \qquad (6)$$

The energy demand is also subject to a limitation in order to cope with utility contractual power (7).

$$P_{Household}(t) \leq P_{Demand}^{max} \qquad \forall\, t \qquad (7)$$

Moreover, constrain (8) is assumed because the system consists in a grid one way and so the energy can be only bought and not sold back.

$$P_{Grid}(t) \geq 0 \qquad \forall\, t \qquad (8)$$

In the household scheduling problem, where OT_i^{opt} is an output to be determined, are also implemented certain constraints related to the operating time of each appliance, the type of operating mode (continuous or interruptible). Beside them, additional constraints can be formulated such as the coordination of multiple appliances and comfort (Setlhaolo and Xia 2015; al-sumaiti, Ahmed, and Salama 2014).

Constraint (10) ensures that, given the time window $[s_i\,; e_i]$, the time slots for appliance *i* are within that one and equal to the required time of execution $(D_i + k_i)$, where D_i is the duration of the appliance *i* and k_i is a flexibility parameter decidable by the user in order to increase or decrease the run time. For example, if the duration of the oven is set to 45 min, the user can use k_i to adjust it.

$$\sum_{s_i}^{e_i} OT_i^{opt}(t) \geq D_i + k_i \qquad \forall i, \forall\, t \qquad (9)$$

$$D_i\ + k_i\ \leq (e_i - s_i) \qquad \forall i, \forall\, t \qquad (10)$$

In order to ensure the continuity of the not interruptible appliances, the OT_i^{opt} vector must have to be positive for a continuous period equal to $D_i + k_i$ between the starting and ending range (Yahia and Pradhan 2018). For the scope is implemented a new auxiliary variable $X_i(t)$ which is used to state the appliance *i*, where $X_i(t) = 1$ establishes the completion of the cycle of appliance i. Furthermore, $X_i(t) = 1$ when $OT_i(t)$ switches from 1 to 0 means that the appliance has just finished to operate (Sou et al. 2011). In detail, constraint (11) assures that if the cycle of appliance i has already been completed, it cannot start again and the cycle must be continuous without interruption. Constraint (12) relates a switch-off transition to a completion flag $X_i(t)$ and constraint (13) ensures that upon completion of a work cycle, it stays completed. These constraints together assure an only possible transition of $X_i(t)$ from 0 to 1 representing a completion of a cycle without interruptions in the middle.

Unlike what is covered by Setlhaolo and Xia (2015) where appliances that may be operated for multiple cycles (i.e. electric heating for multiple times per day) are considered as multiple appliances, e.g. two times corresponding to two different appliances, the constraint (14) allows the reset of the $X_i(t)$ variable, representing the completion of the cycle at the step following the ending time. This can be done for each cycle in order to allow new cycles. For example, if the ending time of the first cycle of an appliance is at $t = e_i = 10$, the constraint (13) will be " $\geq$ " in instant $t = e_i + 1 = 11$ instead of " $\leq$ ".

$$OT_i^{opt}(t) \leq 1 - X_i(t) \qquad \forall i, \forall\, t \qquad (11)$$

$$OT_i^{opt}(t-1) - OT_i^{opt}(t) \leq X_i(t) \qquad \forall i, \forall\, t \geq 2 \qquad (12)$$

$$X_i(t-1) \leq X_i(t) \qquad \forall i, \forall\, t \geq 2 \qquad (13)$$

$$X_i(t-1) \geq X_i(t) \qquad t = e_i + 1 \qquad (14)$$

The logical sequence between some certain appliances have to be of course respected and guaranteed, as for example the operation of the clothes dryer cannot precede the execution of the washing machine. This correlation is given by the constraint (15).

$$OT_{i=Clothes\ dryer}^{opt}(t) \leq X_{i=Washing\ machine}(t) \qquad \forall\, t \qquad (15)$$

In order to reproduce the real pattern of power consumption of certain appliances, as for example the dishwasher which present different cycles during the usage (wash, rinse and dry) with related power absorbed, is therefore introduced the constraint used to model it. For those appliances, the load profile for the model will be made through the concatenation of multiple single appliances. The single appliances will be characterized by the duration of each step of the whole machine and relative power consumption, then in order to make the different parts consecutive, constraint (16) is implemented, which is here reported for the example of two single parts.

$$X_{i=2^{nd}part}(t) = X_{i=1^{st}\,part}\left(t - D_{i=2^{st}\,part}\right) \qquad \forall\, t, t \geq D_{i=2^{st}\,part} \qquad (16)$$

3.1.3. Battery Storage

The battery energy system proposed has three main terms to describe the operational model:

- Capacity of the battery, which is the physical maximum amount of energy that can be extracted or stored from the battery at any time, presented in kWh.
- Stored energy inside the battery: a parameter showing the amount of energy of the battery at any time, reported in kWh.
- Charging/discharging power: the value of power through which the battery can be charged or discharged at any time. Both are mostly defined by the required interfacing converter typically.

The second factor that makes up the objective function is therefore the BS system charging and discharging net cost (17). This cost is increased when charging the battery and reduced by the savings generated when discharging.

$$Cost_{BS} = \sum_{t=1}^{T} RTP(t) \times P_{BS}(t) \times \Delta t \qquad \forall\, t \qquad (17)$$

$$P_{BS}(t) = P_{BS,Ch}(t) - P_{BS,Dis}(t) \qquad \forall\, t \qquad (18)$$

The mathematical dynamic model can be illustrated by equation (19), where the battery's state of charge (SoC) at time t depends on the SoC of the previous time step and the amount of energy charged and discharged in that Δt, considering for t=0 the initial state of charge SoC_{Ini} (Ghasemi, Mortazavi, and Mashhour 2016; Nikmehr, Najafi-Ravadanegh, and Khodaei 2017).

$$SoC_{BS}(t) = SoC_{BS}(t-1) + \frac{\left(\eta_{Ch} \times P_{BS,Ch}(t) - P_{BS,Dis}(t)/\eta_{Dis}\right) \times \Delta t}{E_{tot}} \quad \forall\, t \qquad (19)$$

Furthermore, in order to prevent early degradation of the storage equipment, since the battery life is an important factor affecting the BS process, the charging and discharging powers have to be necessarily restricted. If the battery power exceeds the rated range for a long time, the battery life degradation will be accelerated. It is therefore necessary that the BS be subject to restrictions of the maximum charging and discharging power (22), (23) and state of charge constraint (21), during the operation process, minimizing the loss of the service life of the battery and saving in maintenance costs (Zou et al. 2017).

$$SoC_{min} = (1 - DoD) \times SoC_{max} \qquad (20)$$

The SoC_{min} and SoC_{max} of the equation (21) are relates through the DoD relations of the one above (20).

$$SoC_{min} \leq SoC(t) \leq SoC_{max} \qquad \forall\, t \qquad (21)$$

$$0 \leq P_{BS,Ch}(t) \leq P_{BS,Ch}^{limit} \qquad \forall\, t \qquad (22)$$

$$0 \leq P_{BS,Dis}(t) \leq P_{BS,Disch}^{limit} \qquad \forall\, t \qquad (23)$$

The last battery constraint (24) is the mutually inhibition of the charging and discharging process:

$$P_{BS,Ch}(t) \times P_{BS,Dis}(t) = 0 \qquad \forall\, t \qquad (24)$$

The operation costs of BS, as well as for the following PV power plant, are considered negligible and has not been considered in this work because of the small period of analysis.

3.1.4. Photovoltaic panel

PV production is the third component of the function which, being not a cost but rather savings, as maintenance costs are not considered, as mentioned above. The amount of savings is represented by (25).

$$Cost_{PV} = -\sum_{t=1}^{T} P_{PV}(t) \times RTP(t) \times \Delta t \qquad \forall\, t \qquad (25)$$

The $P_{PV}(t)$ is the power output of the PV power plant in each period and is represented by the equation (26) (H. A. Aalami and Nojavan 2016). The PV panel is assumed to be fixed and the model assumes a fixed angle and orientation that should be a result of a proper study regarding the place of implementation.

$$P_{PV}(t) = \frac{G_a(t)}{G_{a,0}} \times \left\{P_{Max,0}^{M} + \alpha_{P_{max}} \times \left(T_a(t) + G_a(t) \times \frac{NOCT - 20}{800} - T_{M,0}\right)\right\} \qquad \forall\, t \qquad (26)$$

Considering that G_a is the instantaneous irradiation of the panel, $G_{a,0}$ is the irradiation of sun at the standard condition, $P_{Max,0}^{M}$ is the maximum power producible by the module, $\alpha_{P_{max}}$is the PV temperature coefficient for the power, T_a^t the instantaneous temperature, $T_{M,0}$ is the temperature of the module at the standard condition and *NOCT* is the normal operating temperature of cell. For simplicity it's assumed that the panel works at normal conditions, so the part of the equation related to the temperature correction can be negligible.

3.1.5. Inconvenience factor

The last part that makes up the objective function is therefore the one related to the minimization of the scheduling inconvenience factor "I" reported in (27), where the intent is to minimize by a quadratic function the discomfort for the user of using the appliances in the desired time window.

$$I = \sum_{t=1}^{T}\sum_{i=1}^{N_a}\left(OT_i^{user}(t) - OT_i^{opt}(t)\right)^2 \qquad \forall i, \forall\, t \qquad (27)$$

The inconvenience cost in the (28) is based on a weighting factor δ, representing the relative importance of scheduling convenience, which is therefore obtained by the inconvenience factor. The intent of δ is to adjust the importance of the scheduling inconvenience based on the user's preference.

$$Cost_I = \delta \times RTP(t) \times I \times \Delta t \qquad \forall\, t \qquad (28)$$

To conclude the representation of the problem it is possible to summarize the supply and demand part with equations (29) and (30).

$$P_{Supply}(t) = P_{Grid}(t) + P_{PV}(t) + \eta_{Dis} \times P_{BS,Dis}(t) \qquad \forall\, t \qquad (29)$$

$$P_{Load}(t) = \eta_{Ch} \times P_{BS,Ch}(t) + P_{Unc}(t) + \sum_{i=1}^{N_a} P_i(t) \times OT_i^{opt} \qquad \forall i, \forall\, t \qquad (30)$$

3.1.6. Price model

With the emergence of the smart grid, consumers and utilities can exchange real-time information as electricity pricing tariffs and energy demand of the consumer. The two-way communication benefits not only the consumers, but also improve stability of the power grid. As an example of a RTP applied to residential customers is not yet available in Europe, two different price models were designed to represent possible price time-series, one based on the actual wholesale market price, adapted to reflect the average price seen by residential customers, the other based on the trend of the RES production with the aim of analysing how prices reflecting renewable production can have advantageous results or not, given the ever-greater expansion of renewable sources.

In both cases, customers are assumed to receive information on 24-h day-ahead prices through the communication system, which is a common practice in real-life dynamic retail-pricing schemes (Paterakis et al. 2015).

3.2.Evaluation of benefits and possible problems

In order to evaluate the developed model, different scenarios for using a battery unit and a DR program will be implemented, with and without the consideration of a PV panel, in order to see how the existence of self-generation will affect the results. Multiple different values of δ will be used in order to see whether the higher willingness to accept discomfort will significantly change and help the cost reduction. The model will be also implemented and discussed under different periods of the year, where the availability of different solar radiation and different types of loads will 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's based on different parameters and estimations made for the following day, as happens specially for the PV power production, making it therefore an important part which can affect the result. For the model, the negative mismatch between the forecast and the real production (less power than the one forecasted) will be satisfied by purchasing the missing amount by the grid, while in the opposite side, when there will be an excess of power produced which is not been considered to be charged in the battery or used for supplying the demand, it will be injected into the main grid without having a reward for it, representing the worst case scenario because typically if a reward is available is of a very small size. As a result, there will be a potential difference between the amount of expected savings calculated in the previous day and the real amount of savings obtained.

The evaluation of results will then focus:

- 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 analysis will focus the factors which appear to exert a strong influence on the performance of the algorithm.

4. Case study

This chapter details the component data and other required data for performing numerical studies of the proposed HEMS optimization model. The house to control is considered located in Leiria, Portugal. The system, depicted in Figure 4.1 is grid connected 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.

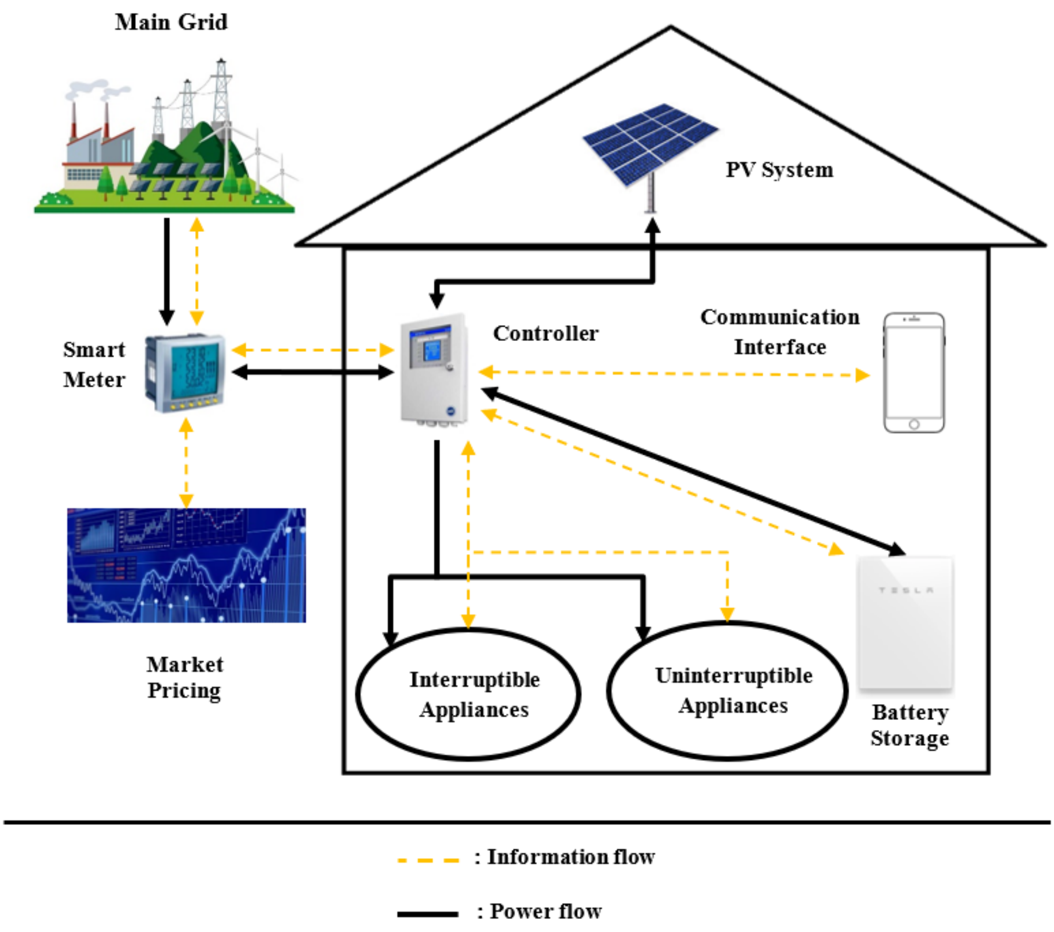

Figure 4.1 – Schematic configuration of the system.

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.

4.1.Household appliances

The set of appliances which define the case study is based on a monitoring study conducted in the Netherlands (Uttama Nambi, Reyes Lua, and Prasad 2015). In addition, some commonly used appliance profiles were obtained from a INESC Coimbra measurement study conducted in Portugal.

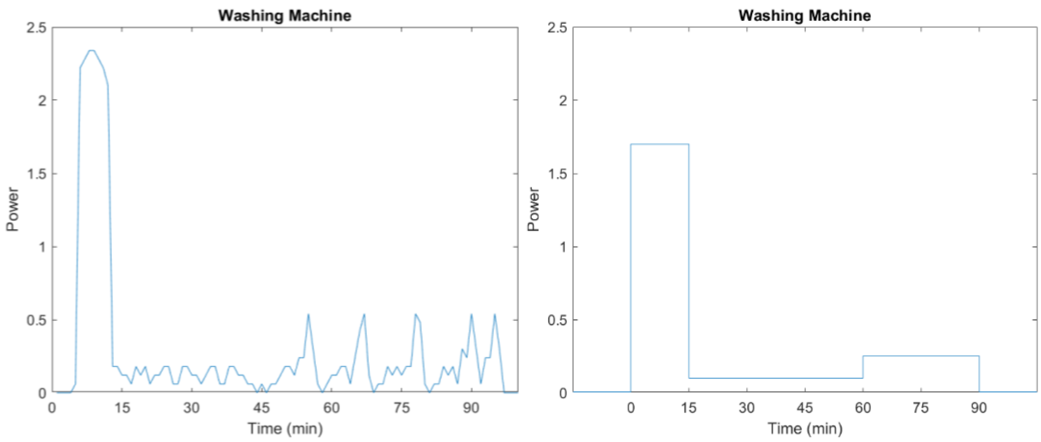

Figure 4.2 – Original washing machine profile (left) and the approximation used in the model (right).

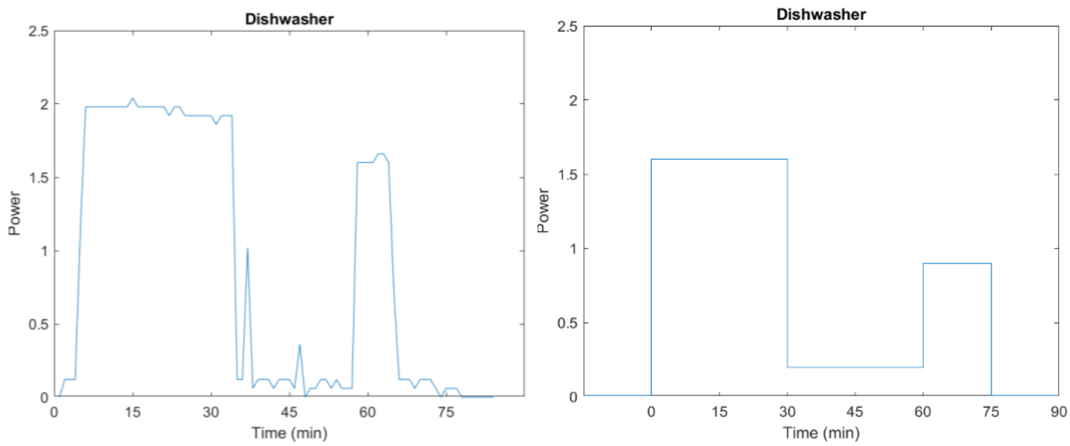

Figure 4.3 – Original dishwasher machine profile (left) and the approximation used in the model (right).

While most of the appliances present a constant value of power in the range of use, for some of them this assumption would not be entirely true, as for example for washing machines and dishwashers. For simplification, the original load profiles were slightly averaged as visible in Figure 4.2 for the washing machine and in Figure 4.3 for the dishwasher.

Charging a plug-in hybrid EV, for the daily case of the references which considers the vehicle's battery not fully out of energy, was considered to take 2.5 hours at a constant power of 3.3 kW (Pipattanasomporn, Kuzlu, and Rahman 2012; Shao, Pipattanasomporn, and Rahman 2013).

The appliances were divided in two categories of usage: uninterruptible and interruptible, where for the former, starting the operation of an appliance implies that the cycle must be completed without interruption in the middle, while for the latter, the continuity of operation is not mandatory, on the condition that the duration of the cycle is respected. In the category of interruptible appliances were 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 be done for electric water heaters with hot water storage, which profit from thermal inertia. However, for simplicity reasons, only the period of usage with relative consumptions without dynamic control of the water temperature were considered.

Table 4.1 shows the details of the considered appliances, with relative power ratings, operating time and flexibility range. Figure 4.4 depicts the reference load profile of the household assuming the load profile being the same for all the months cases for a better comparison, even if the load profiles of certain loads as AC are not properly the same during the whole year.

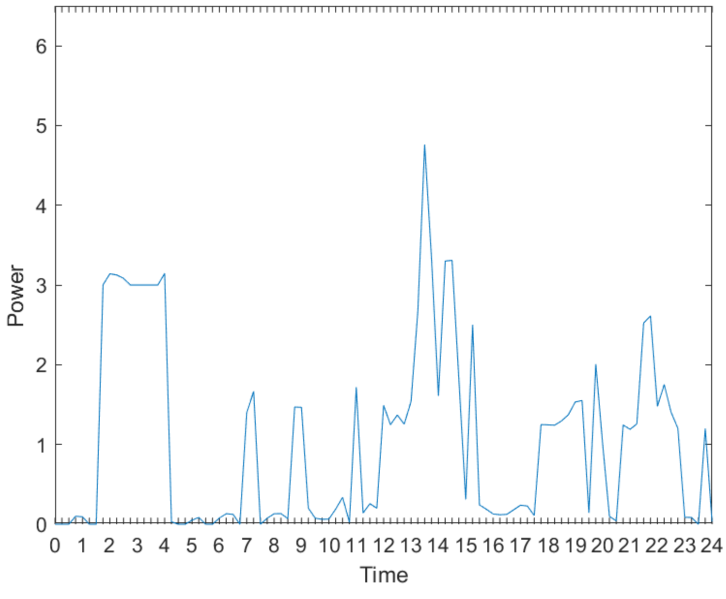

Figure 4.4 – Initial load profile.

Table 4.1 – Appliances data and schedule.

No.	Appliance	Rated Power (kW)	$D_i\ (min)$	OT_i^{user}		OT_i^{opt}	
				s_i^{user}	e_i^{user}	s_i^{opt}	e_i^{opt}
Uninterruptible							
1	Washing Machine	2.50	90	10:45	12:15	10:00	12:45
2	Clothes Dryer	2.20	120	12:45	14:45	11:30	15:30
3	Rice Cooker	0.65	30	13:15	13:45	12:45	14:00
				19:30	20:00	18:00	21:00
4	Dishwasher	2.30	75	14:00	15:15	13:30	16:00
5	Electric Water Heater	1.50	30	6:45	7:15	6:30	7:30
				8:30	9:00	8:15	9:15
			15	13:15	13:30	13:00	13:45
				15:00	15:15	14:45	15:30
				19:00	19:15	18:45	19:30
			75	21:15	22:30	21:00	22.45
6	Oven	1.50	30	13:00	13:30	12:30	13:45
			45	20:45	21:30	20:30	21:45
Interruptible							
7	Car charger	3.30	150	1:30	4:00	00:30	7:30
8	Air conditioner	1.30	60	11:45	12:45	11:30	13:00
			15	13:30	13:45	13:15	14:00
			90	17:30	19:00	17:15	19:15
			15	10:30	10:45	19:15	20:00
				20:30	20:45	20:15	21:00
				21:30	21:45	21:15	22:00
				22:30	22:45	22:15	23:00

4.2.PV system

The household has an own renewable power production system based on solar PV panels, using the silicon crystalline technology, having a peak power of 3kW. The system characteristics were defined as the most common according to the PVGIS[6] website, for Leiria, and are shown in Table 4.2.

Table 4.2 – Solar panel technical data.

PV Panel	
Peak Power	3000 Wp
Slope	34°
Azimuth	9°
System Losses	14%

The power production associated to the PV system is given by the equation defined in section 3.1.4, using yearly solar radiation data for the region of Leiria as provided by PVGIS.

Being the model a day-ahead optimization model, this implies that there will be a forecast of production for the following day which for sure will differ from the real value of production for the next day. Long time series of past data are used to test the model, within which there will be certain days chosen to represent the real case. The meteorologic conditions of the neighbour days are considered sufficiently close to represent a possible forecast error leading to their use to assess the consequences of this difference in the outcomes of the model. Moreover, in order to reproduce and assess worst-case conditions, some variations of the scenario include significant disparities between the forecast and the real case.

The PV generation of the different seasonal periods are therefore depicted in the following Figure 4.5.

[6] https://ec.europa.eu/jrc/en/pvgis

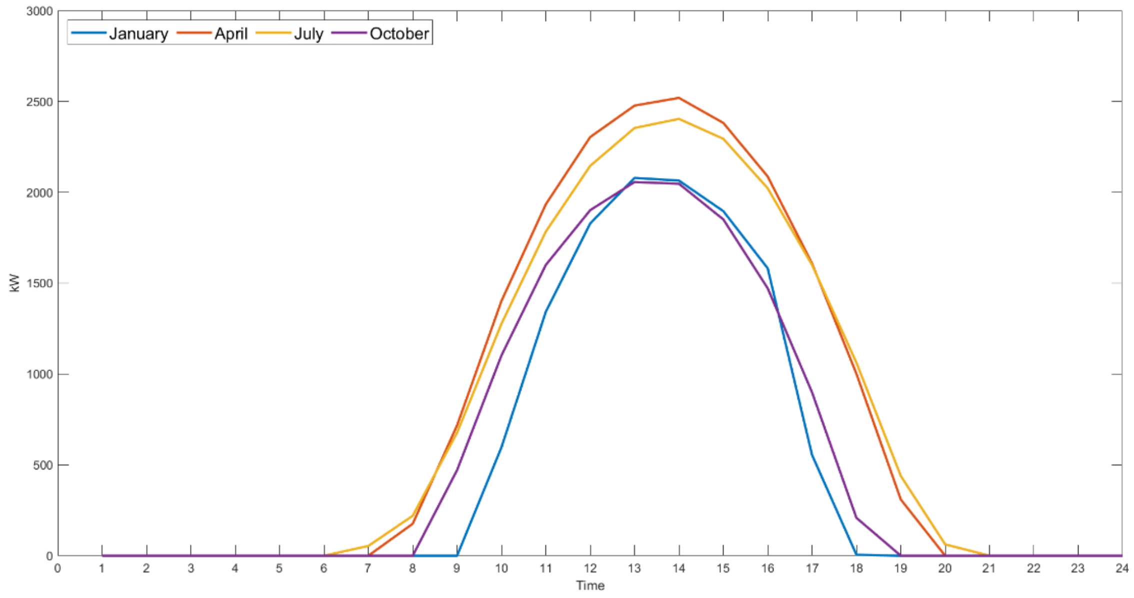

Figure 4.5 – PV system high production case for the four months.

4.3.Battery

The household is considered as owning a Li-on battery unit, which is one of the more used technologies in these types of application for residential sites. The model considered is one of the commercial options described above, Tesla Powerwall 2, which is able to be interfaced with the PV system thanks to the presence of the internal inverter.

Table 4.3 – Tesla Battery Energy Storage technical data[3].

Tesla Powerwall			
Description	**Symbol**	**Value**	**Unit**
Maximum continuous power (charge and discharge)	P_{BS}^{limit}	5	kW
Total Usable Energy	E_{tot}	13.5	kWh
Initial battery SoC	$SoC_{Initial}$	20%	
Maximum battery SoC	SoC_{max}	90%	
Minimum battery SoC	SoC_{min}	20%	
Round trip efficiency	η_{Ch} , η_{Dis}	90%	
Rated Depth of Discharge	DoD_{Rated}	95%	
Depth of Discharge	DoD	80%	

Table 4.3 reports the technical data provided by the manufacturer documentation of the Tesla company, as the efficiency of charging and discharging, the capacity limit, continuous power limits and the rated DoD. However, the DoD used for the model is slightly lower, in order to consider the degradation of the battery, according to studies which have demonstrated its impact in the lifetime of batteries (Wu et al. 2017).

4.4.RTP datasets

The price values datasets created to assess the developed model are based on two different hypothesis, one based on the Iberian wholesale market of 2019 and one based on the renewable energy availability of 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 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 electricity generation cost dynamics in such a situation.

The first model is obtained by equation (34) through data collected from the Iberian Electricity Market Operator[7] (OMIE), the operator of the market where electrical companies in Portugal and Spain perform trade.

$$RTP_{Market}(t) = \frac{avg.price \times Wholesale\ Market\ Price(t)}{mean_{daily}(Wholesale\ Market\ Price)} \qquad (31)$$

The second is created from the data of the renewable production available at the REN[8] information system, using the evolution of the inverse of the hourly solar and wind energy available production with the same weight as reported by equation (35). The price values are later scaled to the average residential user price in Portugal in 2019 of 0.2150 €/kWh, including taxes, according to EUROSTAT[9].

[7] https://www.omie.es/en/file-access-list#Day-ahead%20MarketPrices?parent=Day-ahead%20Market
[8] https://www.mercado.ren.pt/EN/Electr/MarketInfo/Gen/Pages/default.aspx
[9] https://www.dgeg.gov.pt/pt/estatistica/energia/precos-de-energia/precos-de-eletricidade-e-gas-natural/

$$RTP_{RES}(t) = \frac{avg.price \times (solar(t) + wind(t))^{-1}}{mean_{daily}(\frac{1}{solar + wind})} \qquad (32)$$

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. The choices for the first dataset are depicted in Figure 4.7 and Figure 4.8, relatively for small and high price variations, while for the second the choices are shown in Figure 4.10 and Figure 4.11.

For example, in Figure 4.11 it is visible that during a specific day in October, corresponding to the green line, a high peak in the price has occurred, a symptom of a large RES production drop, representing that the RES availability tended to zero, but that followed a period where the opposite was happening with prices close to zero due to an excess of availability. Figure 4.9 shows how these situations occur frequently for the second RTP model during the whole year. For the first RTP model, instead, these variations are more sporadic due to a higher stability of the wholesale market price and lower intensity of the variations as showed in Figure 4.6.

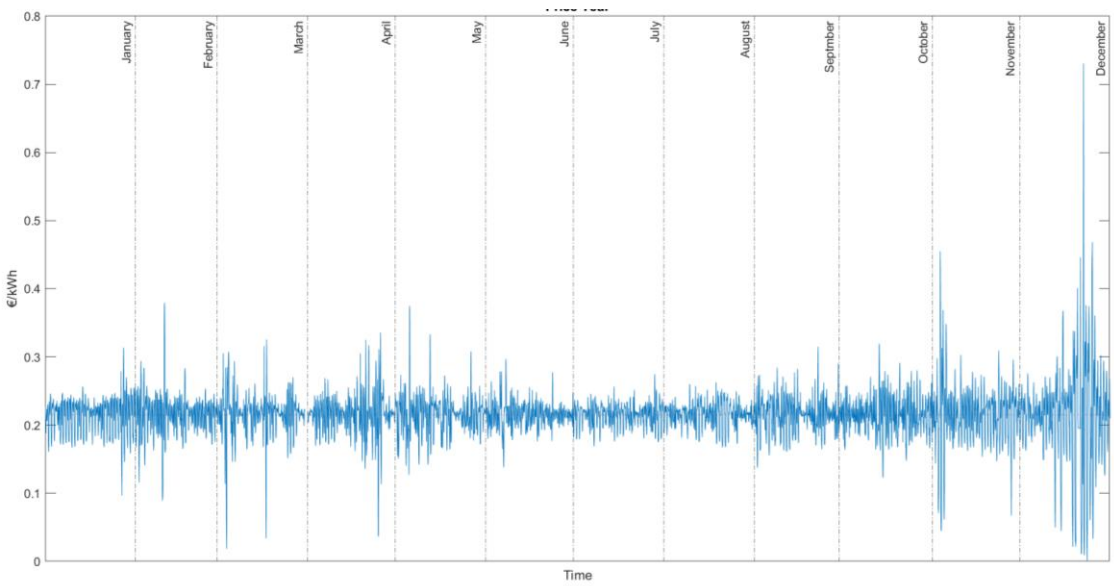

Figure 4.6 – Yearly RTP driven by Iberian Electricity Market Operator.

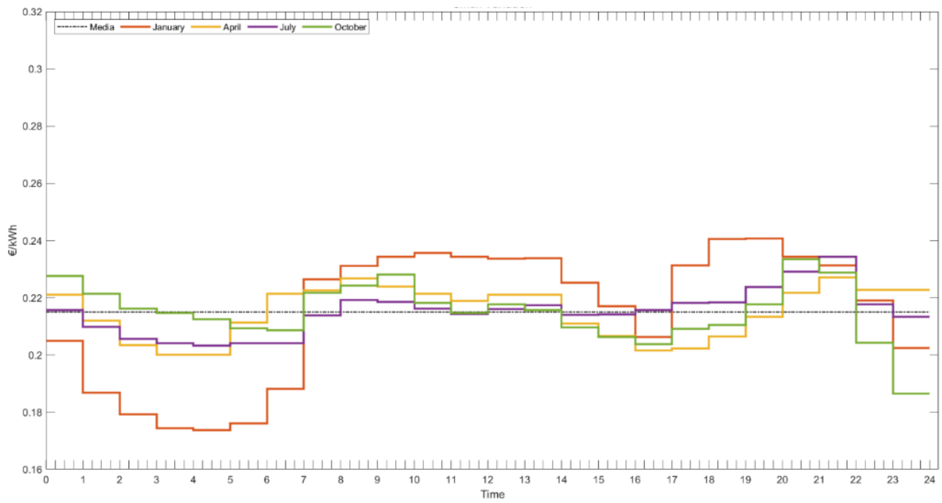

Figure 4.7 – Small variation of RTPs driven by Iberian Electricity Market Operator.

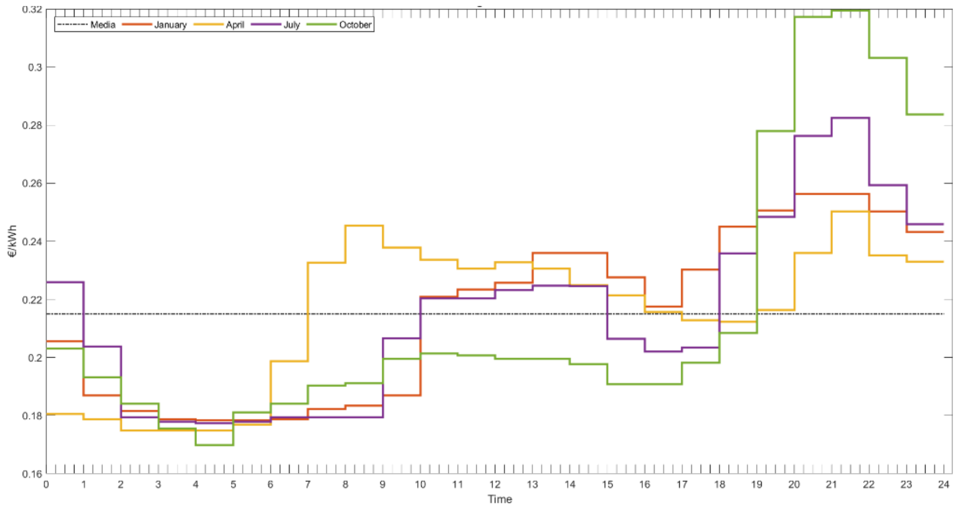

Figure 4.8 – High variation of RTPs driven by Iberian Electricity Market Operator.

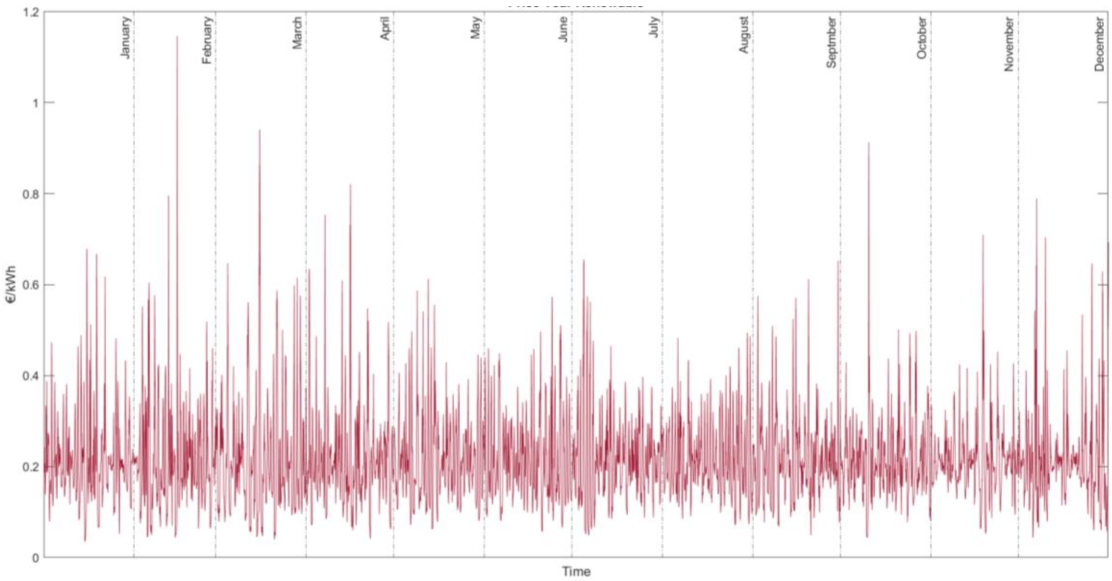

Figure 4.9 – Yearly RTP driven by renewable availability.

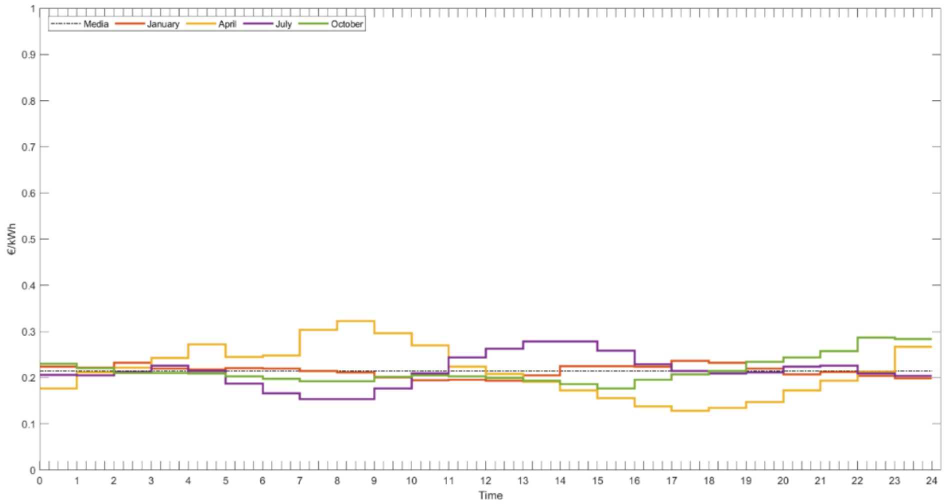

Figure 4.10 – Small variation of RTPs driven by renewable availability.

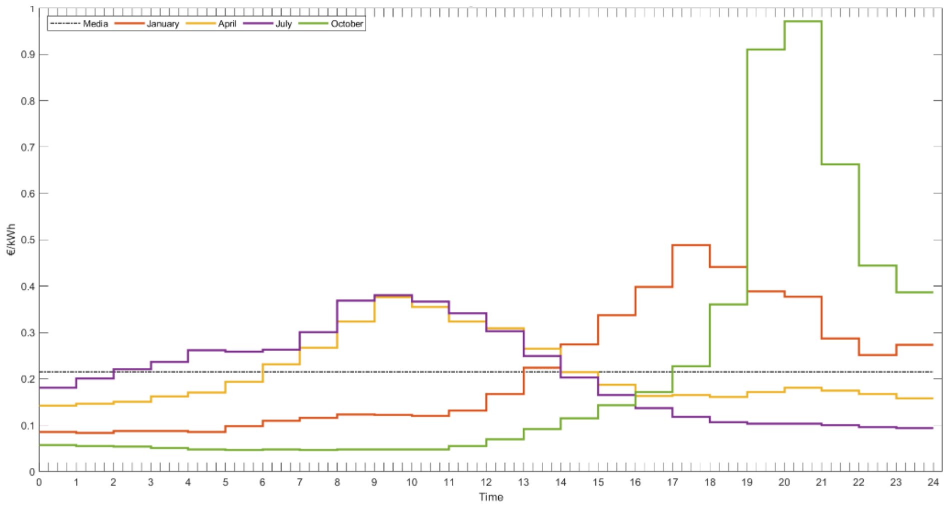

Figure 4.11 – High variation of RTPs driven by renewable availability

4.5. Scenarios

To observe and evaluate how the model evolves and reacts to the different real cases, this section lists the different combinations through which the individual cases are produced. For all the single cases, the base is the consideration of the DR load shifting program under real time price schemes.

The combinations and the relative interest of each choice for the case are reported below:

- The existence of PV panel generation vs a grid-only supply. Different profiles of power production are implemented, according to the different period of the year.
- Wholesale-market based vs RES availability based RTP.
- Different values of weight for the willingness to accept the inconvenience of appliance shifting, considering values for δ of: 100%, 10%,1% and 0.1%.
- Different limits for maximum contracted power, limiting the rate at which energy can be traded with the grid: 6.9kVA and 4.6kVA, considering a power factor of 0.9.
- Different periods of year affecting PV production and RTP price values: January, April, July and October.

5. Analysis of results

The objective of the following computational tests and sensitivity analysis is to investigate the possible consequences of responding to residential DR programs implemented with RTP when scheduling common appliances, as well as a system of batteries.

The proposed MINLP model is solved using a PC with a 1.99 GHz Intel Core i7-8550U CPU of 8th Generation having 16 GB of RAM, running under Windows 10. The model is solved in 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, which means low value of δ, due to the largest possible computable combinations.

The results show that the model performs a good scheduling of the battery operation, in order to compensate and reduce the high peak prices, discharging it during the peak event. When the solar forecast production is significant, the charging is scheduled to use the PV excess energy, avoiding its delivery to the grid without benefits.

In case no PV production is available or the forecast is that it will not be enough for the demand, the model acts to charge the battery with the lower prices, still before the peak event occurs in order to compensate with the discharging.

The following subsections describe the results obtained by implementing the MINLP optimization model, discussing their implications.

The first subsection discusses the first RTP model and how our optimization model reacts to it, while in the second one results show the response to higher variation in prices, as a consequence of the second RTP model, strongly dependent on the RES availability.

5.1. Real time price driven by the actual wholesale market

The first part of the results which are going to be discussed are those regarding the first type of pricing model: the real time market price depicted in Figure 4.7 and Figure 4.8, showing relatively small and high variation of price.

Initially, the PV system is not considered, in order to show and evaluate if and how the DR program combined with the BS system can bring economic benefits for bill reduction, albeit not significantly. Table 5.1 and Table 5.2 report the results for the months of April and October (respectively, yellow and green lines in RTP plots). For the periods with small variation in prices, i.e., without a significant difference between the higher and lower price of the RTP, the savings tend to be almost zero. This is valid for the case of zero inconvenience accepted, implying no load shifting (δ=100%), but also for the case where the allowed inconvenience is very high (δ=0.1%). But, within the same week, a situation with a greater variation of RTP occurs ("High RTP Variation"), leading to an increase in earnings. In fact the BS unit allows for small savings, around 4% even without incurring in discomfort.

Table 5.1 – April case of lower saving without PV panel.

	δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%
Small RTP variation	100.0%	0	5.449	0	0.00	0	0.00
	0.1%	1.919	5.340	0.109	2.00	0	0.00
High RTP variation	100.0%	0	5.244	0.192	3.53	0.192	100.00
	0.1%	1.067	5.216	0.220	4.05	0.189	85.91

Table 5.2 – October case of higher saving without PV panel.

	δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%
Small RTP variation	100.0%	0	5.506	0	0.00	0	0.00
	0.1%	2.246	5.437	0.069	1.25	0	0.00
High RTP variation	100.0%	0	5.005	0.486	8.85	0.486	100.00
	0.1%	1.640	4.938	0.553	10.07	0.452	81.74

Once the PV system is introduced in the system, the expected savings that the system is able to bring grows significantly, namely due to the flexibility that maximizes the value given to the self-generation, avoiding the purchase from the main grid, with contributions from the BS but also from the load shifting. Table 5.3 and Table 5.4 report the case of small PV production in October, where it shows that even a small PV power production can imply a greater percentage of savings, for both cases with high and small variation in the RTP.

Table 5.3 – October case with small variation of RTP driven by OMIE.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: Small - PV Real Production: Small									
100.0%	0	4.423	1.083	19.67	0.299	27.61	4.736	0.313	5.68
10.0%	0	4.423	1.083	19.67	0.299	27.61	4.736	0.313	5.68
1.0%	2.026	4.350	1.156	21.00	0.233	20.11	4.664	0.314	5.70
0.1%	2.779	4.350	1.156	21.00	0.213	18.40	4.660	0.310	5.63

Table 5.4 – October case with high variation of RTP driven by OMIE.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: Small - PV Real Production: Small									
100.0%	0	4.006	1.485	27.04	0.764	51.48	4.296	0.290	5.28
10.0%	0.182	3.976	1.515	27.59	0.760	50.17	4.266	0.290	5.28
1.0%	1.644	3.930	1.561	28.43	0.668	42.79	4.221	0.291	5.30
0.1%	2.244	3.930	1.561	28.43	0.651	41.70	4.219	0.289	5.26

In presence of the PV system, the participation of the BS unit changes from around 20/25 % for the flatter case (Table 5.3) to almost the double when the RTP become more fluctuant during the day (Table 5.4). In this case, the BS unit avoids purchasing energy during high price periods by supplying previously stored energy, as is possible to see in Figure 5.1, where the red part represents the discharging of the battery. It’s also observable that the charging of the battery, represented by blue bars, occurs in part with the storing of the PV excess and in the main part during the lower peak hour.

In addition, also observing Figure 5.2 which depicts the SoC in the citated case, it is possible to see how and when the battery is charged and kept in the same SoC until reaching the region of high price, where the battery starts to be discharged, producing almost the whole savings.

The last 3 columns at the right on the tables (“Real Cost”, “Savings Mismatch” and “%”) are the result of the effect produced when there is an important mismatch between the PV generation data of two consecutive days, representing a possible difference between the forecast which is used to obtain the optimized scheduling, and the real production of the PV system, the difference being covered by the grid but not rewarding the excess .

The different values of δ for the first case ("Small RTP Variation") show that small savings can be obtained even at the expense of a greater discomfort, becoming greater of about 8% thanks to the higher variability which permits a larger usage and so compensation by the BS unit. For the cases discussed until now have to be noticed that in order to be able to have savings the model have to act mainly on the rescheduling program, having so large inconvenience costs greater than the expected savings.

The low values of δ, meaning larger rescheduling, implies also a lower participation of the BS system in the quantity of savings due to the lower necessity of keeping the same initial load profile. In fact, as opposite, for increasing values of δ, the battery is more used to keep the same level of comfort about load scheduling, without having significantly changes about amounts of savings.

Similar effects, as implications of δ values and participation of BS for the maintenance of the same comfort, are obtained also in the others periods of the year chosen for the analysis, for both cases of "Small" and "High" prices variation. These present lower differences from the "Small" to the "High" case and are reported in Appendix A.

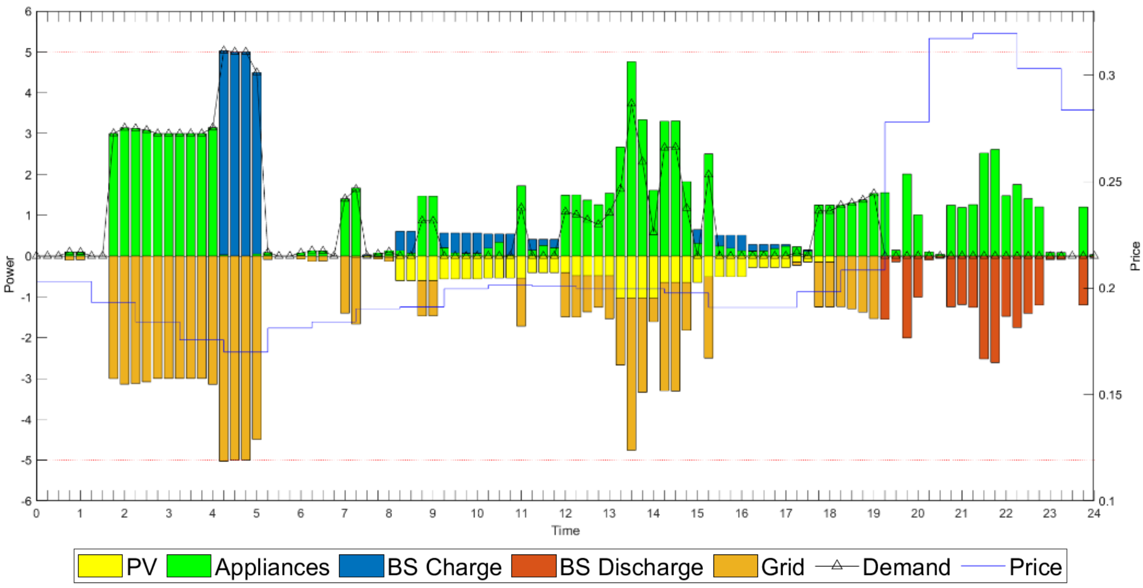

Figure 5.1 – October case, δ=100%, with high variation of RTP driven by OMIE and small PV production.

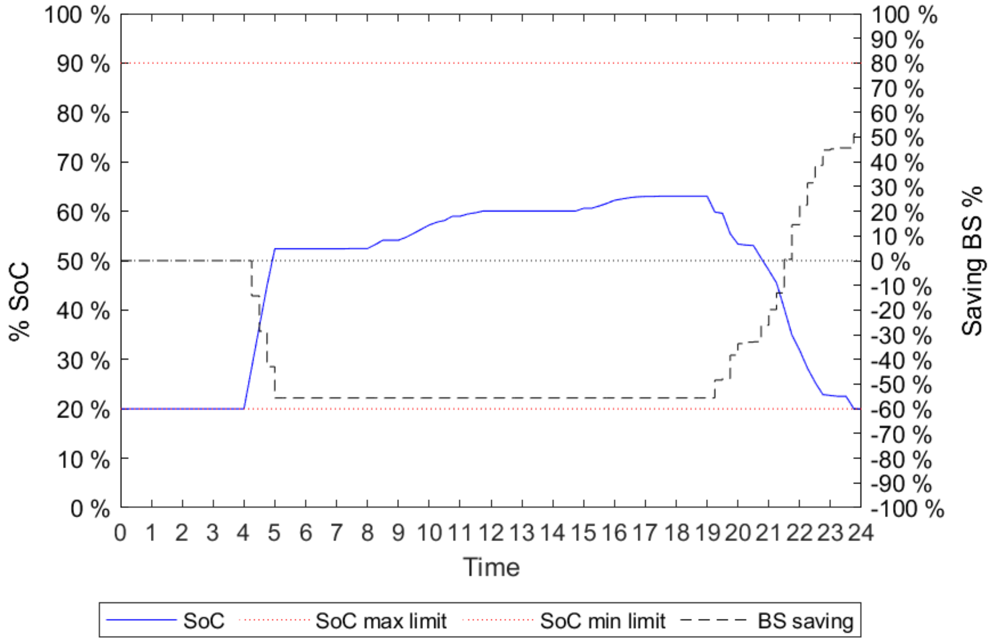

Figure 5.2 – State of charge of the battery for the higher BS saving case.

When the solar production becomes greater, the amount of savings increases due to the higher participation of the PV system in the supply of household demand. Figure 5.3 and Table 5.5 in fact shows that the grater production permits to the model to charge (blue bars) the battery from the excess of the PV energy not used instead of doing it by the main grid. The higher production allows for higher of savings, with only a small participation increase of the BS.

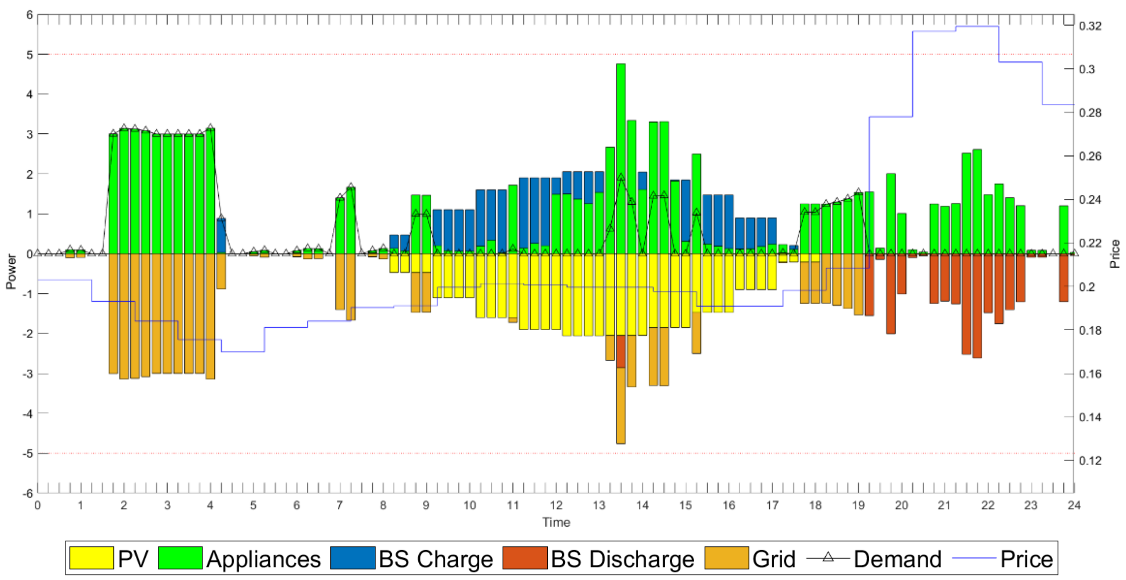

Figure 5.3 – October case, δ=100%, with high variation of RTP driven by OMIE and high PV production.

For the October case this mismatch seems to be expectedly large enough to cause a drop of about 20 percent of the possible savings. The expected mismatch between expected and real savings decreases in July as the mismatch between consecutive days also decreases, as seen in Table 5.6, where the mismatch is about maximum five percentage points. The same happens approximately with April case, reported in Table 5.7, where the expected disparity between possible savings and real savings is quite small.

Table 5.5 – October case with high variation of RTP driven by OMIE.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real production: High									
100.0%	0	2.486	3.005	54.73	1.594	53.04	3.789	1.303	23.73
10.0%	0.358	2.430	3.061	55.75	1.594	52.07	3.733	1.303	23.73
1.0%	1.720	2.379	3.112	56.67	1.346	43.25	3.682	1.303	23.73
0.1%	1.942	2.378	3.113	56.69	1.317	42.31	3.680	1.302	23.71
PV Forecast: Small - PV Real production: Small									
100.0%	0	4.006	1.485	27.04	0.765	51.48	4.296	0.290	5.28
10.0%	0.182	3.976	1.515	27.59	0.760	50.17	4.266	0.290	5.28
1.0%	1.644	3.930	1.561	28.43	0.668	42.79	4.221	0.291	5.30
0.1%	2.244	3.930	1.561	28.43	0.651	41.70	4.219	0.289	5.26

Table 5.6 – July case with high variation of RTP driven by OMIE.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real production: High									
100.0%	0	1.636	3.901	70.45	1.944	49.83	1.878	0.242	4.37
10.0%	0.191	1.597	3.940	71.16	1.944	49.34	1.839	0.242	4.37
1.0%	1.719	1.540	3.997	72.19	1.652	41.33	1.780	0.240	4.33
0.1%	1.952	1.536	4.001	72.26	1.639	40.96	1.780	0.244	4.41
PV Forecast: Small - PV Real production: Small									
100.0%	0	3.603	1.934	34.93	0.776	40.12	3.730	0.127	2.29
10.0%	0.190	3.564	1.973	35.63	0.776	39.33	3.692	0.128	2.31
1.0%	2.200	3.505	2.032	36.70	0.600	29.53	3.633	0.128	2.31
0.1%	2.200	3.505	2.032	36.70	0.600	29.53	3.633	0.128	2.31

Table 5.7 – April case with high variation of RTP driven by OMIE.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real production: High									
100.0%	0	1.534	3.902	71.78	1.884	48.28	1.613	0.079	1.45
10.0%	0.120	1.521	3.915	72.02	1.862	47.56	1.599	0.078	1.43
1.0%	0.405	1.509	3.927	72.24	1.856	47.26	1.588	0.079	1.45
0.1%	0.405	1.509	3.927	72.24	1.856	47.26	1.588	0.079	1.45
PV Forecast: Small - PV Real production: Small									
100.0%	0	4.402	1.034	19.02	0.464	44.87	4.638	0.236	4.34
10.0%	0	4.402	1.034	19.02	0.464	44.87	4.639	0.237	4.36
1.0%	0.954	4.370	1.066	19.61	0.391	36.68	4.607	0.237	4.36
0.1%	1.998	4.366	1.070	19.68	0.369	34.49	4.603	0.237	4.36

Regarding the April case it is interesting to highlight, that although the PV production is similar to July, approximately the same amount of savings can be obtained with a lower level of discomfort, as shown by the inconvenience cost column of Table 5.7, which is much smaller.

Moreover, the RTP price of April presents multiple periods with high peaks, that when not compensated by the PV panel, imply multiple discharges of the battery during the day, favouring a smaller value of inconvenience. This happens when the production of the PV panel is small and can be seen in Figure 5.4.

As the peak occurs when the PV power production is small, the battery must be charged from the main grid, and this happens essentially during the morning, when prices are lower. In this case, the optimizations lead to a higher participation of the BS in supplying, as shown in Figure 5.5.

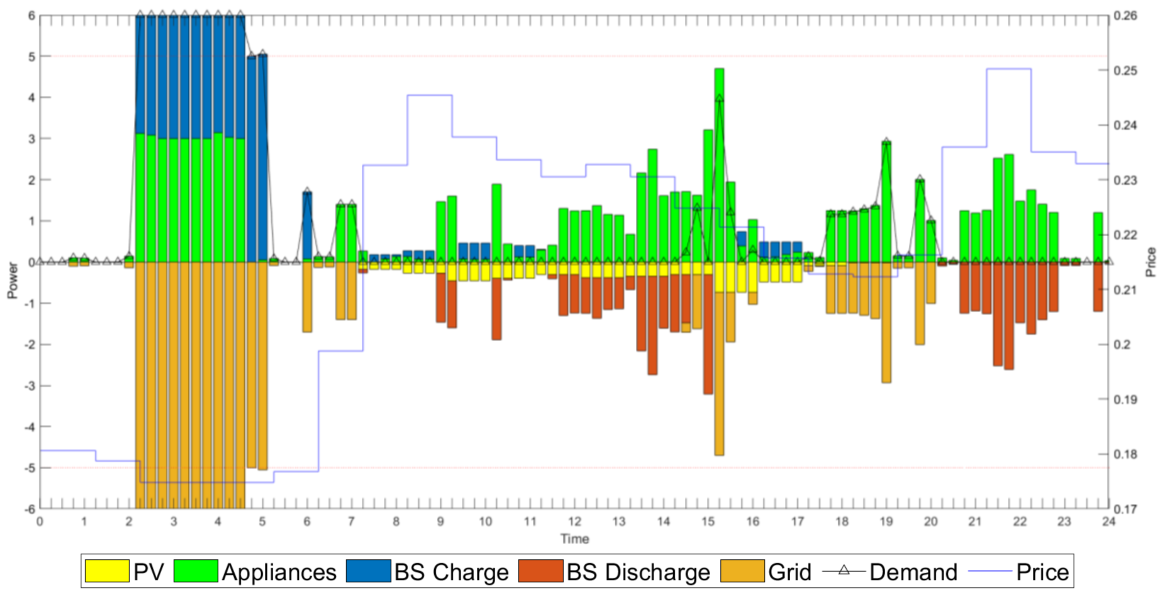

Figure 5.4 – April case with high variation of RTP driven by OMIE, δ=0.10 % and small PV production.

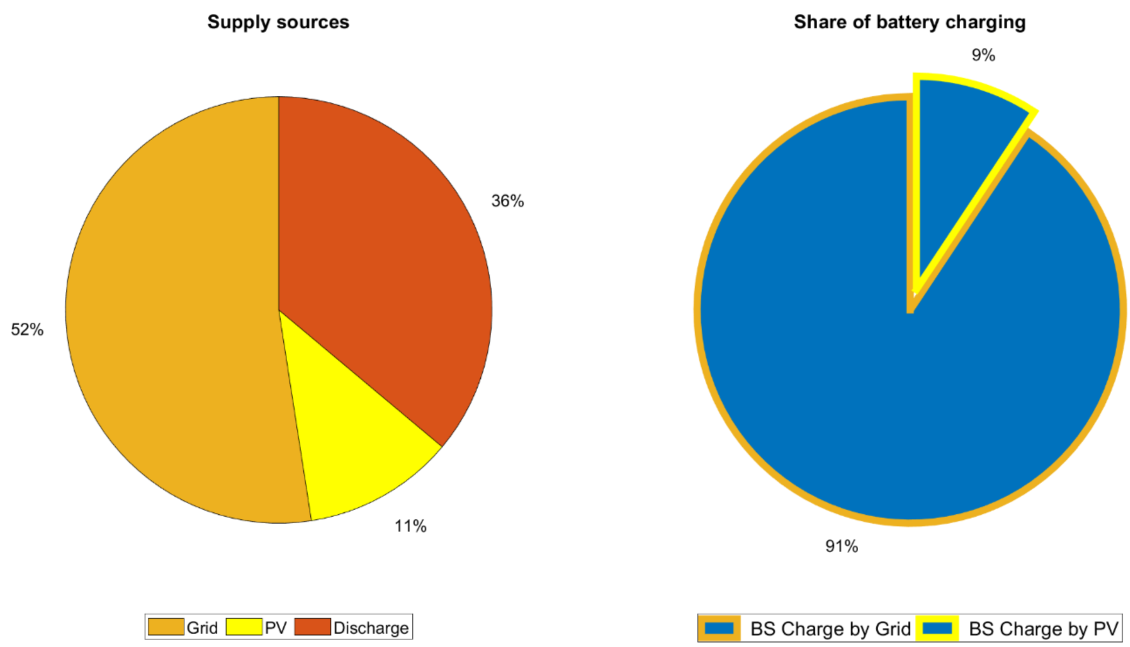

Figure 5.5 – Usage of power in the April case of Figure 5.4.

In the case shown in Figure 5.4, it can be seen that, due to the compensation of the multiple periods with high prices, demand peaks appear where they were not initially present, and it is therefore interesting to analyse possible limitation to such result, even because they represent the average power in 15 min periods, eventually implying higher instant peaks representing a worse problem for the grid. To limit these peaks, a constraint for a maximum demand of 4.1 kW was added to see how the system is going to evolve, the results being reported below.

Table 5.8 – Results applying demand limit for the April case of small PV production.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: Small - PV Real production: Small									
100.0%	0	4.413	1.023	18.82	0.389	38.03	4.650	0.237	4.36
10.0%	0	4.413	1.023	18.82	0.389	38.03	4.650	0.237	4.36
1.0%	0.777	4.386	1.050	19.32	0.321	30.57	4.623	0.237	4.36
0.1%	1.933	4.381	1.055	19.41	0.291	27.58	4.618	0.237	4.36

The limitation of the demand, according to the results of Table 5.8 doesn't change significantly the results, although BS savings do decrease circa 8%, even if the limitation needs the model to figure out other periods with low price. However, this demand limit may represent a significant benefit, avoiding eventual penalties for higher demand, or the tripping of a circuit breaker, causing disruption. Finally, Figure 5.6 shows the results of the model implementation, with the demand limit flattening the demand along the morning hours.

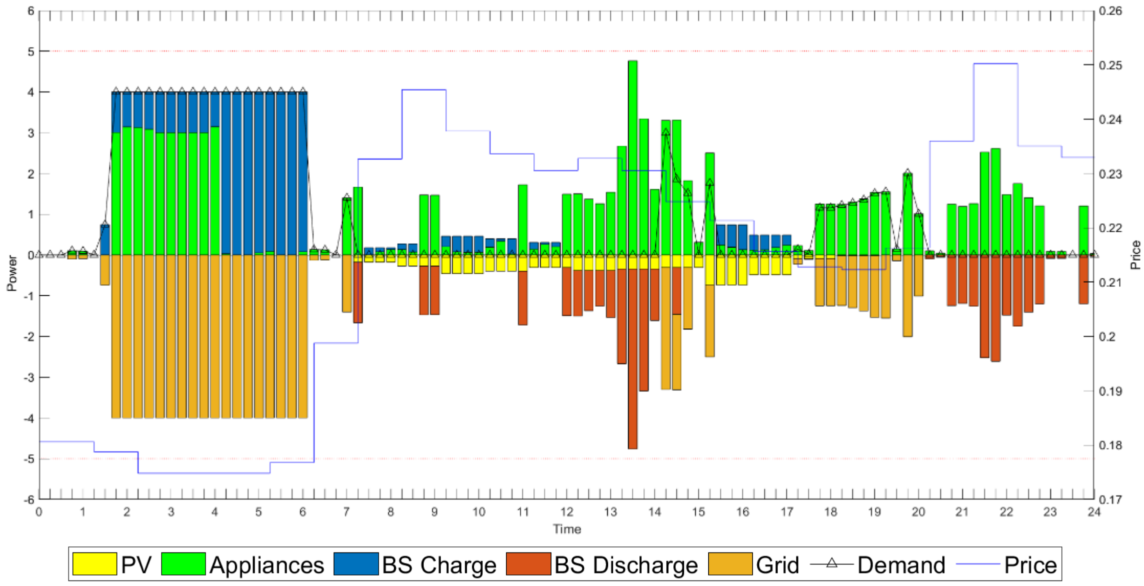

Figure 5.6 – April case, δ=0.10%, high variation of RTP driven by OMIE, small PV production and demand limit.

The discussion related to the market price model is concluded with the analysis of the maximum case of inconvenience for the case study. This happens when δ is equal to 0.1%, the PV production is low and there is no large margin of compensation by the BS due to a flat price variation, as one of the cases of small variation of RTP in July. Figure 5.7 and Table 5.9 show the result of the load shifting program aiming to minimize the cost, in addition to one of the minimum percentages of participation of the BS unit.

Table 5.9 – Higher inconvenience case for small variation of RTP driven by actual wholesale market, in July with small PV production.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
0.1 %	2.787	3.755	1.732	31.57	0.347	20	3.882	0.127	2.31

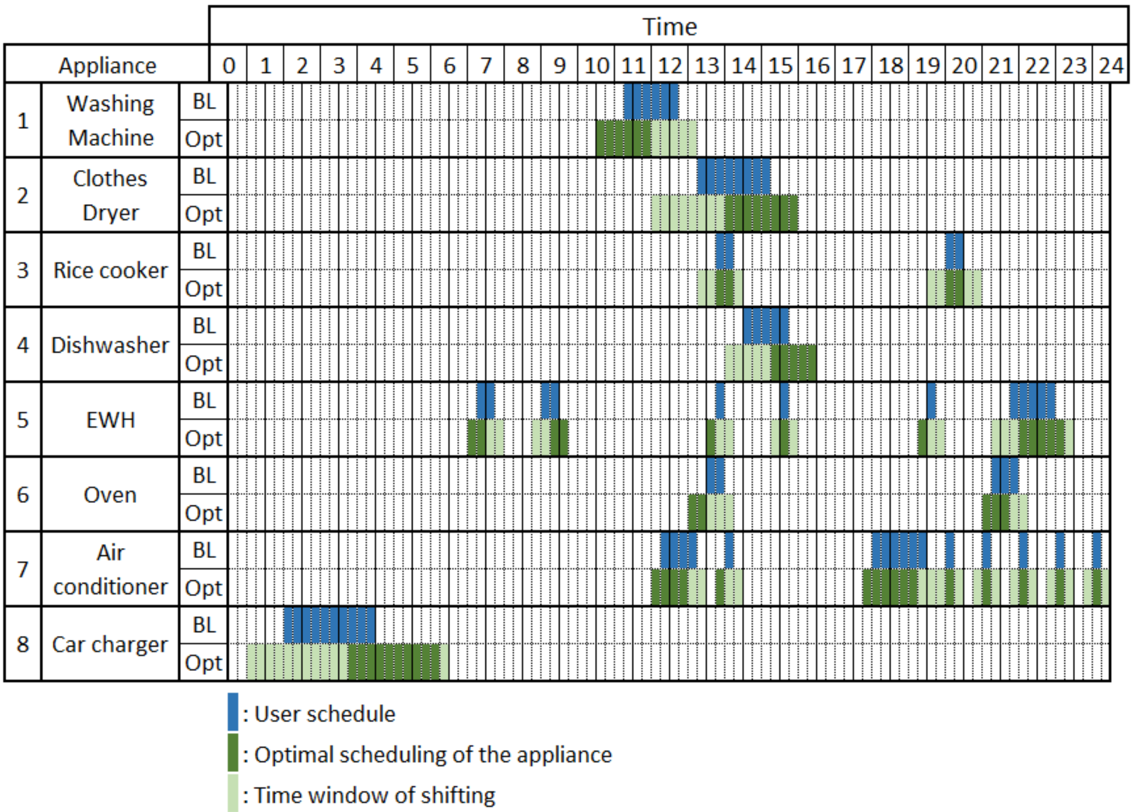

Figure 5.7 – Result of the load shifting for the higher inconvenience cost: July, small PV production, δ=0.1%, small variation of the RTP driven by OMIE.

Further results regarding the different scenarios obtained through the implementation of this first type of RTP model are available in Appendix A.

5.2. Real time prices driven by the availability of renewable sources

This subsection analyses a hypothetical price variation dependent on the availability of renewable generation, trying to emulate a future situation when the generation mix will have no other type of sources.

Like in the previous section, the price models shown in Figure 4.10 and Figure 4.11 present periods with small and high variation of prices.

Using only the BS unit under DR load shifting program without the PV panel production, is noticeable that the possibility to obtain savings is limited if the variation of price is small, even if a high level of discomfort is allowed, as seen in Table 5.10. On the contrary, Table 5.11, shows how that a higher dependence of the prices on the RES sources will produce significant variation in prices which will lead to significant savings. This is due to an increased role of the battery which, if correctly scheduled, is able to benefit from the higher variations in price compared to the previous RTP model. The “High variation” case of October, in which the lack of availability of energy production leads to a price peak, shows that the BS unit can bring significant gains as shown in Table 5.10 and Table 5.11.

Table 5.10 – January case of lower saving without PV panel.

	δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%
Small RTP variation	100.0%	0	5.536	0	0.00	0	0.00
	0.1%	2.552	5.399	0.131	2.40	0	0.00
High RTP variation	100.0%	0	3.351	2.102	38.55	2.102	99.98
	0.1%	2.073	3.083	2.370	43.47	2.073	87.45

Table 5.11 – October case of higher saving without PV panel.

	δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%
Small RTP variation	100.0%	0	5.297	0.165	2.95	0.165	100.00
	0.1%	1.638	5.229	0.233	4.16	0.161	69.10
High RTP variation	100.0%	0	1.651	3.944	70.49	3.940	99.90
	0.1%	0.827	1.495	4.100	73.28	3.990	97.32

To have those profits by the BS, the model schedules the charging process to occur during the morning hours where the price is much lower, in order to be able to discharge the stored energy during peak events, as shown in Figure 5.8. The evolution of BS savings along the day and also the hours where they occur with greater amplitude, for this October case, are reported in Figure 5.9.

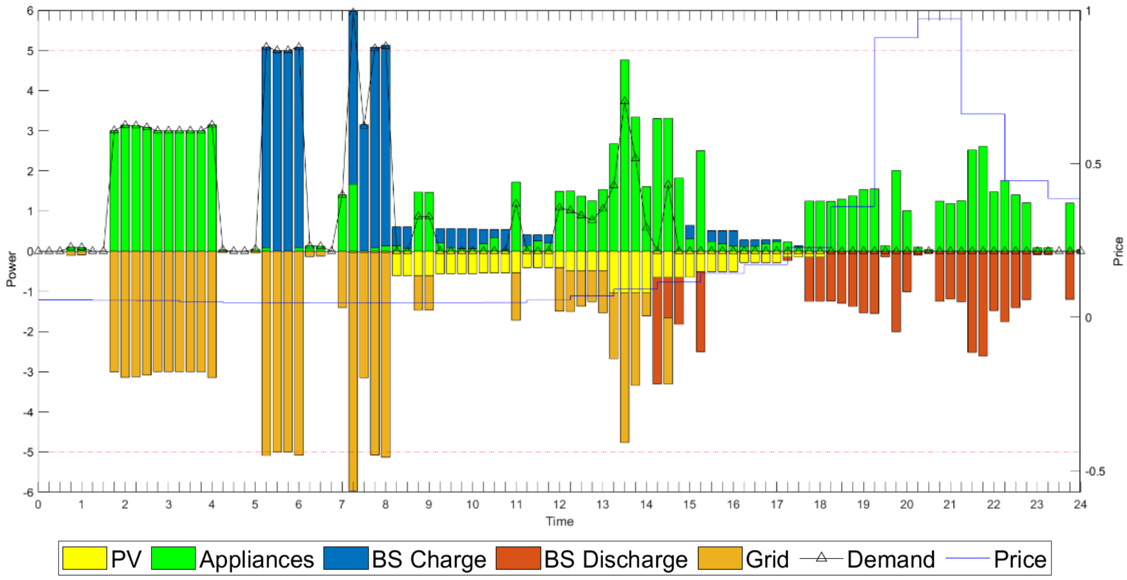

Figure 5.8 – October case with high variation of RTP driven by renewable availability, δ=100% and small PV production.

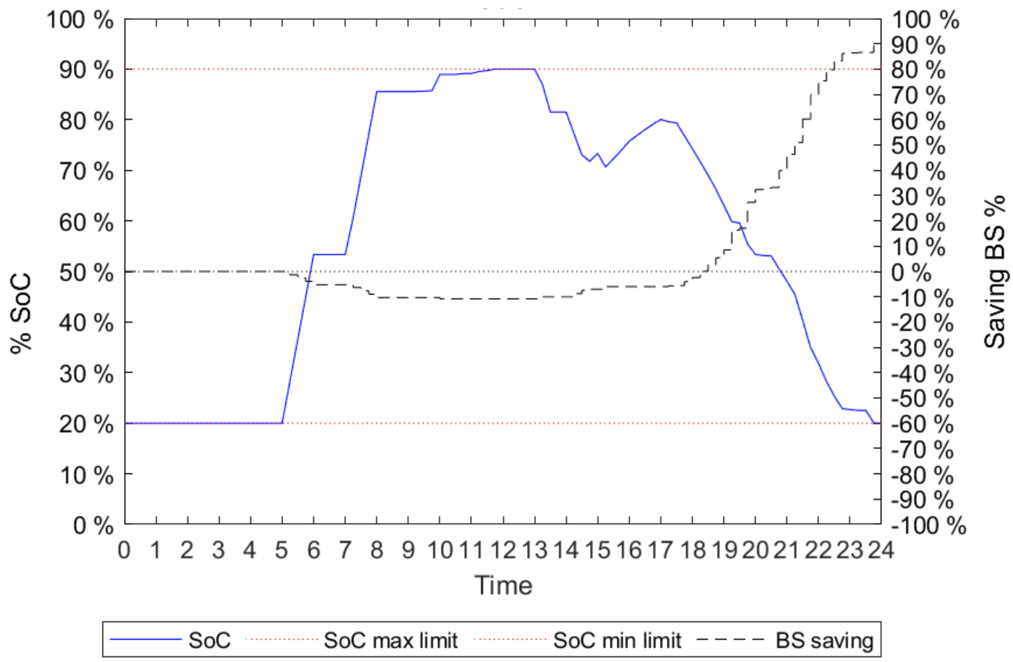

Figure 5.9 – State of charge of charge of the battery for the higher BS saving case.

The combination between BS and DR program for the handling of these extreme situations will become more important if the frequency of these events becomes larger, as happens for this model observable in Figure 4.9. The proper scheduling of BS by the model also avoids increasing the inconvenience costs as observed in Table 5.12 and Table 5.13.

Table 5.12 – October case with high variation of RTP driven by renewable availability.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real Production: High									
100.0%	0	0.709	4.886	87.33	4.227	86.51	1.465	0.756	13.51
10.0%	0.200	0.672	4.923	87.99	4.227	85.86	1.428	0.756	13.51
1.0%	0.604	0.658	4.937	88.24	4.091	82.86	1.413	0.755	13.49
0.1%	0.895	0.657	4.938	88.26	4.043	81.88	1.412	0.755	13.49
PV Forecast: Small - PV Real Production: Small									
100.0%	0	1.242	4.353	77.80	3.980	91.43	1.420	0.178	3.18
10.0%	0.526	1.133	4.462	79.75	4.005	89.76	1.312	0.179	3.20
1.0%	0.775	1.125	4.470	79.89	3.951	88.39	1.304	0.179	3.20
0.1%	0.961	1.124	4.471	79.91	3.960	88.57	1.303	0.179	3.20

Table 5.13 – January case with high variation of RTP driven by renewable availability, with no demand limit.

δ	Inc Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real Production: High									
100.0%	0	1.385	4.068	74.60	2.605	64.03	1.797	0.412	7.55
10.0%	0	1.385	4.068	74.60	2.605	64.03	1.797	0.412	7.55
1.0%	1.216	1.350	4.103	75.24	2.127	51.84	1.762	0.412	7.55
0.1%	1.426	1.349	4.104	75.26	2.250	54.82	1.761	0.412	7.55
PV Forecast: Small - PV Real Production: Small									
100.0%	0	2.067	3.386	62.10	2.342	69.16	3.157	1.09	19.99
10.0%	0.448	2.000	3.453	63.33	2.165	62.69	3.090	1.09	19.99
1.0%	1.403	1.966	3.487	63.95	2.100	60.22	3.057	1.091	20.01
0.1%	1.602	1.966	3.487	63.95	2.223	63.74	3.049	1.083	19.86

While the non-PV case is already interesting and profitable, as just discussed, the introduction of a PV panel production associated to this model of RTP will allow the optimization model to increase savings until circa 89% in October, as shown in Table 5.12.

Moreover, the availability of PV own energy allows an increase of about 20% of savings for the October case, while for January the value is duplicated as visible in Table 5.13.

As already discussed, the mismatch between the forecasts of solar radiation and the real case that will occur the following day is a possible conditioning issue for the model. Here, as in the previous section, significant savings can still be achieved and with a larger intensity, thanks to the greater opportunities of savings given by the RTP model for the battery.

An interesting case to be observed occurs in January, where the RTP model presents high price peaks during periods of high consumption, in the late afternoon and evening time. The occurrence of these two events simultaneously leads to higher contributions of the BS for the generation of savings, especially during periods of higher solar production and lower discomfort allowed by the user (δ=100%), which are following depicted in Figure 5.10 and Figure 5.11.

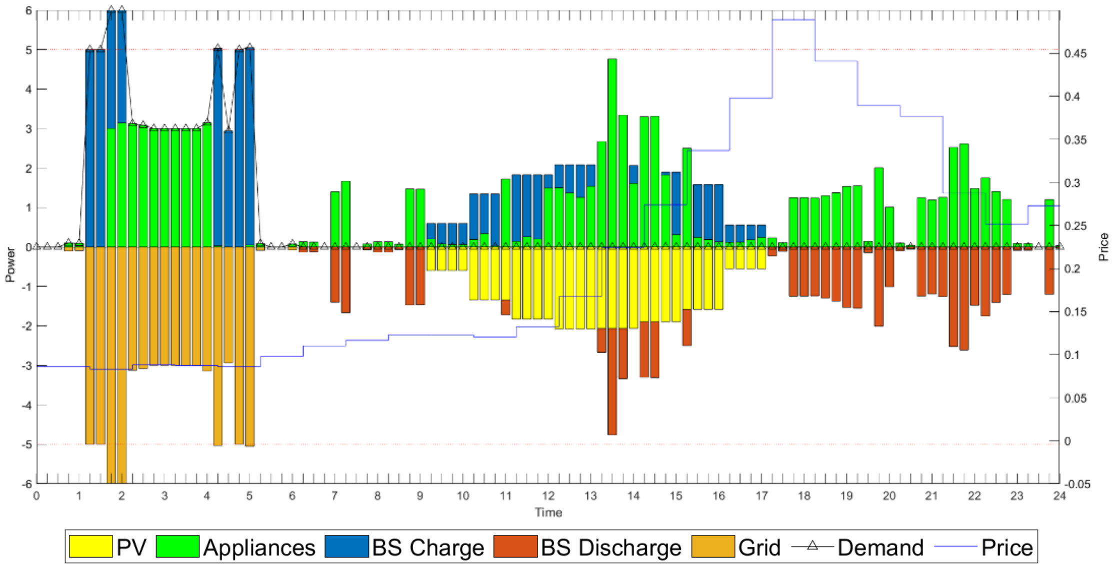

Figure 5.10 – January case with high variation of RTP driven by renewable availability, δ=100% and high PV production, without demand limit.

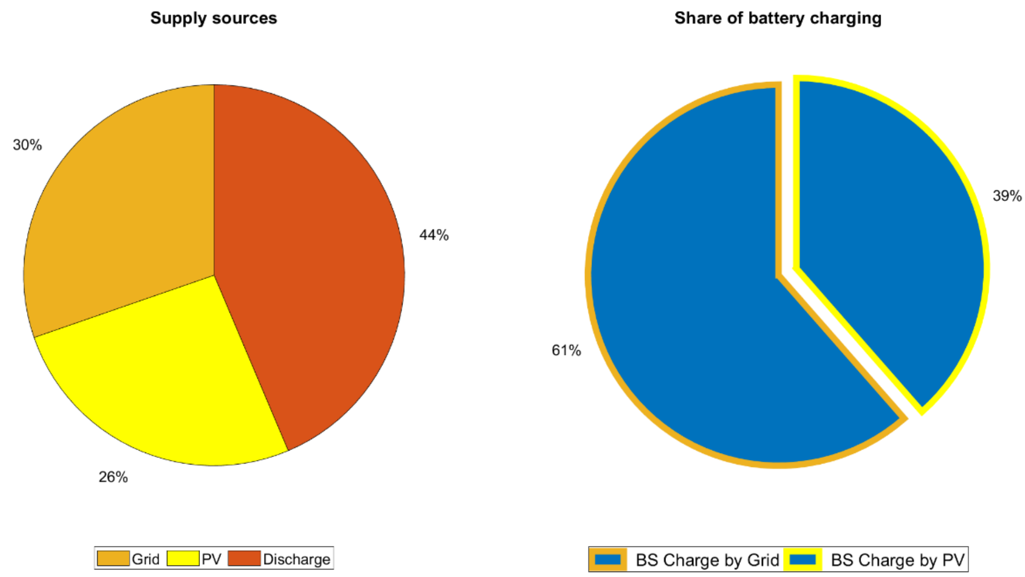

Figure 5.11 – Usage of power in the January case of Figure 5.10.

Table 5.14 – April case with high variation of RTP driven by renewable availability.

δ	Inc Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real Production: High									
100.0%	0	1.345	3.868	74.20	1.590	41.11	1.455	0.110	2.11
10.0%	0.307	1.290	3.923	75.25	1.590	40.53	1.401	0.111	2.13
1.0%	0.606	1.273	3.940	75.58	1.336	33.91	1.383	0.110	2.11
0.1%	0.687	1.272	3.941	75.60	1.532	38.87	1.383	0.111	2.13
PV Forecast: Small - PV Real Production: Small									
100.0%	0	3.642	1.571	30.14	0.908	57.80	3.983	0.341	6.54
10.0%	0.307	3.602	1.611	30.90	0.894	55.49	3.942	0.340	6.52
1.0%	1.250	3.577	1.636	31.38	0.821	50.18	3.917	0.340	6.52
0.1%	2.209	3.575	1.638	31.42	0.849	51.83	3.912	0.337	6.46

Table 5.14 allows a comparison of the same dataset with the wholesales-market based RTP model results shown in Table 5.7.

It is visible that the relative savings slightly increase, although with almost the same gap between the expected and the real result. The BS unit contribution has a negative variation when compared to the previous model for the case of high solar production, while for the case of small production the variation is still positive with an increment form 13% for the lower willingness to inconvenience to 17% for the more flexible case. The inconvenience cost for this RTP model slightly increases for all the δ values combinations remaining in any case below the expected savings' values. The only case where this don't happen is for δ=0.1% where anyway the gap between them is reduced compared to the previous RTP model.

As done for the first RTP price model, Figure 5.10 presents demand peaks in periods when they didn't exist before, suggesting the use of a demand limit, which was set to 4.1 kW. The results are reported in Table 5.15 where it is visible how the limit of demand will not change the results obtained, except for the profile of demand which is smoothed and expanded in time as seen in Figure 5.12.

Table 5.15 – January with high variation of RTP driven by renewable availability, with demand limit.

δ	Inc Cost	Final Cost	Potential Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
PV Forecast: High - PV Real Production: High									
100.0%	0	1.390	4.063	74.51	2.596	63.89	1.805	0.415	7.61
10.0%	0	1.389	4.064	74.53	2.596	63.87	1.801	0.412	7.55
1.0%	1.173	1.358	4.095	75.10	2.244	54.79	1.769	0.411	7.54
0.1%	1.427	1.356	4.097	75.13	2.252	54.96	1.767	0.411	7.54
PV Forecast: Small - PV Real Production: Small									
100.0%	0	2.071	3.382	62.02	2.243	66.31	3.161	1.090	19.99
10.0%	0.448	2.007	3.446	63.20	2.160	62.67	3.100	1.093	20.04
1.0%	1.232	1.976	3.477	63.77	2.232	64.19	3.066	1.090	19.99
0.1%	1.602	1.975	3.478	63.78	2.224	63.94	3.070	1.093	20.04

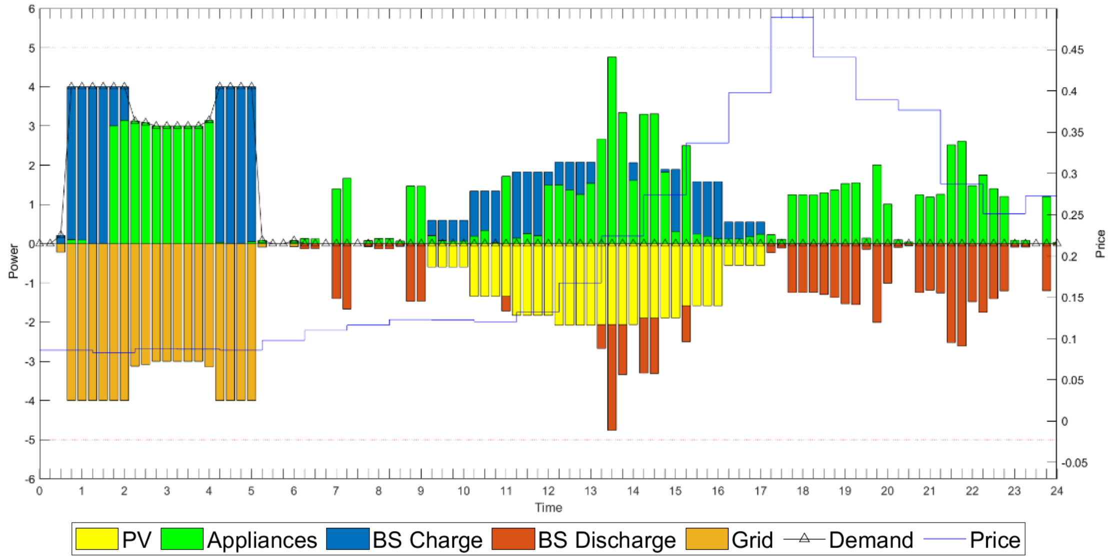

Figure 5.12 – January case with high variation of RTP driven by renewable availability, δ=100 %, high PV production and demand limit.

Finally, the result of the load shifting program on the initial load is reported for the worst case in Table 5.16 and depicted in Figure 5.13.

Table 5.16 – Higher inconvenience case for small variation of RTP driven by renewable availability, δ=0.1%, January with small PV production.

δ	Inc. Cost	Final Cost	Potential Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
0.1 %	3.05	4.130	1.388	25.15	0.330	23.78	4.952	0.822	14.90

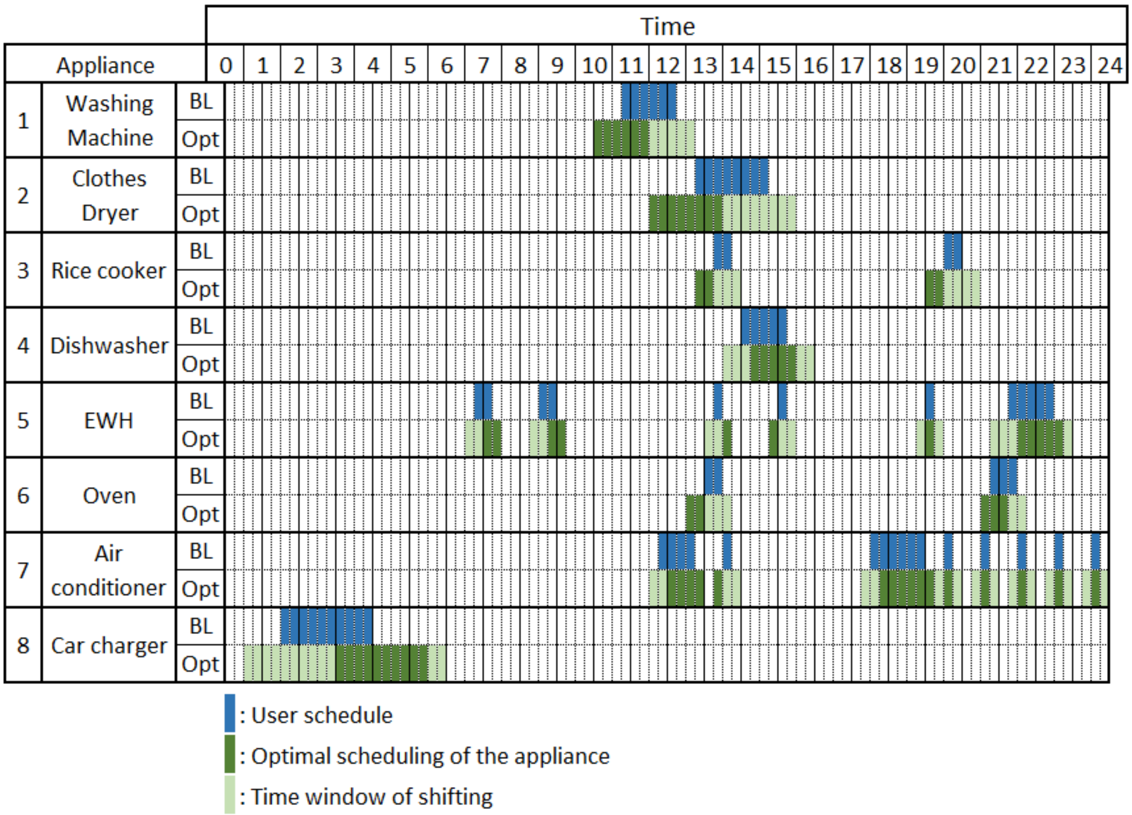

Figure 5.13 – Result of the load shifting for the higher inconvenience cost: January, small PV production, δ=0.1%, small variation of the RTP driven by renewable availability.

Further results regarding the different scenarios obtained through the implementation of this second type of RTP model are available in Appendix B.

As final comments, it is noted that more willingness to accept discomfort generally leads to greater amount of cost savings as a result of the DR actions and higher variability in prices makes the whole system more attractive.

The result of the implemented optimization model scheduling loads as well as a BS unit, taking into consideration the forecast of the output of a PV system is able to produce significant cost savings.

6. Conclusions

The need for the decarbonization of the electricity production sector caused by the understanding of the impact of energy related greenhouse gases emissions in climate change and on the limited resources of fossil fuels led to the rapid expansion of the renewable energy production sector. The electricity generated by this sector is extremely dependent on fluctuations of the primary energy sources which therefore imply difficult constraints to the power system. For example, the energy from the sun is essentially available during daytime and depends on weather conditions. The wind energy and the hydroelectric generation are also dependent on the weather, and suffer also of deep seasonal variations. For a power system becoming more dependent on RES, this adds a significant variability of the supply to the natural variability of the demand, increasing the complexity of finding the essential balance.

Therefore, new solutions are required to grant reliability to the power system as 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 then 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.

The aim included the optimal rescheduling of the appliances with the minimum deviation from the baseline, taking into account a set of parameters defined by the user, as the acceptable shifting time-window and the level of discomfort allowed, responding to the daily prices and to the solar forecasts. The output of the algorithm also defines the periods when to charge and to discharge the battery system in order to complement load-shifting and to obtain larger savings.

Although the first results of applying 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, they increased significantly if a small PV production is considered, and reached significant cost savings (circa 70%) in periods of high solar generation. But, 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 BS system.

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 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.

The comparison of the different RTP models in the month of April revealed that with the same solar production, the amount of savings was larger for the second model, due to the existence of multiple peaks of price which the system avoided.

To note also that possible undesirable effects of causing new demand peaks in different periods were considered, in part assuming that a RTP price scheme will dynamically contribute to avoid this problem, but also by introducing a limit to the interconnection power, which didn't affect significantly the results.

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 minimize battery degradation.

Bibliography

Aalami, H., G. R. Yousefi, and M. Parsa Moghadam. 2008. ‘Demand Response Model Considering EDRP and TOU Programs’. In *2008 IEEE/PES Transmission and Distribution Conference and Exposition*, , 1–6.

Aalami, Habib Allah, and Sayyad Nojavan. 2016. ‘Energy Storage System and Demand Response Program Effects on Stochastic Energy Procurement of Large Consumers Considering Renewable Generation’. *Transmission Distribution IET Generation* 10(1): 107–14.

Alotto, Piergiorgio, Massimo Guarnieri, and Federico Moro. 2014. ‘Redox Flow Batteries for the Storage of Renewable Energy: A Review’. *Renewable and Sustainable Energy Reviews* 29: 325–35.

Aneke, Mathew, and Meihong Wang. 2016. ‘Energy Storage Technologies and Real Life Applications – A State of the Art Review’. *Applied Energy* 179: 350–77.

Arabali, A. et al. 2013. ‘Genetic-Algorithm-Based Optimization Approach for Energy Management’. *IEEE Transactions on Power Delivery* 28(1): 162–70.

Baboli, P Teimourzadeh, M Parsa Moghaddam, and F Fallahi. ‘Utilizing Electric Vehicles on Primary Frequency Control in Smart Power Grids’. : 5.

Bandyopadhyay, Arkasama, Benjamin D. Leibowicz, Emily A. Beagle, and Michael E. Webber. 2020. ‘As One Falls, Another Rises? Residential Peak Load Reduction through Electricity Rate Structures’. *Sustainable Cities and Society* 60: 102191.

Barbose, Galen, Charles Goldman, and Bernie Neenan. 2004. *A Survey of Utility Experience with Real Time Pricing*. Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States). https://www.osti.gov/biblio/836966 (September 9, 2020).

Bayram, Islam Safak, and Taha Selim Ustun. 2017. ‘A Survey on behind the Meter Energy Management Systems in Smart Grid’. *Renewable and Sustainable Energy Reviews* 72: 1208–32.

Bellekom, Sandra, René Benders, Steef Pelgröm, and Henk Moll. 2012. ‘Electric Cars and Wind Energy: Two Problems, One Solution? A Study to Combine Wind Energy and Electric Cars in 2020 in The Netherlands’. *Energy* 45(1): 859–66.

Borenstein, Severin. 2005. ‘The Long-Run Efficiency of Real-Time Electricity Pricing’. *The Energy Journal* 26(3). http://www.iaee.org/en/publications/ejarticle.aspx?id=2101 (September 9, 2020).

Boynuegri, A. Rifat et al. 2013. ‘Energy Management Algorithm for Smart Home with Renewable Energy Sources’. In *4th International Conference on Power Engineering, Energy and Electrical Drives*, , 1753–58.

Burger, Scott, Jose Pablo Chaves-Ávila, Carlos Batlle, and Ignacio J. Pérez-Arriaga. 2017. ‘A Review of the Value of Aggregators in Electricity Systems’. *Renewable and Sustainable Energy Reviews* 77: 395–405.

Burkhardt, Jesse, Kenneth Gillingham, and Praveen K Kopalle. 2019. *Experimental Evidence on the Effect of Information and Pricing on Residential Electricity Consumption*. National Bureau of Economic Research. Working Paper. http://www.nber.org/papers/w25576 (September 4, 2020).

Calvillo, C. F., A. Sánchez-Miralles, J. Villar, and F. Martín. 2016. 'Optimal Planning and Operation of Aggregated Distributed Energy Resources with Market Participation'. *Applied Energy* 182: 340–57.

Carli, Raffaele, Mariagrazia Dotoli, and Roberta Pellegrino. 2017. 'A Hierarchical Decision-Making Strategy for the Energy Management of Smart Cities'. *IEEE Transactions on Automation Science and Engineering* 14(2): 505–23.

Celebi, Emre, and J. David Fuller. 2007. 'A Model for Efficient Consumer Pricing Schemes in Electricity Markets'. *IEEE Transactions on Power Systems* 22(1): 60–67.

Chen, Cheng, Rui Xiong, and Weixiang Shen. 2018. 'A Lithium-Ion Battery-in-the-Loop Approach to Test and Validate Multiscale Dual H Infinity Filters for State-of-Charge and Capacity Estimation'. *IEEE Transactions on Power Electronics* 33(1): 332–42.

Chen, Haisheng et al. 2009. 'Progress in Electrical Energy Storage System: A Critical Review'. *Progress in Natural Science* 19(3): 291–312.

Department of Energy & Climate Change. 2010. 'Estimated Impacts of Energy and Climate Change Policies on Energy Prices and Bills'. https://www.gov.uk/government/collections/estimated-impacts-of-energy-and-climate-change-policies-on-energy-prices-and-bills.

Di Somma, M. et al. 2018. 'Stochastic Optimal Scheduling of Distributed Energy Resources with Renewables Considering Economic and Environmental Aspects'. *Renewable Energy* 116: 272–87.

Díaz-González, Francisco, Andreas Sumper, Oriol Gomis-Bellmunt, and Roberto Villafáfila-Robles. 2012. 'A Review of Energy Storage Technologies for Wind Power Applications'. *Renewable and Sustainable Energy Reviews* 16(4): 2154–71.

Ejaz, Waleed et al. 2017. 'Efficient Energy Management for the Internet of Things in Smart Cities'. *IEEE Communications Magazine* 55(1): 84–91.

Fachechi, A. et al. 2015. 'A New Vehicle-to-Grid System for Battery Charging Exploiting IoT Protocols'. In *2015 IEEE International Conference on Industrial Technology (ICIT)*, , 2154–59.

Faruqui, Ahmad, and Sanem Sergici. 2010. 'Household Response to Dynamic Pricing of Electricity: A Survey of 15 Experiments'. *Journal of Regulatory Economics* 38(2): 193–225.

Federal Energy Regulatory Commission. 2012. 'Assessment of Demand Response & Advanced Metering - Staff Report'.

Figgener, Jan et al. 2020. 'The Development of Stationary Battery Storage Systems in Germany – A Market Review'. *Journal of Energy Storage* 29: 101153.

Ghasemi, Ahmad, Seyed Saeidollah Mortazavi, and Elaheh Mashhour. 2016. 'Hourly Demand Response and Battery Energy Storage for Imbalance Reduction of Smart

Distribution Company Embedded with Electric Vehicles and Wind Farms'. *Renewable Energy* 85: 124–36.

Goel, Lalit, Viswanath P. Aparna, and Peng Wang. 2007. 'A Framework to Implement Supply and Demand Side Contingency Management in Reliability Assessment of Restructured Power Systems'. *IEEE Transactions on Power Systems* 22(1): 205–12.

Gong, Yanmin, Ying Cai, Yuanxiong Guo, and Yuguang Fang. 2016. 'A Privacy-Preserving Scheme for Incentive-Based Demand Response in the Smart Grid'. *IEEE Transactions on Smart Grid* 7(3): 1304–13.

Guena, T., and P. Leblanc. 2006. 'How Depth of Discharge Affects the Cycle Life of Lithium-Metal-Polymer Batteries'. In *INTELEC 06 - Twenty-Eighth International Telecommunications Energy Conference*, , 1–8.

He, Hongwen, Rui Xiong, and Jiankun Peng. 2016. 'Real-Time Estimation of Battery State-of-Charge with Unscented Kalman Filter and RTOS MCOS-II Platform'. *Applied Energy* 162: 1410–18.

He, Y., B. Venkatesh, and L. Guan. 2012. 'Optimal Scheduling for Charging and Discharging of Electric Vehicles'. *IEEE Transactions on Smart Grid* 3(3): 1095–1105.

He, Yongxiu et al. 2012. 'Residential Demand Response Behavior Analysis Based on Monte Carlo Simulation: The Case of Yinchuan in China'. *Energy* 47(1): 230–36.

Hemmati, Reza. 2018. 'Optimal Design and Operation of Energy Storage Systems and Generators in the Network Installed with Wind Turbines Considering Practical Characteristics of Storage Units as Design Variable'. *Journal of Cleaner Production* 185: 680–93.

Ikäheimo, Jussi, Corentin Evens, and Seppo Kärkkäinen. 2010. 'Aggregator Business: The Finnish Case'.

International Energy Agency. 2013. *World Energy Outlook 2013.* Paris: International Energy Agency. http://dx.doi.org/10.1787/weo-2013-en (April 8, 2019).

Izadkhast, S., P. Garcia-Gonzalez, and P. Frías. 2015. 'An Aggregate Model of Plug-In Electric Vehicles for Primary Frequency Control'. *IEEE Transactions on Power Systems* 30(3): 1475–82.

Karellas, S., and N. Tzouganatos. 2014. 'Comparison of the Performance of Compressed-Air and Hydrogen Energy Storage Systems: Karpathos Island Case Study'. *Renewable and Sustainable Energy Reviews* 29: 865–82.

Khan, Imran. 2019. 'Energy-Saving Behaviour as a Demand-Side Management Strategy in the Developing World: The Case of Bangladesh'. *International Journal of Energy and Environmental Engineering* 10(4): 493–510.

Khan, Reduan H., and Jamil Y. Khan. 2013. 'A Comprehensive Review of the Application Characteristics and Traffic Requirements of a Smart Grid Communications Network'. *Computer Networks* 57(3): 825–45.

Kousksou, T. et al. 2014. 'Energy Storage: Applications and Challenges'. *Solar Energy Materials and Solar Cells* 120: 59–80.

Lazard. 2016. 'Lazard's Levelized Cost of Storage'.

Lee, Jeong In et al. 2011. 'A Study on the Use Cases of the Smart Grid Home Energy Management System'. In *ICTC 2011*, , 746–50.

Liu, Zhenhua et al. 2013. 'Data Center Demand Response: Avoiding the Coincident Peak via Workload Shifting and Local Generation'. *Performance Evaluation* 70(10): 770–91.

Lyons, P. F. et al. 2015. 'Design and Analysis of Electrical Energy Storage Demonstration Projects on UK Distribution Networks'. *Applied Energy* 137: 677–91.

Lyons, P. F., P. Trichakis, P. C. Taylor, and G. Coates. 2010. 'A Practical Implementation Of A Distributed Control Approach For Microgrids'. *Intelligent Automation & Soft Computing* 16(2): 319–34.

Ma, Hongrui et al. 2012. 'A New Comparison between the Life Cycle Greenhouse Gas Emissions of Battery Electric Vehicles and Internal Combustion Vehicles'. *Energy Policy* 44: 160–73.

Ma, Jinghuan, He Henry Chen, Lingyang Song, and Yonghui Li. 2016. 'Residential Load Scheduling in Smart Grid: A Cost Efficiency Perspective'. *IEEE Transactions on Smart Grid* 7(2): 771–84.

Ma, Tao, Hongxing Yang, and Lin Lu. 2014. 'Feasibility Study and Economic Analysis of Pumped Hydro Storage and Battery Storage for a Renewable Energy Powered Island'. *Energy Conversion and Management* 79: 387–97.

Manzoor, Awais et al. 2017. 'An Intelligent Hybrid Heuristic Scheme for Smart Metering Based Demand Side Management in Smart Homes'. *Energies* 10(9): 1258.

Mohagheghi, Salman et al. 2010. 'Demand Response Architecture: Integration into the Distribution Management System'. In *2010 First IEEE International Conference on Smart Grid Communications*, , 501–6.

Newsham, Guy R., and Brent G. Bowker. 2010. 'The Effect of Utility Time-Varying Pricing and Load Control Strategies on Residential Summer Peak Electricity Use: A Review'. *Energy Policy* 38(7): 3289–96.

Nguyen, H. K., J. B. Song, and Z. Han. 2015. 'Distributed Demand Side Management with Energy Storage in Smart Grid'. *IEEE Transactions on Parallel and Distributed Systems* 26(12): 3346–57.

Niesten, Eva, and Floortje Alkemade. 2016. 'How Is Value Created and Captured in Smart Grids? A Review of the Literature and an Analysis of Pilot Projects'. *Renewable and Sustainable Energy Reviews* 53: 629–38.

Nikmehr, Nima, Sajad Najafi-Ravadanegh, and Amin Khodaei. 2017. 'Probabilistic Optimal Scheduling of Networked Microgrids Considering Time-Based Demand Response Programs under Uncertainty'. *Applied Energy* 198: 267–79.

Nirmalya Roy, Abhishek Roy, and S.K. Das. 2006. 'Context-Aware Resource Management in Multi-Inhabitant Smart Homes a Nash H-Learning Based Approach'. In *Fourth Annual IEEE International Conference on Pervasive Computing and Communications (PERCOM'06)*, , 11 pp. – 158.

Paterakis, Nikolaos G., Ozan Erdinc, Anastasios G. Bakirtzis, and Joao P. S. Catalao. 2015. 'Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies'. *IEEE Transactions on Industrial Informatics* 11(6): 1509–19.

Peterson, Scott B., Jay Apt, and J. F. Whitacre. 2010. 'Lithium-Ion Battery Cell Degradation Resulting from Realistic Vehicle and Vehicle-to-Grid Utilization'. *Journal of Power Sources* 195(8): 2385–92.

Pillai, J. R., and B. Bak-Jensen. 2010. 'Vehicle-to-Grid Systems for Frequency Regulation in an Islanded Danish Distribution Network'. In *2010 IEEE Vehicle Power and Propulsion Conference*, , 1–6.

Pipattanasomporn, Manisa, Murat Kuzlu, and Saifur Rahman. 2012. 'An Algorithm for Intelligent Home Energy Management and Demand Response Analysis'. *IEEE Transactions on Smart Grid* 3(4): 2166–73.

Rassenti, Stephen J., Vernon L. Smith, and Bart J. Wilson. 2003. 'Controlling Market Power and Price Spikes in Electricity Networks: Demand-Side Bidding'. *Proceedings of the National Academy of Sciences* 100(5): 2998–3003.

Rehman, U. ur, and M. Riaz. 2017. 'Vehicle to Grid System for Load and Frequency Management in Smart Grid'. In *2017 International Conference on Open Source Systems Technologies (ICOSST)*, , 73–78.

RNC2050. 2019. 'Long-Term Strategy for Carbon Neutrality of the Portugese Economy by 2050'.

Sauer, Dirk Uwe, and Heinz Wenzl. 2008. 'Comparison of Different Approaches for Lifetime Prediction of Electrochemical Systems—Using Lead-Acid Batteries as Example'. *Journal of Power Sources* 176(2): 534–46.

Sebastián, R., and R. Peña Alzola. 2012. 'Flywheel Energy Storage Systems: Review and Simulation for an Isolated Wind Power System'. *Renewable and Sustainable Energy Reviews* 16(9): 6803–13.

Setlhaolo, Ditiro, and Xiaohua Xia. 2015. 'Optimal Scheduling of Household Appliances with a Battery Storage System and Coordination'. *Energy and Buildings* 94: 61–70.

Shao, S., M. Pipattanasomporn, and S. Rahman. 2013. 'Development of Physical-Based Demand Response-Enabled Residential Load Models'. *IEEE Transactions on Power Systems* 28(2): 607–14.

Shareef, Hussain, Maytham S. Ahmed, Azah Mohamed, and Eslam Al Hassan. 2018. 'Review on Home Energy Management System Considering Demand Responses, Smart Technologies, and Intelligent Controllers'. *IEEE Access* 6: 24498–509.

Shi, Yuanyuan, Bolun Xu, Yushi Tan, and Baosen Zhang. 2018. 'A Convex Cycle-Based Degradation Model for Battery Energy Storage Planning and Operation'. In *2018 Annual American Control Conference (ACC)*, , 4590–96.

Siano, Pierluigi. 2014. 'Demand Response and Smart Grids—A Survey'. *Renewable and Sustainable Energy Reviews* 30: 461–78.

Sou, Kin Cheong, James Weimer, Henrik Sandberg, and Karl Henrik Johansson. 2011. 'Scheduling Smart Home Appliances Using Mixed Integer Linear Programming'. In

2011 50th IEEE Conference on Decision and Control and European Control Conference, , 5144–49.

Stenner, Karen, Elisha R. Frederiks, Elizabeth V. Hobman, and Stephanie Cook. 2017. ‘Willingness to Participate in Direct Load Control: The Role of Consumer Distrust’. *Applied Energy* 189: 76–88.

al-sumaiti, Ameena Saad, Mohammed Hassan Ahmed, and Magdy M. A. Salama. 2014. ‘Smart Home Activities: A Literature Review’. *Electric Power Components and Systems* 42(3–4): 294–305.

Terci Flores, Jardel et al. 2016. ‘Demand Planning in Smart Homes’. *IEEE Latin America Transactions* 14(7): 3247–55.

Ummel, Kevin. 2012. ‘CARMA Revisited: An Updated Database of Carbon Dioxide Emissions from Power Plants Worldwide - Working Paper 304’. *Center For Global Development*. https://www.cgdev.org/publication/carma-revisited-updated-database-carbon-dioxide-emissions-power-plants-worldwide-working (September 6, 2020).

University of Delaware. 2019. ‘The Grid-Integrated Vehicle with Vehicle to Grid Technology’. http://www1.udel.edu/V2G/index.html (April 17, 2019).

U.S. Department of Energy. 2006. *Benefits of Demand Response in Electricity Markets and Recommendations*.

Uttama Nambi, Akshay S.N., Antonio Reyes Lua, and Venkatesha R. Prasad. 2015. ‘LocED: Location-Aware Energy Disaggregation Framework’. In *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, BuildSys ’15, New York, NY, USA: Association for Computing Machinery, 45–54. https://doi.org/10.1145/2821650.2821659 (August 21, 2020).

Wang, John et al. 2011. ‘Cycle-Life Model for Graphite-LiFePO4 Cells’. *Journal of Power Sources* 196(8): 3942–48.

Wang, Z. et al. 2013. ‘Active Demand Response Using Shared Energy Storage for Household Energy Management’. *IEEE Transactions on Smart Grid* 4(4): 1888–97.

Wolak, Frank A. 2007. ‘Residential Customer Response to Real-Time Pricing: The Anaheim Critical Peak Pricing Experiment’. https://escholarship.org/uc/item/3td3n1x1 (September 9, 2020).

Wu, Xiaohua et al. 2017. ‘Optimal Battery Sizing of Smart Home via Convex Programming’. *Energy* 140: 444–53.

Yahia, Z., and A. Pradhan. 2018. ‘Optimal Load Scheduling of Household Appliances Considering Consumer Preferences: An Experimental Analysis’. *Energy* 163: 15–26.

Yao, Leehter, Jin-Yi Shen, and Wei Hong Lim. 2016. ‘Real-Time Energy Management Optimization for Smart Household’. In *2016 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*, , 20–26.

Yu, Zhe et al. 2013. ‘Modeling and Stochastic Control for Home Energy Management’. *IEEE Transactions on Smart Grid* 4(4): 2244–55.

Zakeri, Behnam, and Sanna Syri. 2015. ‘Electrical Energy Storage Systems: A Comparative Life Cycle Cost Analysis’. *Renewable and Sustainable Energy Reviews* 42: 569–96.

Zhang, Qin, and Juan Li. 2012. ‘Demand Response in Electricity Markets: A Review - IEEE Conference Publication’. *2012 9th International Conference on the European Energy Market*. https://ieeexplore.ieee.org/abstract/document/6254817 (January 14, 2020).

Zhang, Yang et al. 2017. ‘Battery Sizing and Rule-Based Operation of Grid-Connected Photovoltaic-Battery System: A Case Study in Sweden’. *Energy Conversion and Management* 133: 249–63.

Zhao, Haoran et al. 2015. ‘Review of Energy Storage System for Wind Power Integration Support’. *Applied Energy* 137: 545–53.

Zhao, Zhuang, Won Cheol Lee, Yoan Shin, and Kyung-Bin Song. 2013. ‘An Optimal Power Scheduling Method for Demand Response in Home Energy Management System’. *IEEE Transactions on Smart Grid* 4(3): 1391–1400.

Zheng, Menglian. 2015. ‘Smart Households: Economics and Emission Impacts of Distributed Energy Storage for Residential Sector Demand Response’. https://academiccommons.columbia.edu/doi/10.7916/D89P315H (September 9, 2020).

Zheng, Menglian, Christoph J. Meinrenken, and Klaus S. Lackner. 2015. ‘Smart Households: Dispatch Strategies and Economic Analysis of Distributed Energy Storage for Residential Peak Shaving’. *Applied Energy* 147: 246–57.

Zheng, Menglian, Xinhao Wang, Christoph J. Meinrenken, and Yi Ding. 2018. ‘Economic and Environmental Benefits of Coordinating Dispatch among Distributed Electricity Storage’. *Applied Energy* 210: 842–55.

Zhong, Haiwang, Le Xie, and Qing Xia. 2013. ‘Coupon Incentive-Based Demand Response: Theory and Case Study’. *IEEE Transactions on Power Systems* 28(2): 1266–76.

Zhou, Suyang, Zhi Wu, Jianing Li, and Xiao-ping Zhang. 2014. ‘Real-Time Energy Control Approach for Smart Home Energy Management System’. *Electric Power Components and Systems* 42(3–4): 315–26.

Zou, Changfu, Xiaosong Hu, Zhongbao Wei, and Xiaolin Tang. 2017. ‘Electrothermal Dynamics-Conscious Lithium-Ion Battery Cell-Level Charging Management via State-Monitored Predictive Control’. *Energy* 141: 250–59.

A. RTP model driven by the actual OMIE - implementation results

Table A.1 – "Small Peak" case implementation.

δ	Inc. Cost	Final Cost	Potential Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JANUARY									
PV Forecast: High - PV Real Production: High									
100.00%	0	2.838	2.628	48.08	1.100	41.86	3.156	0.318	5.82
10.00%	0.203	2.816	2.650	48.48	1.050	39.62	3.135	0.319	5.84
1.00%	1.896	2.756	2.710	49.58	0.806	29.74	3.054	0.298	5.45
0.10%	1.896	2.736	2.730	49.95	0.806	29.52	3.054	0.318	5.82
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.941	1.525	27.90	0.511	33.51	4.783	0.842	15.40
10.00%	0.103	3.928	1.538	28.14	0.434	28.22	4.770	0.842	15.40
1.00%	1.455	3.863	1.603	29.33	0.351	21.90	4.705	0.842	15.40
0.10%	2.593	3.858	1.608	29.42	0.331	20.58	4.700	0.842	15.40
APRIL									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.765	3.684	67.61	1.771	48.07	1.834	0.069	1.27
10.00%	0.113	1.752	3.697	67.85	1.754	47.44	1.83	0.078	1.43
1.00%	0.630	1.720	3.729	68.43	1.750	46.93	1.795	0.075	1.38
0.10%	0.734	1.719	3.730	68.45	1.707	45.76	1.794	0.075	1.38
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.636	0.813	14.92	0.276	33.92	4.859	0.223	4.09
10.00%	0	4.636	0.813	14.92	0.276	33.92	4.850	0.214	3.93
1.00%	1.919	4.578	0.871	15.98	0.196	22.50	4.800	0.222	4.07
0.10%	2.470	4.576	0.873	16.02	0.187	21.42	4.799	0.223	4.09

δ	Inc. Cost	Final Cost	Potential Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JULY									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.636	3.901	70.45	1.944	49.83	1.878	0.240	4.37
10.00%	0.191	1.597	3.940	71.16	1.944	49.34	1.839	0.240	4.37
1.00%	1.719	1.540	3.997	72.19	1.652	41.33	1.780	0.240	4.37
0.10%	1.952	1.536	4.001	72.26	1.639	40.96	1.780	0.242	4.41
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.603	1.934	34.93	0.776	40.12	3.730	0.127	2.31
10.00%	0.190	3.564	1.973	35.63	0.776	39.33	3.692	0.127	2.31
1.00%	2.200	3.505	2.032	36.70	0.600	29.53	3.633	0.127	2.31
0.10%	2.200	3.505	2.032	36.70	0.600	29.53	3.633	0.127	2.31
OCTOBER									
PV Forecast: High - PV Real Production: High									
100.00%	0	2.806	2.700	49.04	1.174	43.48	4.206	1.400	25.43
10.00%	0	2.806	2.700	49.04	1.174	43.48	4.206	1.400	25.43
1.00%	2.461	2.699	2.807	50.98	0.908	32.35	4.100	1.401	25.44
0.10%	2.461	2.699	2.807	50.98	0.908	32.35	4.100	1.401	25.44
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.423	1.083	19.67	0.299	27.61	4.736	0.313	5.68
10.00%	0	4.423	1.083	19.67	0.299	27.61	4.736	0.313	5.68
1.00%	2.026	4.350	1.156	21.00	0.233	20.11	4.664	0.314	5.70
0.10%	2.779	4.350	1.156	21.00	0.213	18.40	4.660	0.310	5.63

Table A.2 – "Big Peak" case implementation

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JANUARY									
PV Forecast: High - PV Real Production: High									
100.00%	0	2.849	2.716	48.81	1.188	43.74	3.168	0.319	5.73
10.00%	0.116	2.837	2.728	49.02	1.133	41.53	3.168	0.331	5.95
1.00%	1.785	2.765	2.800	50.31	0.910	32.50	3.095	0.330	5.93
0.10%	1.964	2.765	2.800	50.31	0.910	32.50	3.090	0.325	5.84
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.966	1.599	28.73	0.529	33.08	4.833	0.867	15.58
10.00%	0	3.966	1.599	28.73	0.548	34.27	4.833	0.867	15.58
1.00%	1.433	3.905	1.660	29.83	0.368	22.17	4.772	0.867	15.58
0.10%	2.184	3.901	1.664	29.90	0.373	22.42	4.768	0.867	15.58
APRIL									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.534	3.902	71.78	1.884	48.28	1.613	0.079	1.45
10.00%	0.120	1.521	3.915	72.02	1.862	47.56	1.599	0.078	1.43
1.00%	0.405	1.509	3.927	72.24	1.856	47.26	1.588	0.079	1.45
0.10%	0.405	1.509	3.927	72.24	1.856	47.26	1.588	0.079	1.45
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.402	1.034	19.02	0.464	44.87	4.638	0.236	4.34
10.00%	0	4.402	1.034	19.02	0.464	44.87	4.639	0.237	4.36
1.00%	0.954	4.370	1.066	19.61	0.391	36.68	4.607	0.237	4.36
0.10%	1.998	4.366	1.070	19.68	0.369	34.49	4.603	0.237	4.36

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JULY									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.636	3.901	70.45	1.944	49.83	1.878	0.242	4.37
10.00%	0.191	1.597	3.940	71.16	1.944	49.34	1.839	0.242	4.37
1.00%	1.719	1.540	3.997	72.19	1.652	41.33	1.780	0.240	4.33
0.10%	1.952	1.536	4.001	72.26	1.639	40.96	1.780	0.244	4.41
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.603	1.934	34.93	0.776	40.12	3.730	0.127	2.29
10.00%	0.190	3.564	1.973	35.63	0.776	39.33	3.692	0.128	2.31
1.00%	2.200	3.505	2.032	36.70	0.600	29.53	3.633	0.128	2.31
0.10%	2.200	3.505	2.032	36.70	0.600	29.53	3.633	0.128	2.31
OCTOBER									
PV Forecast: High - PV Real Production: High									
100.00%	0	2.486	3.005	54.73	1.594	53.04	3.789	1.303	23.73
10.00%	0.358	2.430	3.061	55.75	1.594	52.07	3.733	1.303	23.73
1.00%	1.720	2.379	3.112	56.67	1.346	43.25	3.682	1.303	23.73
0.10%	1.942	2.378	3.113	56.69	1.317	42.31	3.680	1.302	23.71
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.006	1.485	27.04	0.7645	51.48	4.296	0.290	5.28
10.00%	0.182	3.976	1.515	27.59	0.760	50.17	4.266	0.290	5.28
1.00%	1.644	3.930	1.561	28.43	0.668	42.79	4.221	0.291	5.30
0.10%	2.244	3.930	1.561	28.43	0.651	41.70	4.219	0.289	5.26

B. RTP model driven by RES availability - implementation results

Table B.1 – "Small Peak" case implementation.

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JANUARY									
PV Forecast: High - PV Real Production: High									
100.00%	0	3.163	2.354	42.66	0.986	41.88	3.480	0.3162	5.73
10.00%	0.107	3.149	2.369	42.93	0.929	39.21	3.467	0.318	5.76
1.00%	2.128	3.049	2.469	44.74	0.725	29.36	3.366	0.317	5.74
0.10%	2.350	3.040	2.478	44.91	0.710	28.65	3.360	0.320	5.80
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.250	1.268	22.98	0.349	27.52	5.079	0.313	5.68
10.00%	0.107	4.245	1.273	23.07	0.317	24.90	5.065	0.313	5.68
1.00%	2.242	4.148	1.370	24.83	0.389	28.39	4.967	0.314	5.70
0.10%	3.150	4.130	1.388	25.15	0.330	23.78	4.952	0.310	5.63
APRIL									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.869	3.366	64.30	1.63	48.43	1.960	0.091	1.74
10.00%	0.437	1.789	3.446	65.83	1.565	45.41	1.880	0.091	1.74
1.00%	0.729	1.767	3.468	66.25	1.433	41.32	1.857	0.090	1.72
0.10%	0.795	1.766	3.469	66.27	1.206	34.77	1.857	0.091	1.74
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.112	1.123	21.45	0.568	50.58	4.402	0.290	5.54
10.00%	0.706	3.987	1.248	23.84	0.526	42.15	4.277	0.290	5.54
1.00%	1.453	3.956	1.279	24.43	0.478	37.37	4.246	0.290	5.54
0.10%	1.609	3.955	1.280	24.45	0.469	36.64	4.246	0.291	5.56

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JULY									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.900	3.336	63.71	1.149	34.44	2.211	0.311	5.94
10.00%	0.427	1.800	3.436	65.62	1.110	32.31	2.110	0.310	5.92
1.00%	1.700	1.758	3.478	66.42	0.829	23.84	2.070	0.312	5.96
0.10%	1.874	1.757	3.479	66.44	0.826	23.74	2.068	0.311	5.94
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.237	1.999	38.18	0.629	31.47	3.350	0.113	2.16
10.00%	1.038	3.000	2.236	42.70	0.604	27.01	3.123	0.123	2.35
1.00%	1.584	2.990	2.246	42.90	0.537	23.91	3.106	0.116	2.22
0.10%	2.777	2.980	2.256	43.09	0.507	22.47	3.100	0.120	2.29
OCTOBER									
PV Forecast: High - PV Real Production: High									
100.00%	0	2.725	2.737	50.11	1.256	45.89	3.988	1.263	23.12
10.00%	0	2.725	2.737	50.11	1.261	46.07	3.988	1.263	23.12
1.00%	1.993	2.650	2.812	51.48	1.230	43.74	3.915	1.265	23.16
0.10%	2.585	2.647	2.815	51.54	1.119	39.75	3.910	1.263	23.12
PV Forecast: Small - PV Real Production: Small									
100.00%	0	4.266	1.196	21.90	0.427	35.70	4.545	0.279	5.11
10.00%	0	4.267	1.195	21.88	0.443	37.07	4.480	0.213	3.90
1.00%	1.537	4.203	1.259	23.05	0.416	33.03	4.482	0.279	5.11
0.10%	1.911	4.200	1.262	23.11	0.407	32.25	4.479	0.279	5.11

Table B.2 – "Big Peak" case implementation

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JANUARY									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.385	4.068	74.60	2.605	64.03	1.797	0.412	7.55
10.00%	0	1.385	4.068	74.60	2.605	64.03	1.797	0.412	7.55
1.00%	1.216	1.350	4.103	75.24	2.127	51.84	1.762	0.412	7.55
0.10%	1.426	1.349	4.104	75.26	2.250	54.82	1.761	0.412	7.55
PV Forecast: Small - PV Real Production: Small									
100.00%	0	2.067	3.386	62.10	2.342	69.16	3.157	1.090	19.99
10.00%	0.448	2.000	3.453	63.33	2.165	62.69	3.090	1.090	19.99
1.00%	1.403	1.966	3.487	63.95	2.100	60.22	3.057	1.091	20.01
0.10%	1.602	1.966	3.487	63.95	2.223	63.74	3.049	1.083	19.86
APRIL									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.345	3.868	74.20	1.590	41.11	1.455	0.110	2.11
10.00%	0.307	1.290	3.923	75.25	1.590	40.53	1.401	0.111	2.13
1.00%	0.606	1.273	3.940	75.58	1.336	33.91	1.383	0.110	2.11
0.10%	0.687	1.272	3.941	75.60	1.532	38.87	1.383	0.111	2.13
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.642	1.571	30.14	0.908	57.80	3.983	0.341	6.54
10.00%	0.307	3.602	1.611	30.90	0.894	55.49	3.942	0.340	6.52
1.00%	1.250	3.577	1.636	31.38	0.821	50.18	3.917	0.340	6.52
0.10%	2.209	3.575	1.638	31.42	0.849	51.83	3.912	0.337	6.46

δ	Inc. Cost	Final Cost	Expected Savings	%	BS Savings	%	Real Cost	Savings Mismatch	%
JULY									
PV Forecast: High - PV Real Production: High									
100.00%	0	1.460	4.163	74.04	1.682	40.40	1.763	0.303	5.39
10.00%	0	1.460	4.163	74.04	1.699	40.81	1.763	0.303	5.39
1.00%	1.433	1.405	4.218	75.01	1.362	32.29	1.706	0.301	5.35
0.10%	1.678	1.403	4.220	75.05	1.352	32.04	1.705	0.302	5.37
PV Forecast: Small - PV Real Production: Small									
100.00%	0	3.226	2.397	42.63	0.967	40.34	3.390	0.164	2.92
10.00%	0	3.226	2.397	42.63	0.967	40.34	3.390	0.164	2.92
1.00%	0.863	3.200	2.423	43.09	0.786	32.44	3.360	0.160	2.85
0.10%	1.786	3.189	2.434	43.29	0.749	30.77	3.350	0.161	2.86
OCTOBER									
PV Forecast: High - PV Real Production: High									
100.00%	0	0.709	4.886	87.33	4.227	86.51	1.465	0.756	13.51
10.00%	0.200	0.672	4.923	87.99	4.227	85.86	1.428	0.756	13.51
1.00%	0.604	0.658	4.937	88.24	4.091	82.86	1.413	0.755	13.49
0.10%	0.895	0.657	4.938	88.26	4.043	81.88	1.412	0.755	13.49
PV Forecast: Small - PV Real Production: Small									
100.00%	0	1.242	4.353	77.80	3.980	91.43	1.420	0.178	3.18
10.00%	0.526	1.133	4.462	79.75	4.005	89.76	1.312	0.179	3.20
1.00%	0.775	1.125	4.470	79.89	3.951	88.39	1.304	0.179	3.20
0.10%	0.961	1.124	4.471	79.91	3.960	88.57	1.303	0.179	3.20