Impact of flexible assets on a microgrid

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Abstract

The current decarbonization of the energy sector has led to an impressive increase of the variable renewable energy (VRE) capacity installed in the network. To provide the electric power system with the required flexibility to efficiently integrate the growing VRE capacity, innovative solutions have to be developed. Additionally, the current energy sector is revolutionizing: its electrification, digitalization and decentralisation are offering more opportunities to tackle these challenges.

This work studies how the introduction of a cluster of flexible assets – electric water heaters (EWHs) – affects a community energy self-sufficiency and, thus, how it could help to integrate VRE in the network. To pursue this goal, economic and self-consumption benefits have been studied and quantified selecting a well-defined sample of customers, composed by low voltage and medium voltage clients, fed by the grid and locally installed solar photovoltaic power plants. The cluster of locally existing EWHs has been controlled by a load-shifting Demand Response (DR) strategy aiming to increase the self-consumption – and consequently delivering economic savings – while maintaining the end-users' comfort. Finally, to quantify the flexible assets' impacts, it has been developed an energy balance simulation tool to analyse the changes in the demand profiles between the scenarios with and without DR implementation.

Keywords

Microgrid; Demand Response; Variable Renewable Energy system integration; Self-consumption

Resumo

As preocupações com a descarbonização do setor energético têm levado a um aumento significativo da capacidade instalada de Energias Renováveis Variáveis (ERV). Para dotar o sistema de energia elétrica da flexibilidade necessária à integração crescente deste tipo de capacidade, têm sido propostas soluções inovadoras que devem ser desenvolvidas no contexto das alterações que se perspectivam para o setor energético, nomeadamente a sua eletrificação, digitalização e descentralização.

Neste trabalho é estudado o impacto da introdução de um *cluster* de ativos flexíveis – termoacumuladores eléctricos (TE) – sobre a auto-suficiência energética de uma pequena comunidade, avaliando simultaneamente o potencial deste tipo de flexibilidade para permitir aumentar a integração de ERV. Para alcançar este objetivo, foram quantificados os benefícios económicos do autoconsumo, selecionando para isso uma amostra bem definida de clientes de baixa e média tensão, alimentados pela rede e por centrais solar fotovoltaicas instaladas nas imediações da comunidade. Foi desenvolvida e implementada uma estratégia de Gestão de Consumos (GC) referentes ao *cluster* de TEs que se baseia na possibilidade de adiar os períodos de aquecimento da água com o objetivo de aumentar o autoconsumo e, consequentemente, a factura energética dos consumidores, garantindo o conforto do utilizador final. Finalmente, para quantificar os impactos da flexibilidade conseguida com a GC, foram comparados com recurso a simulação os balanços energéticos que resultam das alteações aos diagramas carga entre cenários com e sem CG.

Palavras-Chaves

Microgrid; Gestão de Consumos; Integração de Energias Renováveis Variáveis; Autoconsumo

Table of Contents

List of Figures

List of Tables

List of Abbreviations

DER	Distributed Energy Resource
DR	Demand Response
DSM	Demand Side Management
EDP	Energia De Portugal
EWH	Electric Water Heater
ICES	Integrated Community Energy System
IEA	International Energy Agency
IoT	Internet of Things
MV	Medium Voltage
O&M	Operation and Maintenance
LC	Levelized Cost
LCOE	Levelized Cost of Electricity
LV	Low Voltage
NPC	Net Present Cost
PCG	Prosumers Community Group
PV	Photovoltaic
SCR	Self-Consumption Rate
SSR	Self-Sufficiency Rate
TCL	Thermostatically Controlled Load
VRE	Variable Renewable Energy
VPP	Virtual Power Plant

1. Introduction

In the last few years, the decarbonization of the energy sector has led to a significant increase in the renewable power generation capacity worldwide. In 2015, for the first time, the renewable added power in the World has been greater than half of the total net power addition, overcoming even the share of new coal power plants installed. The majority of the new renewable power plants in 2015, accounting for over 70%, has been solar Photovoltaic (PV) and wind – referred as Variable Renewable Energy (VRE) – and a similar trend has been forecasted for the coming years. An increased share of VRE brings several advantages to the system, such as reduction in fuel costs and CO_2 emissions, but, where a proper system integration is not performed, it could also lead to significantly increased costs due to the need of improvements in the infrastructure. The International Energy Agency (IEA) has performed a study, [1], to analyse how these new technologies impact the traditional system and it has defined four phases of VRE deployment:

1. At this stage, the electricity provided by VRE is lower than 3 % of the total consumption and the system is not significantly affected by it;
2. When VRE contributes between 3 – 15 % of the total electricity production the system has to adopt some operation upgrades to face the volatility of this share of power generation. An example of a strategy implemented to deal with this situation is to forecast the VRE plants' output;
3. In the situation where the share reaches higher values, between 10 to 25 %, the VRE starts to impact also the other power plants besides the overall system operations. Starting from this phase, the system requires some degree of flexibility, therefore the ability to react to variability and uncertainty in the demand-supply balance. Nowadays, the main flexible resources exploited are the transmission grid and the dispatchable power plants such as hydroelectric and natural gas ones;
4. In the last phase, where VRE share reaches values higher than 25 %, new complex challenges related to the stability of the power system are emerging. At this stage, the system requires enough resilience to react to fast changes – in the order of magnitude of second or less – compared to its normal operation.

Currently (2018), many European countries are in the third and fourth stages of VRE development. Ireland and Denmark account an annual relative VRE generation share between 25 and 50 %, while Italy, the United Kingdom, Spain, Greece, Germany and Portugal have a VRE electricity production around 10 - 25 %.

To promptly tackle the challenges related to the increased volatility in the supply side, new innovative solutions need to be implemented. Demand Side Management (DSM) is one of those and it has recently attracted a significant attention from many experts and researchers in the energy field. As reported in [2], DSM is referred to as the "[…] planning, implementation, and monitoring of activities designed to encourage consumers to modify patterns of energy usage, including the timing and level of electricity demand". Demand response (DR) is a type of DSM and, quoting [3], it can be defined as "a change in the consumption pattern of electricity consumers […] in response to a signal […] or due to other incentives or objectives […]". Compared to other solutions that could increase the electrical system flexibility, by adopting DR strategies, it is possible to exploit the flexible potential of several assets already present in the grid, therefore minimizing the need to implement other technologies or operational strategies.

1.1. Aims and objectives

This thesis aims to analyse the impacts generated by introducing a cluster of flexible assets controlled with a specific DR strategy in a well-defined community. In order to do so, the focus is set on a specific asset, electric water heaters (EWHs), in a realistic but not existing community placed in Algarve, Portugal. The cluster of clients considered is fed by the grid and by locally installed PV power systems. By studying the energy balance between the community consumption and the local production, this work main objective is to quantify the technology delta induced by the implementation of the selected DR strategy. More specifically, the focus will be on:

1. Assessing the impacts related to the network perspective;
2. Quantifying the economic advantages related to the electricity bill of a community sharing part of its assets' flexibility;
3. Defining the changes in the self-consumption, therefore the consumption of locally produced electricity, derived from the control of the defined flexible load;
4. Studying how varying the locally installed VRE and the number of flexible assets impact the above-mentioned factors.

1.2. Document layout

For a more efficient reading, a simple document layout is below described.

In Chapter 2 there is a description of the work's background and motivations, with a focus on the current context, the methodology that has been implied in the literature to quantify the impact of DR programs and a review of previous works on this topic.

Chapter 3 presents the methodology adopted to analyse the impact of the flexible assets with a description of the energy balance between the community, the grid and the locally installed PV power systems, with a specific focus on the inputs and the outcomes of the simulation tools developed.

The results of the simulation code with related qualitative and quantitative descriptions are reported in Chapter 4.

Chapter 5 reports the work's conclusions with a proposal for future works.

2. Background and motivation

The energy system, as described in [4], is now facing a terrific transformation lead by three main pillars: electrification, digitalization and decentralization. All these trends are reshaping the current energy sector individually and by interacting with each other as shown in Figure 2.1. The electrification, specifically occurring in the heat and the transportation sector, is a key factor to decarbonize energy services historically provided by fossil fuels. The significant drop in the costs for distributed energy resources (DER), such as PV panels and battery storages, are increasing the share of active prosumers, therefore consumers that produce electricity, transforming the traditional end-users from passive to active players in the electrical system. Finally, as a result of decreased costs of microcontrollers, sensors and communication technologies, the dawn of the Internet of Things (IoT) era is offering the opportunity to provide new services for the grid and for the citizens. Consequently, the traditional roles of producers, distributors and customers are now being reshaped.

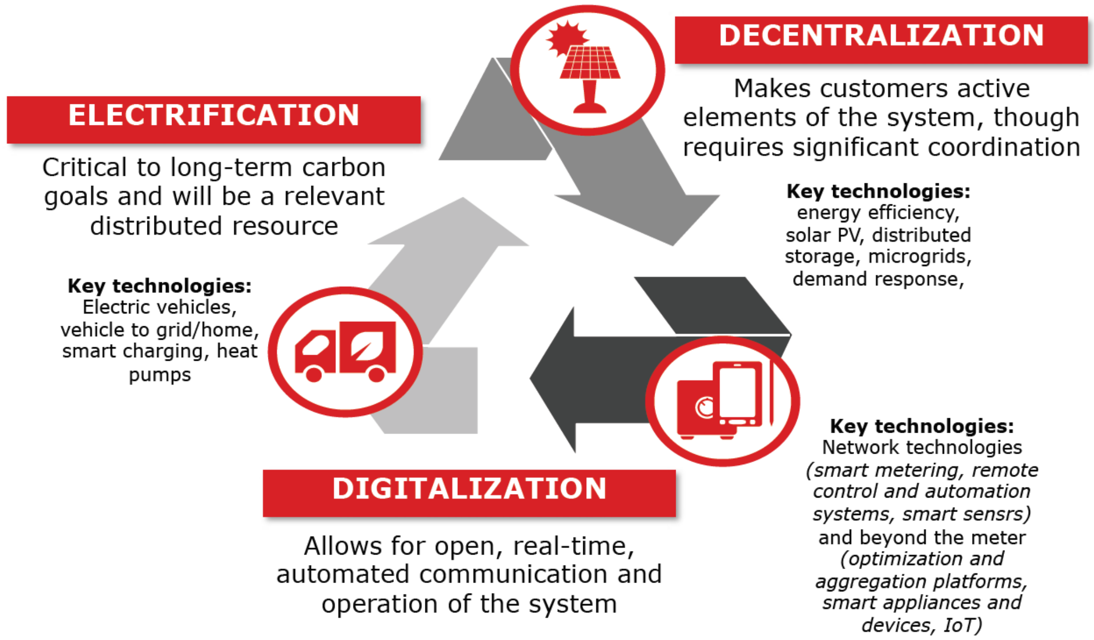

Figure 2.1. The three trends of the grid transformation [4]

Each of these three trends is strongly influencing and facilitating the implementation of DR strategies. The electrification of the heating and the transportation sectors is increasing the number of available flexible loads – assets that can provide flexibility to the electrical grid. The digitalization occurring in the electricity sector – specifically the deployment of technologies such as the smart meters, advanced communication and control technologies – is allowing to monitor and to control smaller loads in a more cost-effective way. Additionally, the increasing number of DER is significantly reshaping the old electrical system, transforming it from a one-directional system to a more complex multi-directional one. DR solutions present the potential to exploit the opportunities and help facing the challenges created by the above-mentioned evolution.

DSM is not a new concept: it has, in fact, already been implemented in the past, principally focusing on big customers' load's curtailment or interruption. Due to the electricity sector transformations described, the attention has now shifted to small users as well, creating the need to develop new effective DR programs and how to successfully implement them. For this reason, many research projects and centres have started worldwide: LINEAR [5] in Belgium, Demand Response Research Centre [6] in the USA and the IEA Demand Side Management Program [7] internationally are just a few examples.

2.1. European regulations related to Demand Response programs

Before analysing the potential outcomes derived from implementing DR programs, it is important to analyse the institutional context to comprehend the challenges and opportunities related. In the European Union, all the states member are encouraged to follow certain common rules about the energy sector. The recommendations come in form of directives that describe the requirements and guidelines for the national policies. However, this type of regulations does not specify all the details and, as a result, the laws adopted in each member state can differ noticeably.

The most important European directives related to DR are linked to the internal electricity markets – specifically the Directive 2009/72/EC [8] – and to energy efficiency with the Directive 2012/27/EU [9]. While the first directive does not directly mention DR, but only the empowerment of the end-users and how data should be treated, the second directive acknowledges the importance of DR programs and set several requirements for reducing regulatory barriers to implementing such solutions. Additional favourable guidelines arrived with the "Clean Energy for All Europeans" [10] – also called "Winter Package" – in November 2016. This package of directives highlights the importance to set standards to integrate variable renewable sources and to empower the European citizens by offering them the possibility to be rewarded for their flexibility – generation, demand or storage. Only a portion of the measures reported in the "Winter Package", however, is intended to become mandatory by 2020, while for the others no timetable has been set yet.

The most comprehensive analysis about the current European situation is described by the Smart Energy Demand Coalition. In their latest report [11], released in 2017, it is described the regulatory conditions for 18 European nations in terms of demand response access to the market, service provider access, product requirements, measurement and verification, payment and penalties. An overall picture of the market situation in Europe is represented in Figure 2.2.

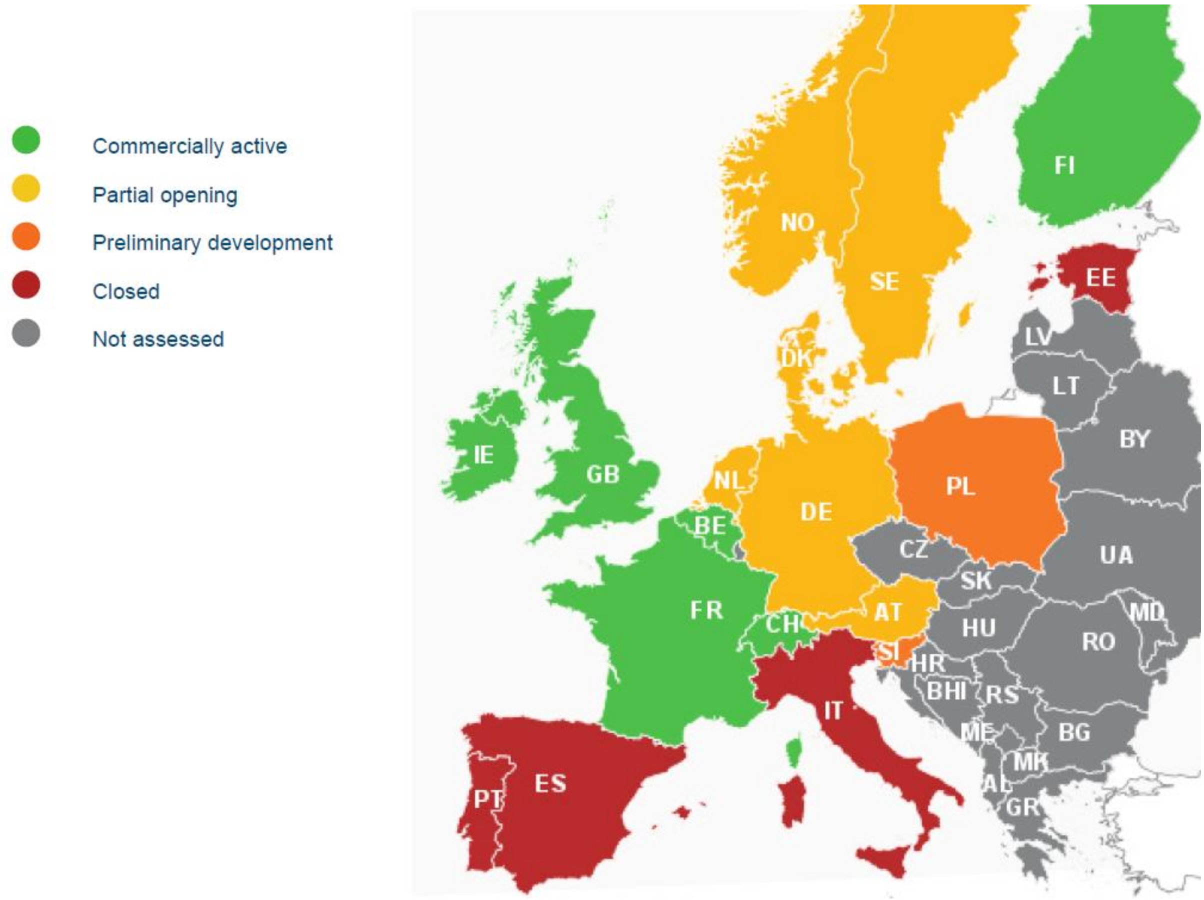

Figure 2.2. Map of explicit demand response development in Europe today [11]

As shown above, the current situation is still quite diverse among different European markets and there are still many important markets such as the Portuguese, Spanish and Italian ones completely closed to DR. However, the situation is rapidly evolving, with most European nations expected to become increasingly active and open, also due to the influences of the directives described in this section.

2.2. Markets for Demand Response programs and technical consideration

The electrical market structure has been significantly impacted by the recent evolution of the energy sector and the changes to regulation stemming from it. Particularly, the evolving context has allowed the creation of new actors that are starting to play along with the traditional market players such as producers, Transmission System Operators (TSOs), Distribution System Operators (DSOs), retailers and consumers. Traditional consumers are transforming into *prosumers* by partly producing their electricity and injecting their surplus into the grid; additionally, new legal entities, referred to as *aggregators*, have started combining and managing the flexibility potential of different demand and/or generation units, thus creating a portfolio of flexible assets able to deliver useful services to the system. This emerging role is met by either existing market actors or by new specialized companies, allowing more players to participate in the electrical markets.

Figure 2.3 represents a simple diagram exemplifying the cases in which flexibility use is employed, expressed with the red numbering, and the coordination required between the interested system's actors in grey letters. In most use cases, the flexibility of the prosumer/producers/consumers is gathered and managed by the actors in the light orange box that are acting as flexible sources' aggregators. Suppliers, Balancing Responsible Parties (BRPs) and Balancing Service Providers (BSPs), then, re-distribute the valuable resource to the other network's stakeholders as specific services.

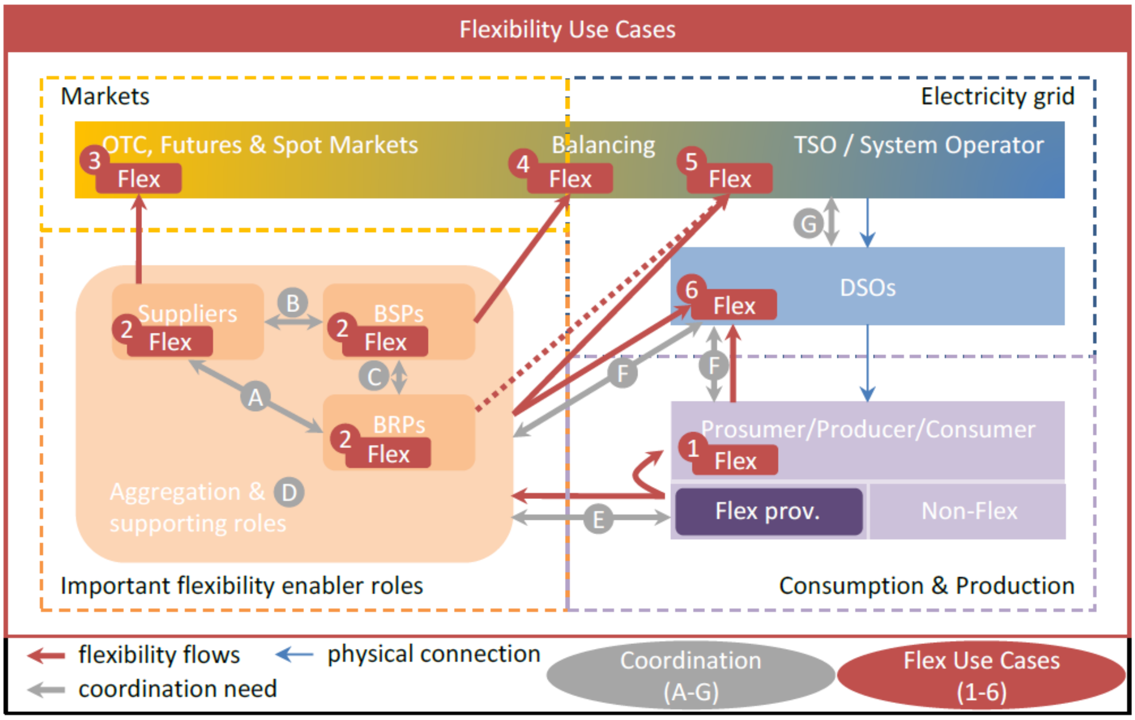

Figure 2.3. Flexibility Use Cases for different roles and coordination needs [3]

In the above, the following flexibility use cases are reported:

1. Maximization of own self-consumption for the prosumers, minimization of the costs associated with the grid and flexibility provided to the aggregator
2. Portfolio optimization
    a. Exploiting price gaps in the energy markets
    b. Minimizing imbalance settlement costs
    c. Participation in the balancing markets
3. Extract the flexibility value related to the integration of VRE in the spot market
4. System balancing mechanism – frequency and voltage control
5. Grid services for the TSO such as black start, island operation, etc.
6. Grid services for the DSO

Figure 2.3 shows that flexibility can be delivered as a service to conventional electricity markets, where local policies and regulations allow so. Apart from regulation constraints, different technical requirements are also needed to participate in specific markets. For each country and each market, specific technical parameters are set for flexibility providers, particularly: (1) a minimum bid size, (2) a defined available time of the resources,

(3) the ability to respond within a precise notification time and (4) a certain level of granularity control to deliver the required services.

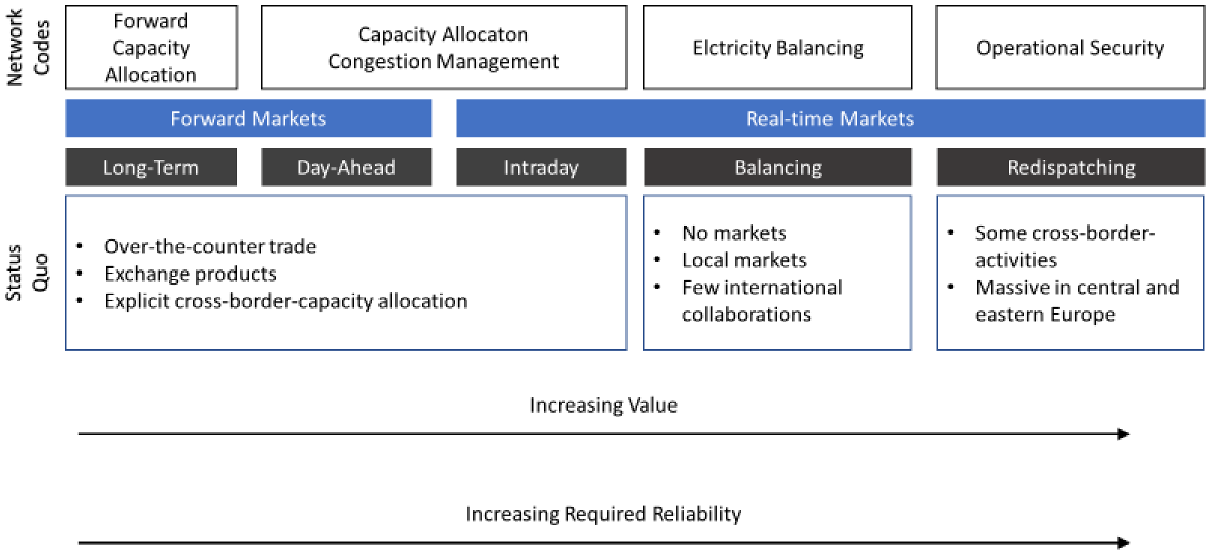

Figure 2.4. The current relationship between networks codes and the European market status quo with a qualitative perspective on demand response value and technical requirements

Figure 2.4 shows the current European market status quo with a qualitative perspective on the value of the services provided in the different market and the evolution of the level of required reliability. Moving from left to the right the potential value that can be extracted from the market increases. However, the technical barriers to enter the markets also rise, particularly due to a drastic drop in (3) and an increase of (4). While (1) and (2) can easily be tackled by aggregating multiple sources of flexibility, (3) and (4) significantly depend on the type of flexible loads available and on the type of control measures adopted. Additionally, the necessity to fine-tune demand loads and to respond within short notification times requires an increased speed of telemetry, which in turn increases costs associated with data transmission and processing. The flexibility services delivered in the market are usually paid for the energy provided during the required periods, usually referred to as events, or for the available capacity offered during the year.

2.3. Quantifying the impacts related to the implementation of Demand Response programs

Understood the context, specifically related to the current situation of the electrical system, the markets and the European regulations, it is possible to correctly analyse with a broad view of the potentiality of implementing DR strategies. Besides the significant benefits for the power system and its stakeholders, DR programs could lead to non-negligible costs, especially where new modern technologies need to be implemented to allow more complex automatic DR. Assessing the positive impacts a priori is important to correctly estimate the savings and costs related to these solutions. Before analysing the different methodologies that could be adopted to solve such exercise, an insight into the different categories of DR programs is given in Table 2.1.

Table 2.1. Categorization of DR programs [12]

Classification Criteria	Dualities		Source
Purpose	Reliability	Economics	[13]
Trigger Factor	Emergency-based	Price-based	[14]
Origin of Signal	System-led	Market-led	[15]
Type of Signal	Load response	Price response	[13]
Motivation method	Incentive-based	Time-based rates	[16]
Control	Direct load control	Passive load control	[17]

To further simplify this classification, the different DR programs can be clustered into two main categories corresponding to the two *Dualities columns* reported above. All DR strategies aiming to increase the power system's reliability are generally emergency-based, system-led, load response, incentive-based and rely on a direct load control. Otherwise, when DR is economically driven, it is usually based on price-based, market-led, price response, time-based rates and passive load control programs.

To properly evaluate the benefits and costs for each of the above-mentioned typologies of DR, an effective methodology to estimate the changes in the demand induced by DR programs has to be developed. Literature offers some relevant, varying approaches, which are explored in the following sections.

2.3.1. Price elasticity estimates

The first type of methodology considers and implies the price elasticity estimates derived from previous studies. It is important to mention that the customers' response is also influenced by other factors than simply costs, therefore a proper clusterization that would group the end-users considering a wider range of aspects will lead to more accurate results. The climate condition, the customer type – including income, available electric appliances, education … – and available enabling technologies are just a few examples of the additional parameters that affect the consumption.

While studying DR programs, two main elasticity parameters are considered: own-price elasticity and cross-price elasticity. The first one refers to the demand change in a time period for the price variation in the related period, while the latter identifies the variation in the load for the price variation of another period. Usually, for the cross-price elasticity, the two interested periods are the off-peak and on-peak time frame and it is also possible to refer to this parameter as the elasticity of substitution.

2.3.2. Econometric models

A different strategy is to develop a model that estimates the demand patterns based on microeconomic principles. In this case, the idea is to maximize the interest of the final customers based on their budget availability – the income – and the price of electricity. Other factors such as climate, dwelling typology or available technologies can be included in this type of analysis. The inputs are usually data collected from real experiences and thus, price-elasticity parameters usually derive from these models. To obtain a valuable output, it is important to consider the most relevant factors and properly evaluate how they impact the final customers demand. Therefore, the found outcomes are very likely to be strongly dependent on the set underlying conditions, limiting in this way the possibility to extrapolate the results for different cases.

Moreover, it is important to take into account that the overall load is composed by a variegated diversity of appliances that present a consumption pattern strongly related to their final use. Not considering this aspect will very likely lead to models that may not be sufficiently accurate to assess the effective impact of DR programs.

2.3.3. Bottom-up demand models

Bottom-up demand models estimate the load profile by aggregating specific elements' loads, thus single customers or appliances. The consumption pattern for each fundamental load can be extrapolated adopting a statistical approach, based on a solid base of data and machine learning algorithms for example, or elaborating physical models as for the case of specific controlled loads' studies.

To simulate the consumption of the single devices, with or without an implemented DR program, it is convenient to divide the most common appliances into clusters. Table 2.2 represents a common classification of the major residential appliances, following the same logic proposed by other authors [18]–[20]. The two main categories are non-controllable and controllable appliances; the latter can be further split in thermostatically controlled and non-thermostatically controlled loads.

Non-controllable appliances are all those devices that present a consumption strongly correlated in time to the service provided. Thus, as the name suggests, is not possible to induce changes in their load demand since the end-users' comfort would be significantly affected by modifying their electric use. Examples falling into this category are the lighting, television, radio etc. Oppositely, controllable appliances allow a certain degree of flexibility based on the specific device characteristics. All the thermostatically controlled loads – such as air conditioner, space heater or water heater – presents intrinsically a thermal inertia that can be treated as an internal energy storage. This allows the possibility to shift the device's load while maintaining or not significantly impacting the service delivered by the controlled appliance. Non-thermostatically controlled loads – as clothes washers, clothes dryer or dishwashers – do not possess any thermal inertia, however, they allow a certain amount of flexibility related to the power required for their correct functioning. This last sub-category is often referred to as deferrable loads.

Table 2.2. Major residential appliances categories [21]

Non-controllable Appliances	Controllable Appliances	
	Thermostatically Controlled	*Non-thermostatically Controlled*
Lighting	Air Conditioner	Clothes Washer
Refrigerator	Space Heater	Clothes Dryer
Television	Water Heater	Dishwasher

2.4. Demand Response programs areas of impacts

Once assess the changes in the demand patterns it is possible to compare and quantify the impacts of implementing a DR strategy. Usually, the main outcomes are reflected in the system operations and design.

Regarding the operations, DR programs could play a significant role to improve the balance between supply and demand and thus delivering several benefits. DR potentially enables the reduction of CO_2 emissions, by providing a tool to shift the demand toward periods where less polluting power generators are operating. Additionally, it is possible to boost the consumption of locally produced electricity and thus increase the network efficiency by reducing the needs of distribution and transmission. Furthermore, DR strategies could help to handle unexpected extreme system events and, generally speaking, price and production volatility, therefore reducing the cost of imbalances. With more advanced control systems, it is also possible to increase the network reliability by offering ancillary services to the grid such as voltage support, frequency regulation, power factor correction or active-reactive power balance.

The network is designed to handle the highest expected demand; by modifying the latter it is possible, therefore, to have an impact on the grid sizing. The opportunity to reduce demand peaks with DR in specific systems would diminish the peak capacity required, thus minimizing the investment related to the capacity reserves required. Finally, DR programs could influence by a certain extent the integration of VRE, therefore allowing a higher share of green technologies in the network.

Table 2.3. Fundamental value drivers of demand flexibility [22]

CATEGORY	DEMAND FLEXIBILITY CAPACITY	GRID VALUE	CUSTOMER VALUE
Capacity	Can reduce the grid's peak load and flatten the aggregate demand profile of customers	Avoided generation, transmission, and distribution investment; grid losses; and equipment degradation	Under rates that price peak demand (e.g. demand charges), lowers customer bills
Energy	Can shift load from high-price to low-price times	Avoided production from high-marginal-cost resources	Under rates that provide time-varying pricing (e.g. time-of-use or real-time pricing), lower customer bills
Renewable energy integration	Can reshape load profiles to match renewable energy production profiles better (e.g. rooftop solar PV)	Mitigated renewable integration challenges (e.g. ramping, minimum load)	Under rates that incentivize onsite consumption (e.g. reduced PV export compensation), lower customer bills

Table 2.3 summarizes the main advantages that demand flexibility, therefore DR programs, could deliver to the grid and to the consumers.

2.5. Previous works' outcomes on the quantification of the benefits induced by Demand Response Programs

In the following sections there are going to be presented several works performed to quantify the possible impact of implementing DR programs.

2.5.1. Studies focusing on the single customers

A significant number of studies related to single households focus their attention on the benefits of introducing improved control strategies on flexible assets to maximize the local consumption of PV systems. Three significant examples are: [23] where the authors study a use case of an household equipped with a rooftop PV installation and an EWH in Italy, [24] that presents an evaluation of the impact of a smart EV charging strategy for individuals and an aggregation of 1 000 household provided with solar PV installations and [25], [26] that analyse the synergies between solar PV and battery storage for individual users in different European countries.

[23] reports an improvement of almost 300% in the electricity consumed by the EWH during the PV production time adopting a smart control, while [24] evaluates increments around +3% at the individual level and +6% at the aggregated level looking at the share of electricity produced by the PV power plants consumed on-site. These last results are significantly low considering that the electricity consumption due to the EV is about 27% of each household. However, these values are considerably affected by the window period the EVs are usually charged that, in this case, is mainly after 16:00, therefore during the last solar hours. By introducing the possibility to have charging during the middle hours of the day, the improvements due to the DR strategy implementation would be more significant.

The last two studies, [25], [26], prove how the integration of electrical energy storage with solar PV system can significantly improve the autonomy of the end users from the electrical network. In both studies, it is highlighted how the benefits of increasing the battery capacity saturate after a specific threshold and, specifically in the case of [25], how this is only partly affected by the location or the orientation of the panel, therefore by the PV system's production performance. Finally, [26] remarks how increasing the value of electricity self-consumed would relevantly help the integration of distributed VRE in the grid.

2.5.2. Studies at the national level

Several types of research have been developed to study the technical potential of controlling flexible assets to have an impact on the national electrical network. Two relevant examples are: (1) a work developed to study the impact of a control strategy to minimize the peak load in Québec, Canada, [27] and (2) one performed to analyse the DR potential to mitigate the minimum generation conditions (MGCs) in Ontario, Canada [28]. When the demand reaches values below the MGCs, the supply's efficiency in the network get compromised, especially the one related to the generator assets with low flexibility – thus nuclear, coal, closed-cycle natural gas power plant and a certain type of hydro plants. As previously discussed in the Introduction, when the VRE generation share reaches values higher than 10%, the added volatility on the supply side could increase the hours where oversupply occurs.

The two papers present DR strategies that aim to increase the performance and, consequently, the reliability of the system. As previously seen in Table 2.1, these type of programs received a signal that is system-led and responsive to the load. Moreover, they assume a direct control of the flexible loads, in these two cases a cluster of EWHs. To quantify the impacts, both papers focus only on the load related to the EWHs and, when implementing the scenario with the DR, analyse the changes at the individual asset level to afterwards aggregate them to create the new demand load of the flexible cluster. The load profiles are simulated by implementing a physical model that takes into account the water thermodynamics and a stochastic model to simulate the water usage during the day, in case (1) verified with a sample of empirical data.

The two studies report positive outcomes, but they both focus only on the technical aspects without considering the costs or the economic benefits related to the implementation of the two different DR strategies. In the case (1), with a fleet of 900 000 EWHs, it has been simulated a potential peak reduction of

525 MW, while for the case (2) an upward potential of 900 MW delivered from 1 200 000 flexible units, in both cases without compromising the end-users comfort while considering technical and physical constraints.

Similarly [18], [29], [30] and [31]have analysed the technical DR potential of TCLs, including also air conditioning (AC) systems, with similar methodologies. Oppositely, a significantly different approach has been adopted by the authors of the report [22] published by the Rocket Mountain Institute in 2015. The aim of this work is not only to prove the technical potential of DSM, but mainly to economically quantify the benefits for the grid and the customers in two use cases focuses in the USA. Specifically the goal is to identify how much DR program can influence (1) the customer bills in presence of a time-varying pricing and (2) the increase of on-site consumption of rooftop solar PV by controlling ACs, EWHs, electric dryers, electric vehicle (EV) charging stations and energy storage batteries.

In both cases the purpose of the two programs is to improve the economics of the system, mainly by reducing the customer bills, but the two implementations would also affect the system reliability by reducing the peak demand in (1) and reducing the need to invest in the distribution network (2). While for case (1) the load control would be mainly market-led and would respond to the variation of the price, for case (2) the DR strategy would be system-led and would be influenced by the load. Oppositely to the general trends highlighted in section 2.3, in both the assets analysed would be directly controlled. Also in these works it has been adopted a bottom-up approach, performing an analysis on the flexibility of the single chosen assets and how this influence a reference customer. The results have been then properly weighted for the required sample of the study, therefore clusters from about 10 000 households to 300 000 customers between the residential and the industry sector for each case study.

The results obtained following this methodology are positive and reports a 48% reduction potential of the peak specifically in Arizona, between 10-40% of savings for the customer bills and an increase of on-site consumption of PV in Hawaii from 53% to 89%.

2.5.3. Findings of the shared use of energy assets in communities

Besides the studies at the individual and at the national perspectives presented in the above sections, more interest is rising to understand how flexibility could deliver benefits at the community level. Especially talking about energy system integration, different terminologies have been used in literature to identify and analyse such energy networks:

- Microgrids include locally consumers and prosumers considering their aggregated demand and supply as a single customer from the network perspective. This type of communities usually includes generation systems - such as solar, wind, combined heat and power –, storages and demand response. The aim of the microgrids is to optimize the usage of local energy resources to increase the efficiency of the energy distribution systems;
- Virtual Power Plants (VPP) aggregate the consumption and the production of various households – also not technically connected – to form a flexibility capacity similar to a power plant. This resource

can be composed by distributed generators, flexible loads and energy storages. The VPP created this way can then participates in the electricity market or help to support the system operations;

- Energy hubs manage multiple energy carriers to optimize the energy flows in a district. Electricity, heat, natural gas and other fuels are included and the hubs operate to store, convert and distribute these resources.
- A Prosumers Community Group (PCG) is, as reported in [32], " […] a network of prosumers having similar energy sharing behaviour and interests, which make an effort to pursue a mutual goal and jointly compete in the energy market".
- Community energy systems are small electricity or heat production systems managed by the local people or for the local community to provide their members direct beneficial outcomes such as economic savings or reduction of pollutants emissions.
- Integrated community energy system (ICES) concept includes all the above-mentioned terminologies. Thanks to the coordination of the local energy systems, they lead to an increased self-consumption and an optimal matching between local demand and supply. The ICESs aggregate all type of energy systems from co-generation or tri-generation to DSM solutions as well as energy storages.

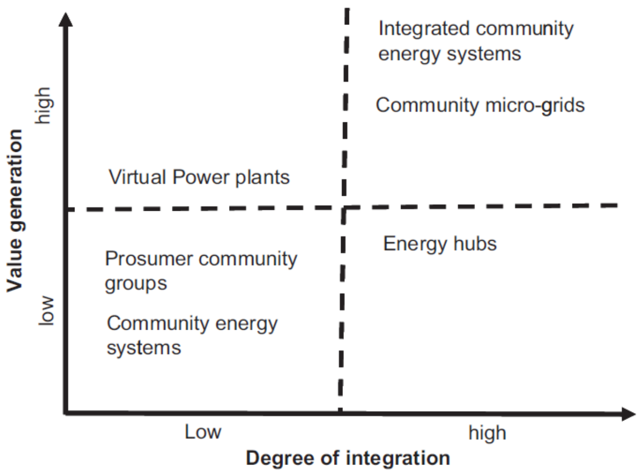

Figure 2.5. Classification by value generation and degree of integration of different energy system integration strategies [33]

All the described energy system integration options are represented in Figure 2.5 grouped by their related degree of integration and the value created. The degree of integration is referred to as the internal value delivered to the local network in terms of self-sufficiency and local resources self-consumption. On the other side, the value created is the one provided to other energy systems; these could be the national grid or other energy communities.

Even though, many works and research have been developed to analyse the impact at this scale, very few papers reports analysis on systems with only DSM measures implemented such as the case of this thesis. Overall, the presented networks show a higher variety of energy assets and therefore the impacts on the community delivered by every single technology or solution implemented are harder to appreciate.

3. Methodology – Simulation set up

To evaluate the impact of a cluster of flexible assets in a community, it has been adopted a bottom-up approach – as described in section 2.3.3. The community demand has been considered as two different independent components: a fixed, non-controllable part and a flexible one, composed by an aggregation of the same specific assets that are individually affected by the DR strategy adopted. To quantify the changes induced by the set DR program, it has been developed a Python code that follows the logic presented in Figure 3.1. The energy balance simulation among the grid, the locally installed PV panels and the community demand is based on a time frame of 15 minutes. For the scope of this work, it has been adopted a deterministic approach by assuming a perfect knowledge of the community consumption patterns and the power generation form the PV power systems.

Due to a shortage of data availability, the analysis focused on four weeks representing the different quarters in the year – two for each season according to the Portuguese tariff scheme – therefore including the seasonal consumption differences. Then, the results have been properly weighted to obtain the outcomes from an annual perspective.

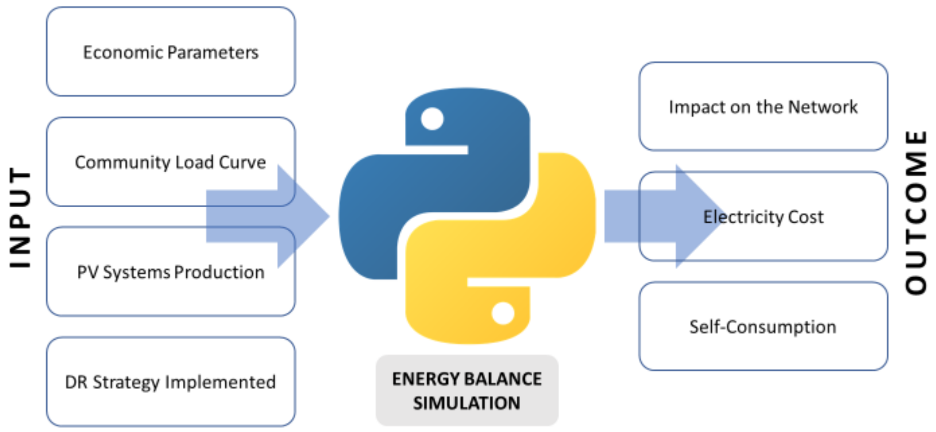

Figure 3.1. The methodology logic scheme

The outcome parameters, apart from the *Impact on the Network*, have been first calculated varying the PV capacity installed in the system, therefore varying the local *PV Systems Production*, and then modifying the *Community Load Curve*, by changing the number of EWHs installed. During the first case the number of EWH units has been set to 50 while during the latter, the number of PV systems installed has been fixed as the economic optimal for the case without implementing the DR strategy as it will be discussed in Section 3.4. The *Impact on the Network* has been instead quantified for a scenario with a fixed PV capacity installed and number of EWHs.

The *Input* and the *Outcome* parameters listed in Figure 3.1 are going to be further described in the following sections.

3.1. Economic Parameters

During the energy balance simulation, the whole community has been considered as a single MV customer from the grid perspective. The year 2018 has been selected as the reference for the electricity tariffs and the PV panels related expenses.

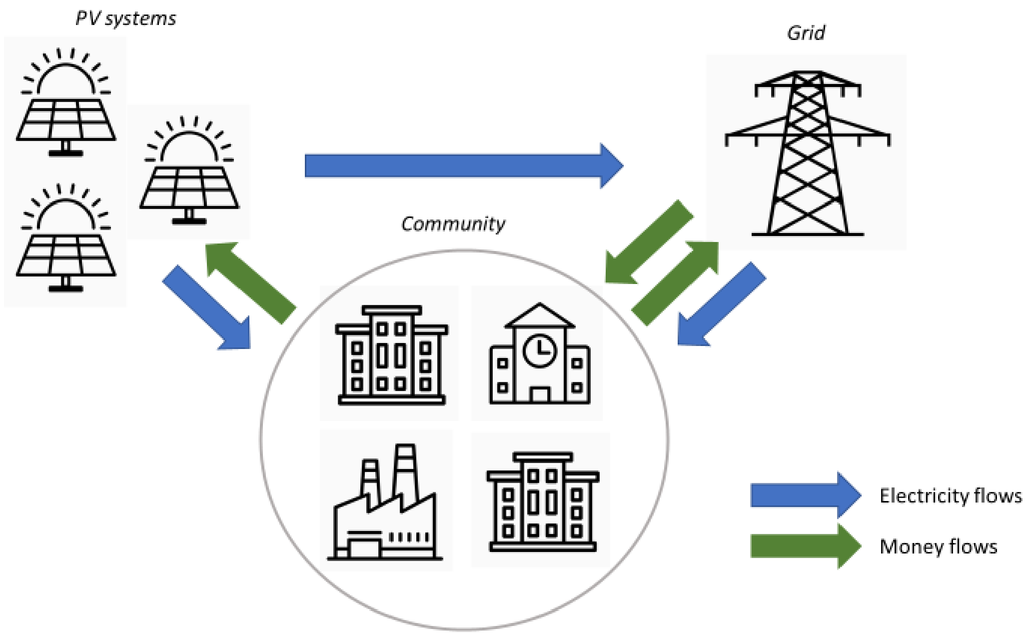

Figure 3.2. Scheme of the electricity (in blue) and the money flows (in green) between the community, the grid and the locally installed PV power systems

Figure 3.2. Scheme of the electricity (in blue) and the money flows (in green) between the community, the grid and the locally installed PV power systemsFigure 3.2 represents a scheme of the electricity and the money flows among the community, the grid and the PV power systems. The power generated can flow to the community or to the grid, as shown by the blue arrows; all the surplus electricity injected in the network is paid back to the community through a Feed in Tarif (*FiT*) calculated with the formula *(3.1)*.

$$FiT_m = OMIE_m \times 0.9 \, [€/kWh] \qquad (3.1)$$

The Feed in Tariff (FiT_m) for each month *m* is set as the 90% of the average price in the Portuguese electricity spot market in the month ($OMIE_m$). For the scope of this analysis, due to the negligible differences, it has been considered a fixed value for the *FiT* based on the average values reported in [34], [35] of 4 years starting from 2014 included.

All the PV systems' costs, such as installation, operation and maintenance (O&M), are covered by the community. All the values have been the result of a research conducted on the Portuguese PV market, focusing on ground-mounted power plants with an installed capacity higher than 100 kW. Table 3.1 reports the costs and other related economic factors adopted for the analysis; the inverter replacement and O&M expenses are expressed as a percentage of the installation costs.

Table 3.1. Summary of costs and economic factors related to the PV power systems

Installation Costs [€/kW$_p$]	900
Inverter Replacement Costs	10%
O&M Costs	1.5%
Power Plant lifetime [years]	25
Discount rate (d)	7%
Inverter lifetime [years]	10

With the following assumptions and the equation *(3.2)*, it is possible to calculate the net present cost (*NPC*) of the PV systems, where CF_n is the negative cash flow, therefore the costs, in € relative to the year *n* and *d* the discount factor. Then, the levelized cost (*LC*) per kW installed per year is computed assuming the power plant lifetime of 25 years with the *(3.3)*.

$$NPC = \sum_{n=0}^{25} \frac{CF_n}{(1+d)^n} \tag{3.2}$$

$$LC = \frac{NPC}{1 - (1 + d)^{-25}} \times d \tag{3.3}$$

To compare the economic values obtained, it has been also calculated the levelized cost of electricity (*LCOE*) related to the same PV system. The yearly solar irradiation has been gathered from the global irradiation map developed by IRENA [36] considering Martim Longo, a municipality in the region of Algarve, Portugal, as the location. Then, using the peak hours approach, therefore considering this value (*H*) as the amount of equivalent hours where the solar radiation is equal to 1 kW/m^2/year, the formula *(3.4)* leads to an estimation of the yearly energy produced (E_y) for a power plant with a capacity installed *P* and with an overall derate factor (η) of 0.72. The obtained result has been used in the formula *(3.5)* to calculate the *LCOE*. It has been considered a degradation factor (*degradation)* of 1% per year, value which leads to a panel yield performance of 78.6% after 25 years. All the calculation are shown in the Annex Economic Parameters Calculation**.**

$$E_y = P \times H \times \eta \tag{3.4}$$

$$LCOE = \sum_{n=1}^{25} \frac{E_y \times (1 - degradation)^{(1-n)}}{(1+d)^n} \times \frac{1}{NPV} \tag{3.5}$$

The obtained *LCOE*, 0.0755 €/kWh, is in line with the findings of [37] that reports values that vary between 4 to 7 cents €/kWh for the German market.

Finally, all the electricity provided by the grid is paid back considering the cluster of consumers as a single MV client, following the tariff reported in [38].

3.1. Photovoltaic Systems Production

To simulate the energy production of the locally installed PV power systems it has been set the location of the community in Martim Longo, a municipality in the region of Algarve, Portugal. Then, it has been defined a reference ground-mounted PV system of 5 kW to study technical and economic performance. The reference power plant is composed by 20 *Solar World Sunmodule 250* panels, arranged in 2 strings of 10 modules each, paired with an inverter *SunnyBoy 5000TL* from *SMA* (see Annex Solar Photovoltaic System Technical Details for technical details). Finally, it has been assumed that all the panels are ground mounted, titled with an angle of 37° and facing south to maximize the energy yielded throughout the year.

The production has been simulated starting from the meteorological parameters gathered from Meteonorm [39] with a 1-minute resolution. To define the effective radiation hitting the surface of the panels it has been adopted the Perez model, [40]–[43]. Then, to simulate the related production of the system, a single diode equivalent model approach has been considered. Finally, the energy yielded has been clustered in 15 minutes time frames by summing up the minute resolution production. All the distribution losses have been assumed negligible, also compared to other assumptions that have been made during this analysis.

All the calculation are reported in the Annex Photovoltaic System Production Calculation.

3.2. Community Load Curve

The demand load curve is composed of load profiles provided by Energias De Portugal (EDP), Estabanell Energia, relatively a Portuguese and Catalan DSO, and by the flexible assets load. The community considered is composed by 162 Low Voltage (LV) profiles gathered from EDP, a and 5 Medium Voltage (MV) provided by Estabanell Energia, including 1 school and 4 commercial sites.

Due to a complete lack of data related to EWHs consumption profiles, a simplified approach has been adopted to simulate them. All the thermal dynamics that are usually considered in the papers investigating TCLs' DR potential, for example [18], [23], [28]–[31], have not been considered in this analysis. To generate the load profiles related to EWHs, the following hypothesis have been taken into account:

1. Domestic Water (DW) consumption coming from the EWHs is only related to hot showers. The electricity required (E_{req}) to recover the heat used has been assumed considering the equation *(3.6)* and the followings:
    a) a total DW consumption (m) of 40 litres per shower, considering an average time per shower of 5 minutes;
    b) a constant power (P_{nom}) required to heat the water equal to 4.2 kW;
    c) a temperature flowing in (T_{in}) of 15 °C and a temperature flowing out (T_{out}) of 60 °C the tank's heater;
    d) a constant specific heat (c_p) for the water of 4.186 J/kg K and
    e) no conversion losses.

$$E_{req} = \frac{c_p \times m \times (T_{out} - T_{in})}{3600} \ [kWh] \tag{3.6}$$

2. Each appliance can provide a maximum of two hot showers per day, one per each half of the day. To determine when DW consumptions occur, for each time frame of 15 minutes it has been assigned a probability to have a hot shower based on the vector showed in Figure 3.3. The morning and evening peaks have been assumed relatively at 8 am and 7 pm, then the curve follows a normalized Gaussian distribution around those two setpoint;

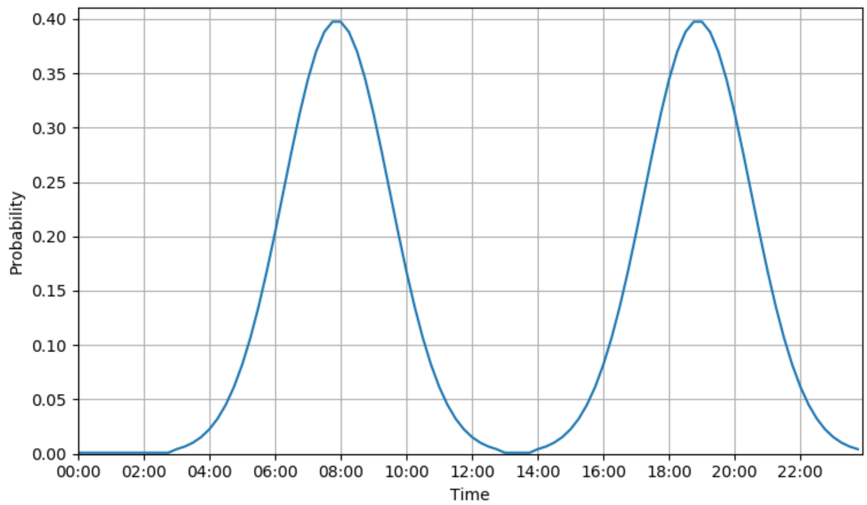

Figure 3.3. Probability vector considered to determine the EWH load profiles

3. EWHs are "black boxes" that can only be fully discharged in a one-time frame and charged in two-time frames – no partial charges or discharges are allowed. In order to maintain the water temperature, the charges occur straight after the water consumption, later also referred to as bus signal.

Finally, the total community demand has been built as the sum of the LV and MV profiles and the load profiles of 50 EWHs when varying the solar PV capacity installed, for a total peak capacity of 307.15 kW.

All the calculation related to this section are reported in the Annex Load Community Calculation.

3.3. Demand Response Strategy Implemented

The DR strategy adopted in this analysis aims to (1) increase the consumption of electricity locally produced while (2) maintaining the end users comfort. Figure 3.4 reports a simple sketch of the logic and the constraints considered for the simulation. The sun surplus, below graphically represented with the sun icons, is calculated for each time frame *i* using the formula *(3.7)*.

$$\begin{cases} \{\textbf{if } (PV_i - D_i) \geq E_{EWH} \textbf{ then } sun\ surplus_i = int\left[\frac{(PV_i - D_i)}{E_{EWH}}\right] \\ \textbf{else } sun\ surplus_i = 0 \end{cases} \tag{3.7}$$

In the above equation, E_{EWH} is the energy consumed by the water heater to re-heat the tank water in a time frame considering the P_{nom} defined in section 3.1, while the function *int[R]* rounds the real value *R* to the closer minor integer.

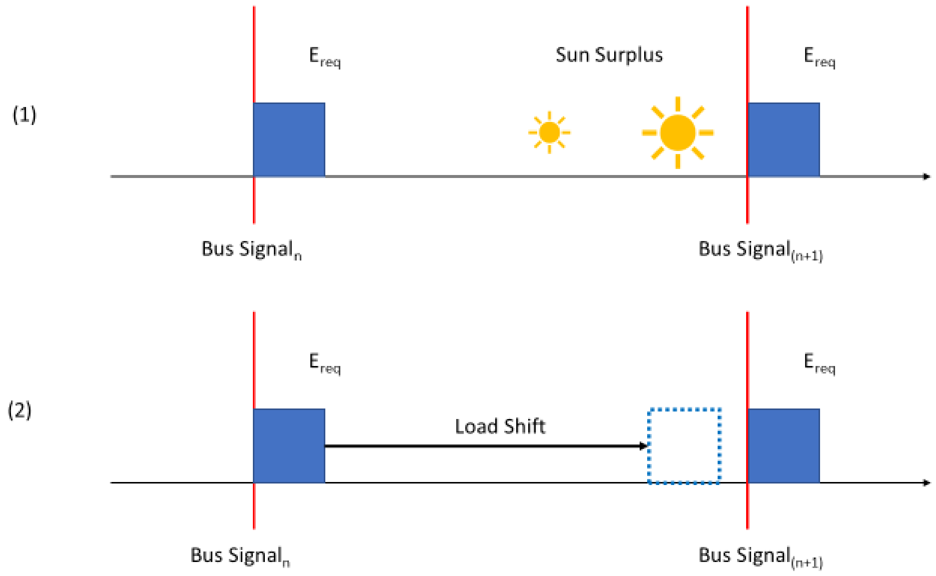

Figure 3.4. Sketch of the logic and the constraints used for DR strategy

Once created the time series of sun surplus for the studied period, for each EWH profile the following logic is adopted:

```
identify all the Bus Signal for the selected EWH*
for n to total number of Bus Signal:
        search for sun surplus > 0 between Bus Signal_n and Bus Signal_(n+1) as
        shown in (1)
        shift E_req in time frame i with max(sun surplus) as shown in (2)
        update sun surplus time series and consumption for EWH*
```

This operation is repeated until the sun surpluses finish or until all the EWH profiles have been checked.

3.4. Impact on the Network

To quantify the impact of the DR strategy implemented on the electrical network it has been analysed a scenario with a fixed amount of PV capacity installed and a fixed number of EWH units. As discussed in section 2.4, DR has the potentiality to positively influenced the grid in two different way: (1) by facilitating the system operations, increasing the local flexibility, and (2) by reducing the network size, due to the possibility to reduce the peak demand.

In the Results, it is going to be discussed only the point (2), by looking at and comparing the net peak load obtained for the scenarios without and with DR implementation.

3.5. Electricity Cost

To assess the total electricity cost for the community in the 4 weeks examined, the following equations system *(3.8)* has been used, considering all the 15 minutes time frame *i* for the four weeks analysed.

$$\begin{cases} \textbf{if } D_i > PV_i \textbf{ then } C_i = (D_i - PV_i) \times p_i \\ \qquad \textbf{else } C_i = (D_i - PV_i) \times FiT \end{cases} \tag{3.8}$$

In the above, C_i is the cost associated with each time frame, D_i is the energy required from the community in kWh, PV_i is the total energy produced by the systems installed in kWh, p_i the price of electricity delivered by the grid considering the 2018 tariffs for MV clients and *FiT* the feed-in tariff when injecting electricity in the grid, calculated considering the assumption of section 0.

PV_i has been calculated accordingly to *(3.9)*, where pv_i is the electricity produced in the time frame *i* by the reference PV power plant described in Section 3.1 and *n* is the number of systems installed.

$$PV_i = pv_i \times n \tag{3.9}$$

Finally, the total cost for the community is calculated using the *(3.10)* – 2688 are the total amount of 15-minutes time frames present in the studied four weeks.

$$C_{tot,n} = \sum_{i=1}^{2688} C_i + n \times LC \times 5 \tag{3.10}$$

$C_{tot,n}$ represents the total *Electricity Cost* for the community related to the PV power systems and the provision of the electricity from the grid, excluding the fixed expenses. *LC* is the levelized costs of the PV systems expressed in €/kW/year calculated following the method reported in Section 0. Finally, it has been evaluated the optimal PV capacity installed with an iteration, varying the number of the PV power systems *n* between 1 to 100, and defining the optimum value as the one that corresponds to the minimum $C_{tot,n}$.

For the purpose of this analysis, all the fixed costs related to the grid connection have been neglected since the introduction of the PV power systems in the community and the implementation of the DR strategy is not affecting the community peak demand. Therefore there is no impact in the comparison of the two cases.

3.6. Self-Consumption

Another important factor to be taken into account while analysing the impact of flexible assets in a community fed by locally installed PV systems is the impact of the DR strategies on the self-consumption. This value is of significant importance, especially in those countries where the surplus electricity produced is poorly paid and therefore corresponds to a loss of the invested money; higher values of self-consumption, in fact, lead to higher values of economic savings. Additionally, a micro-grid that can significantly rely on local energy sources increases the efficiency of the transmission and distribution systems and it reduces the CO_2 emissions when the on-site produced power comes from renewable sources.

The self-consumption has been evaluated considering the *Self-Sufficiency Rate* (*SSR*) and the *Self-Consumption Rate* (*SCR*), already adopted by [25], [26], also referred to as solar fraction or load fraction by other authors [24]. In this work, the self-sufficiency rate is defined as the ratio between the total energy self-consumed ($E_{SC,tot}$) and the total energy consumed by the community (D_{tot}), as shown by the equation *(3.11)*. The self-consumption rate is instead calculated using the *(3.12)* as the ratio between the total energy self-consumed ($E_{SC,tot}$) and the total electricity yielded by the PV systems (PV_{tot}). Finally, $E_{SC,i}$, the energy self-consumed per each time frame *i*., have been determined using the relations in *(3.13)*.

$$SSR = \frac{E_{SC,tot}}{D_{tot}} = \sum_{i=1}^{2688} \frac{E_{SC,i}}{D_i} \tag{3.11}$$

$$SCR = \frac{E_{SC,tot}}{PV_{tot}} = \sum_{i=1}^{2688} \frac{E_{SC,i}}{PV_i} \tag{3.12}$$

$$\begin{cases} \textbf{if } D_i \geq PV_i \textbf{ then } E_{SC,i} = PV_i \\ \qquad \textbf{else } E_{SC,i} = D_i \end{cases} \tag{3.13}$$

4. Results

Before analysing the obtained values of the outcomes described in Chapter 0, some general considerations have to be taken into account. First of all, the share of the EWH profiles' consumption, reported in Figure 4.1 as the ones of MV and LV profiles, is only the 6.5% compared to the total community. This would already limit the impact that the flexible loads could deliver to the whole system.

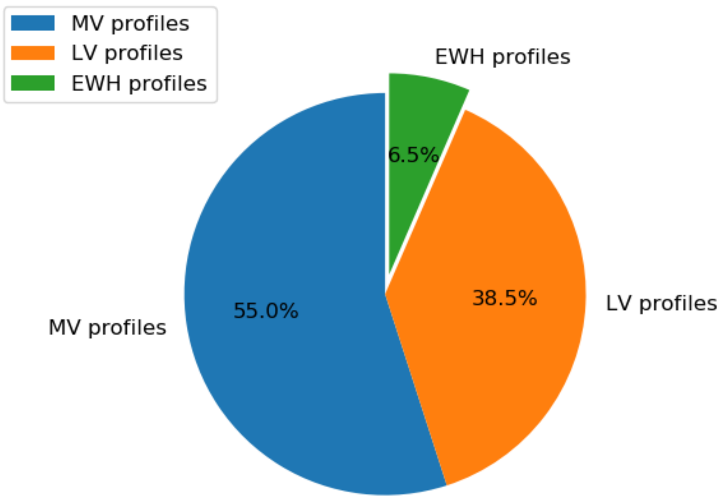

Figure 4.1. The share of consumption between the community' composition profiles

Moreover, it is important to observe the average and peak load for the total community and its composition profiles, reported in Table 4.1. Likewise the consumption shares, the flexible part of the load, the EWH profiles, has an average and peak load one orders of magnitude lower compared to the MV and LV profiles and two compared to the total community's average one.

Table 4.1. Average and Peak Load for the total community composition profiles

	MV Profiles	LV Profiles	EWH Profiles	Community
Average Load [kW]	73.52	51.56	8.74	133.74
Peak Load [kW]	231.98	94.72	54.60	307.15

Another relevant factor that will affect the outcomes is the distribution of the load profiles of the single components of the community compared with the normalized PV production presented in Figure 4.2 (a) for a selected weekday and (b) for a holiday in March.

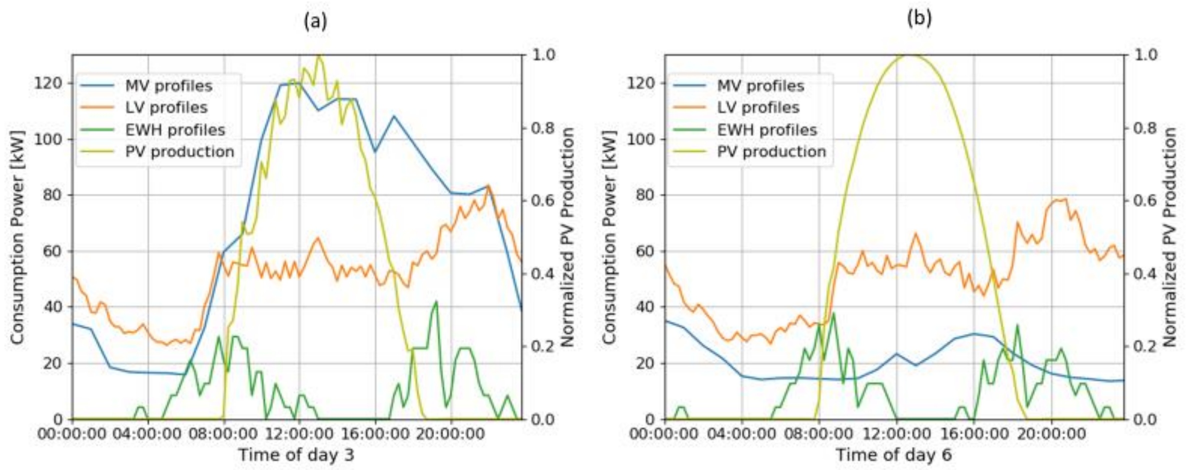

Figure 4.2. The load profiles and normalized PV power production profiles of a selected weekday (a) and a holiday (b) in March

In the Figure 4.2, it is possible to observe that each profile curve presents different trends. For the MV cluster, reported with the blue lines, the consumption curve varies significantly between the weekday and the holiday; while in the graph (a) the curve presents a clear peak around mid-day, in correspondence with the peak PV production, in (b) the profile get flatter with a significantly lower average demand. Oppositely, the LV cluster, illustrated with the orange curves, show a similar trend for the weekday and the holiday; in both days the distribution of the values is closer to the average consumption and the peak occurs in the evening between the 80th and 96th time frames, corresponding to 8 pm and 12 am, outside the PV production hours. Finally, the EWH profiles, identified with the green lines, present, as expected, a trend that follows the probability vector shown in Figure 3.3 which has been used to define them. As the probability vector, the flexible load profiles reveal two peaks – both for the weekday and the holiday – that occur close to the hours when the PV production starts and ends. From this initial information, it is possible to qualitatively estimate the potential impact of a DR strategy that aims to maximize the self-consumption on the single community's components. The profiles that have already similar trends compared to the normalized PV production will be less affected; oppositely, the ones with significantly different shapes should potentially be more positively altered.

4.1. General impact on the Network

Before looking at the specific outcomes related to the community, it is going to be analysed the effects of the DR strategy on the electricity network. To quantify the impacts, a fixed amount of EWHs and PV power system capacity have been set – respectively 50 units and 460 kW – and then, the community load has been studied for the scenario without and with DR strategy implemented.

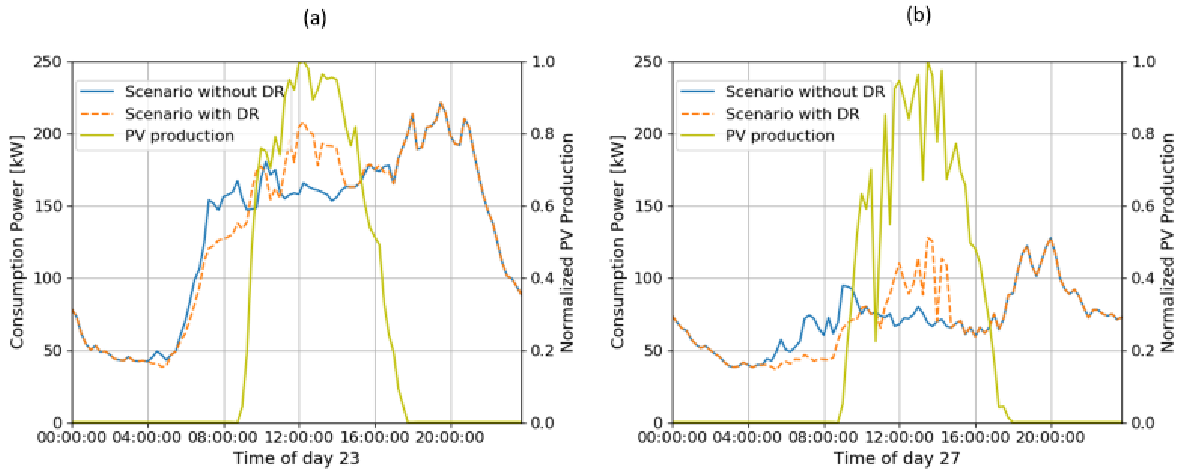

Figure 4.3. Community load profile and normalized PV power production in a weekday (a) and a holiday (b) on December

Figure 4.3 shows the load profile of the community in the scenario without DR implementation, represented by the blue lines, and the scenario with DR, identified by the dashed orange curves, on a weekday (a) and a holiday (b). In the two graphs, it is possible to see the effects of the DR strategy described in section 3.3; the load curves are partly reduced before the PV production begins and the load is then increased in the hours with full generation, corresponding at the time frames with higher values of sun surplus.

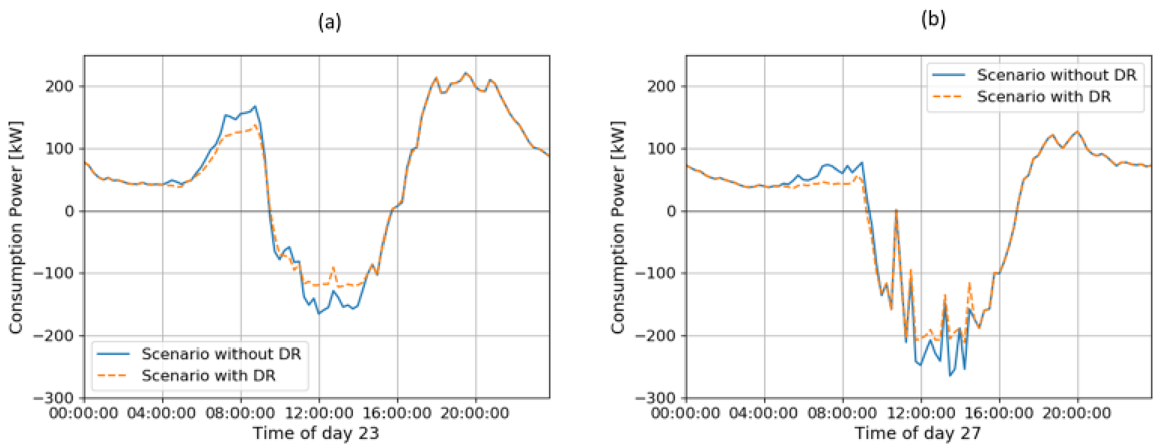

Figure 4.4. Net community load profile for a weekday (a) and a holiday (b) on December

The impact on the net load, therefore subtracting the PV production from the overall load, is more clearly visualized in Figure 4.4. As in Figure 4.3, the blue lines represent the scenario without DR while the dashed orange ones the scenario with the DR strategy implemented. Furthermore, the days shown are the same.

The net load is the value that expresses how the electrical network perceives the community at the point of common coupling (PCC). Compared to the community load profile, the net load presents more evident ramp-ups and ramp-downs due to the presence of a significant amount of local PV power capacity.

Table 4.2. Impact of DR strategies on the net and regular Peak Load for the community

	Peak Load [kW]	Net Peak Load [kW]
Scenario with DR	343.64	306.74
Scenario without DR	307.15	307.15

The impact of the DR strategy is reported in Table 4.2. It can be seen that the benefits of the DR strategy on the peak power demand is limited, especially when considering the net load. This result shows that, in this particular case study, the DR strategy adopted has no influence on the network design since the latter has to be sized to handle the highest expected load demand. This is partly due to the fact that reducing the peak demand is not in the aims of the control strategy adopted. Moreover, as reported in [44], the highest impact on the peak reduction has to be expected from other types of sources such as the traditional curtailment of big customers in the industrial or commercial sectors.

4.2. Impact on the Community varying the PV Capacity Installed

In the following sections the results of the outcomes presented in the

Methodology – Simulation set up section while varying the PV capacity installed.

4.2.1. Electricity Cost varying the PV Capacity Installed

The first tangible impact that can be measured while considering the implementation of a new technological solution is the economic benefit.

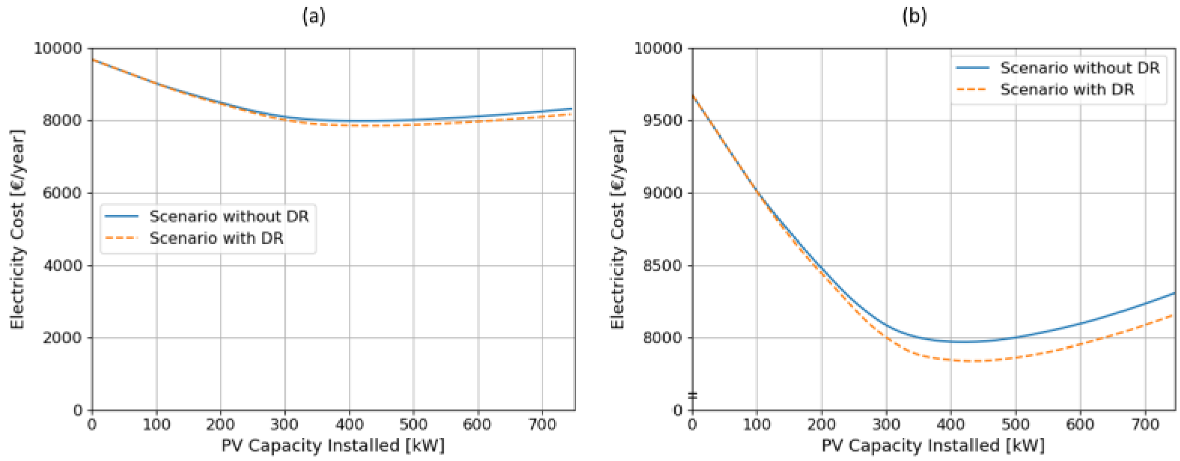

Figure 4.5. Evolution of the cost varying the PV capacity installed (a) and a focus on the interested region of the chart (b)

Figure 4.5 shows the electricity costs' differences between the scenario without the DR strategy in blue and, with the orange dashed line, the one with DR employed. While the graph (a) is relevant to see the impact on the cost, the (b) is a zoom on the interested area of the chart to appreciate the optimal PV capacity to be installed – the point corresponding to the minimum of the two curves. Since the difference between the curves is significantly stable after a specific setpoint – 350 kW of PV capacity installed – the average distance between the two lines can be considered as an indicator of an economic value of the flexible loads' cluster: 137.57 €/year.

Table 4.3. Comparison of Electricity Cost and Optimal PV Capacity in the scenarios with and without DR strategy implemented

	Electricity Costs [€/year]	**Optimal PV Capacity [kW$_p$]**
Scenario without DR	7 888	460
Scenario with DR	7 763	465
Δ [%]	- 1.58	+ 1.09

Table 4.3 reports the comparison between the values obtained, confirming what could be observed in Figure 4.5: the impact of the DR strategy on the costs and on the optimal PV capacity to be installed is irrelevant. The two outcomes' delta (*Δ*) has been calculated with the formula *(4.1)*.

$$\Delta = \frac{Outcome_{with\ DR} - Outcome_{without\ DR}}{Outcome_{without\ DR}} \tag{4.1}$$

4.2.2. Self-Consumption varying the PV Capacity Installed

Figure 4.6 (a) shows the evolution of the SSR varying the PV Capacity installed while the graph (b) the one related to the SCR. In both (a) and (b) the blue line is associated with the scenario without DR while the dashed orange curve with the DR strategy implemented. The effect of the DR implementation starts to be significant after a certain threshold for both graphs as it was the case for the cost.

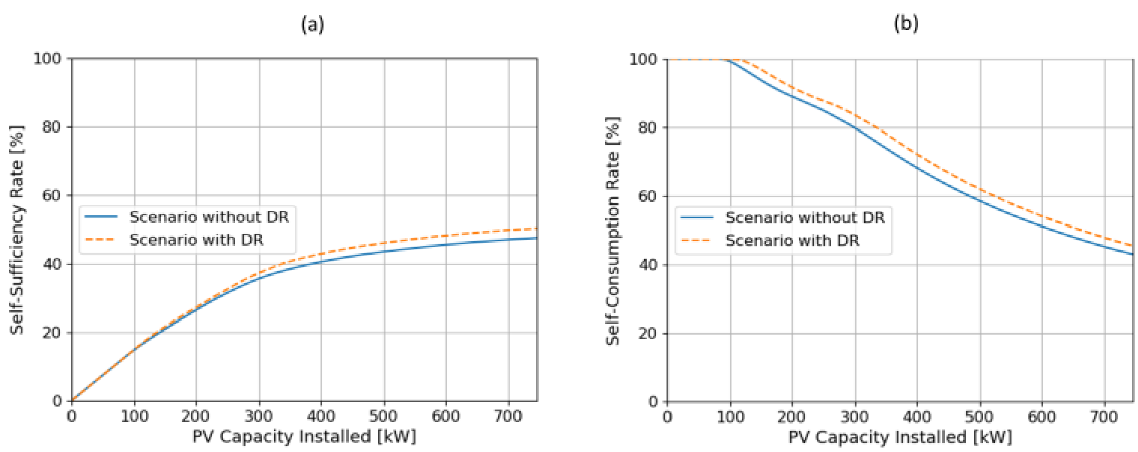

Figure 4.6. Evolution of the Self-Sufficiency Rate (a) and the Self-Consumption Rate (b) varying the PV capacity installed

For the SSR, the setpoint is around 350 kW of PV capacity installed as it was for the electricity cost; this correlation is due to the fact that the community savings are directly correlated to the amount of consumed electricity coming from the locally installed power systems. Regarding the SCR, the threshold is around 150 kW; from this point, the extra electricity produced by the PV power systems that are added each iteration becomes higher than the electricity consumption shifts due to the EWHs' flexibility and therefore the dashed orange line decrease with a similar trend as the blue curve.

Table 4.4 reports the values at the optimum for the scenario without DR implemented and the average difference between the two curves from a fixed setpoint: for the SSR from PV capacity 350 kW while for SCR from 150 kW.

Table 4.4. Comparison of Self-Sufficiency Rate and Self-Consumption Rate in the scenarios with and without DR strategy implemented

	Self-Sufficiency Rate [%]	Self-Consumption Rate [%]
Scenario without DR	42.47	62.10
Scenario with DR	44.97	65.75
Average Difference	+ 2.57	+ 3.26

As from the previous outcomes, even in this case, the impact of the DR strategy is not significant considering the effects on the overall community.

4.3. Impact on the Community varying the number of Electric Water Heaters installed

The same outcomes, fixing the number of PV Capacity Installed as the economic optimal for the Scenario without DR reported in Table 4.3 – 460 kW, can be evaluated varying the number of EWHs instead of the local renewable power capacity.

4.3.1. Electricity Cost varying the number Electric Water Heaters installed

The first outcome discussed is the electricity cost paid by the community. The graphs in Figure 4.7 (a) and (b) show the evolution of the electricity cost varying the number of EWHs installed in the community. With the blue line is represented the scenario without DR while with the dashed orange one the scenario with DR.

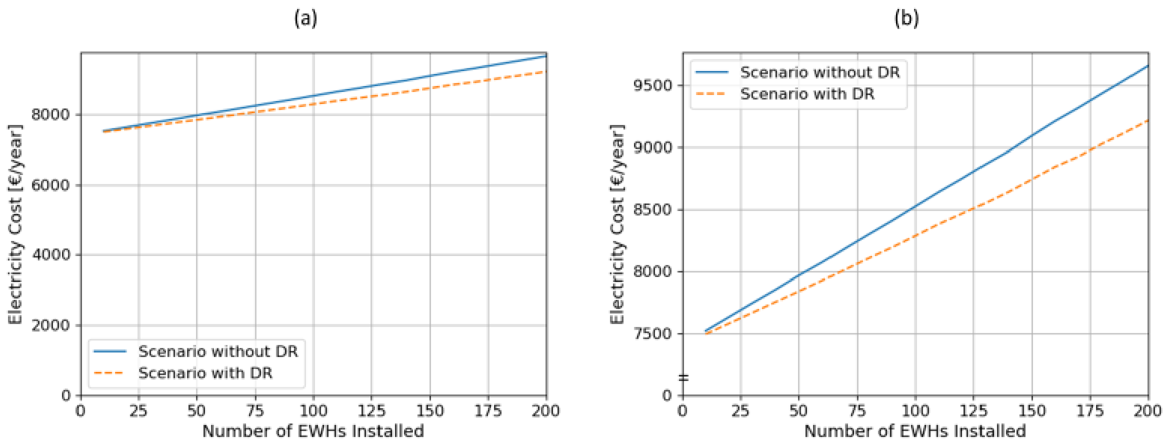

Figure 4.7. Evolution of the cost varying the number of EWHs installed (a) and a focus on the interested region of the chart (b)

By growing the number of flexible assets, the price increases for both scenarios due to the increased electricity consumption. With the highest diffusion of EWHs, the impact of the DR strategy is more significant due to the increased share of the flexible load in the community. In the scenario with 200 flexible units the electricity cost drops by -4.67% in the scenario with the DR strategy.

4.3.2. Self-Consumption varying the number of Electric Water Heaters installed

A similar trend can be observed for the self-consumption indicators adopted in this work. Figure 4.8 reports the evolution of SSR and SCR with the dashed orange line related to the scenario with DR and the plain blue one representing the scenario without DR. Looking at the SSR in (a), the blue line decreases increasing the consumption, while the dashed orange one present more stable values due to the effects of the DR strategy. For the SCR (b), the value slightly increases without DR strategy, while employing it helps to boost the consumption of locally produced electricity.

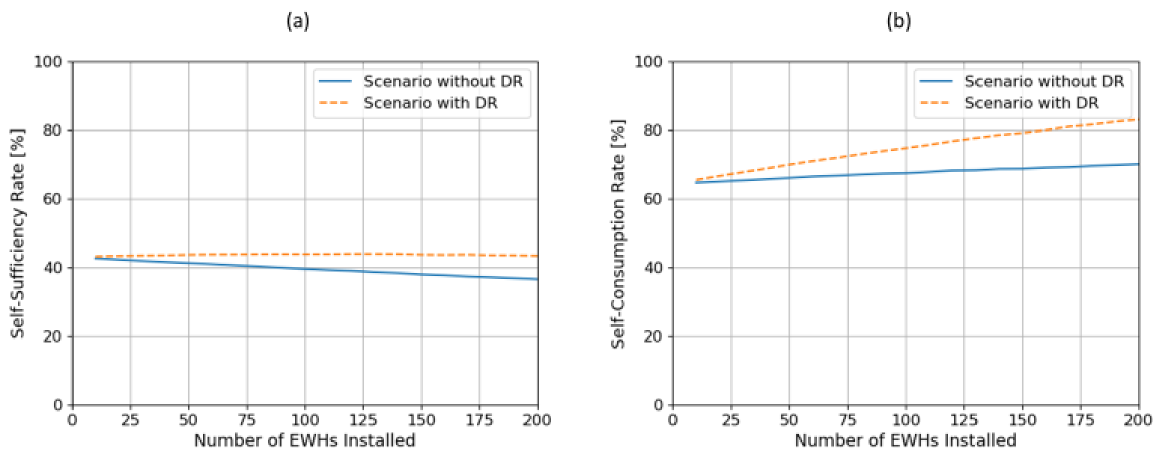

Figure 4.8. Evolution of Self-Sufficiency Rate (a) and Self-Consumption Rate (b) varying the number of EWHs installed

Similar to the electricity cost evolution, the difference between the two scenarios is directly related to the increasing number of the EWHs, reflecting the increased share of the flexible load in the total community consumption. The increases registered with the DR strategy in the self-sufficiency rate and in the self-consumption rate are relatively +7.25% and +12.67% in the scenarios with 200 units installed.

4.4. Impact considering the Electric Water Heater only

To have a better understanding of the effects of the DR strategy adopted during this work, it has been also analysed its impact related only to the cluster of the flexible loads. Every comment about the impact on the electricity cost has been avoided because of the significant difference between the PV power system yearly costs and the consumption cost of this specific single component. For this reason, the focus has only be set on the SSR regarding the impact on the self-consumption; the PV production derived from the power systems sized to feed the whole community is remarkably higher than the consumption of the EWHs, therefore any changes would be barely noticeable looking at the SCR.

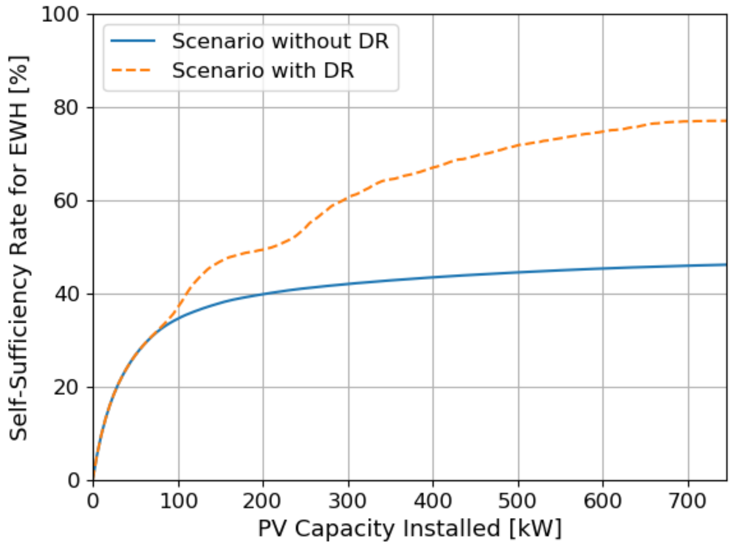

Figure 4.9. Self-Sufficiency Rate evolution for the EWH profiles varying the PV capacity installed

Figure 4.9 shows the evolution of the SSR, considering only the EWHs consumption, varying the PV capacity installed. It is possible to observe that after 100 kW the dashed orange line, identifying the scenario with the DR strategy implemented, starts to visibly diverge from the blue one, representing the scenario without DR. From a certain threshold, similar to the case of Figure 4.5 and Figure 4.6 (a) graphs, the difference between the two curves starts to settle. However, opposite to Figure 4.6 (a) that is showing the SSR evolution but considering the whole community, the impact on the EWHs consumption is more tangible in this case. The average difference between the two lines is more than 10 times higher compared with the Community scenario; the average gap after the 350 kW threshold is, in fact, + 27.65 % against the + 2.57 % of the scenario reported in Figure 4.6 (a).

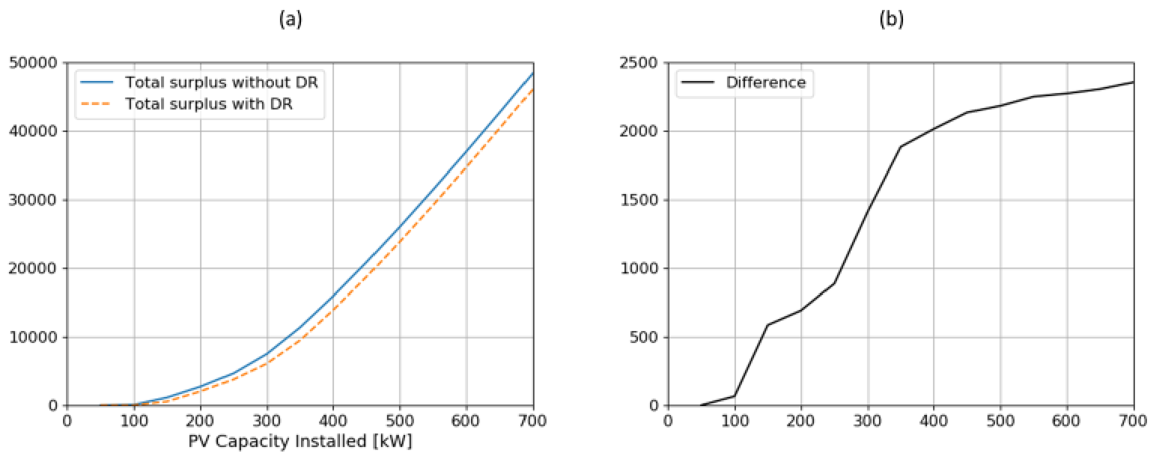

Figure 4.10. The evolution of the total sun surplus without and with DR (a) and the difference between the two scenarios (b)

Figure 4.10 reports the evolutions of the sun surplus varying the PV capacity installed. The difference reported in the graph (b) reveals, as in Figure 4.9 and Figure 4.6 (b), two changes in the curve concavity. One of this two particular point may be due the fact that a certain point the available sun surplus is enough to allow shifts intraday, therefore to shift the charges related to the night bus to the morning of the day after.

5. Conclusion

This thesis assessed the benefits of introducing a cluster of flexible assets in a specific microgrid use case: a Portuguese community equipped with a relevant capacity of solar PV and composed by LV and MV customers. To quantify the impacts of the behind-the-meter flexibility, a DR logic was developed and implemented. The load control strategy aims to shift the electric water heaters' consumption under growing PV penetration towards periods of local overproduction to increase the self-sufficiency of the community. The results of the DR strategy were presented and discussed to gain insight into the possible future impacts of flexible loads in a context of high RVE penetration. Specifically, it has been analysed the improvements related to the network connection capacity, the community's self-consumption and the related economic savings.

The specific use case analysed has highlighted that the DR strategy adopted delivered positive benefits to the community, though not significantly. The model developed reported the following variation between the scenarios with and without DR implementation: -0.13% related to the net peak load, +2.50% and +3.65% respectively for self-sufficiency and self-consumption rates and a -1.58% in the yearly electricity cost expenditures. The irrelevant simulated impact on the net peak load, thus on the network connection capacity, is due to the fact that the DR strategy implemented aims only at increasing the self-consumption without any other specific purposes. Among the three indicators analysed – electricity cost, self-sufficiency rate and self-consumption rate – the one that varies the most is the self-consumption rate, representing the share of electricity consumed on-site compared to the total production deriving from the PV systems. By increasing the relative share of flexible loads, however, it is possible to obtain more relevant impacts. When the flexible load consumption's share reaches a value above 20%, a self-sufficiency rate above 45% and a self-consumption rate of about 80% have been obtained by simulation. This corresponds to an increase of 7% and 12% over the scenario without DR strategy implemented. The DR program's effect becomes even more evident when analysing its impact on the flexible assets individually: in this case, the self-sufficiency rate increase by 26% while adopting the load control strategy.

From the obtained results, it is possible to state that DSM cannot provide alone the required flexibility to face the increasing supply volatility driven by the growing deployment of VRE. This corroborates the findings reported in the literature. DSM will, however, play an important role in the electricity system transformation; the increasing number of available flexible assets due the electrification of the transportation and the heating sectors combined with the reducing costs of advanced control and monitoring technologies are offering a new innovative way to transform the traditional consumers into active prosumers. Furthermore, as shown in this thesis, when the share of flexible assets in the electrical network will reach significant values, the implementation of proper DR strategies would deliver substantial benefits.

5.1. Future work

Similar works could be performed by replacing or integrating in the community other types of flexible assets controlled by the same DR strategy proposed in this thesis. Such appliances could be EV charging stations, washing machines or dish washers. Similarly to the EWHs' cluster, their impact could be studied with a simple methodology as the one adopted in this work.

To improve the results of the work developed on the EWHs' flexibility, the probability vector adopted in this thesis could be updated assigning the values looking at a real database of water consumption related to the analysed community. If a continuous data flow could be provided, machine learning algorithms could be implemented to maintain the DW consumption behaviours up to date. At this point, to simulate the EWH performance it could be developed a physical model that could take into account (1) the water usages – in terms of energy – during the day, (2) the thermal losses due the temperature difference between the water in the tank and the ambient temperature and (3) the energy gains due the thermal resistance of the EWH. The constraints of such a model would be then based on the water temperature in the tank to (1) maintain the water temperature above a certain minimum in order not to impact on the comfort of the end users and to assure the elimination of the legionella bacteria and to (2) not surpass the maximum temperature allowed by the component material of the tank. This more realistic model should lead to an increased electrical consumption for the EWH and asset's flexibility, thus the DR impacts should become more evident.

By changing the DR strategy it would be possible to analyse the impact of flexibility on objectives different from those analysed in this thesis. An interesting objective would be the mitigation of ramp-up and ramp-down events and how such mitigation could reduce the net peak load or the hours of minimum generation.

As discussed in section 2.2, the markets are opening to DR services and this could allow the community to gather more economic benefits from its flexible assets. In order to quantify this new kind of revenues, a detailed study on the technical performance achievable from the specific type of appliances controlled should be performed to identify the accessible markets, specifically the time availability and time of response. At this point, a related cost analysis should be included taking into account the frequency of the data transmission and data processing required for the markets selected. Further studies could also quantify the security risks by analysing the achievable accuracy of load and generation forecasts. This type of work should not only highlight the estimated frequency of imbalance's cost, but also the number of discomfort events experienced by the end-users.

References

[1] International Energy Agency, "System Integration of Renewables," 2018.

[2] M. Stifter *et al.*, "Roles and Potentials of flexible consumers and prosumers," *IEA DSM Task 17*, 2016.

[3] T. Esterl *et al.*, "Valuation Analysis of Demand Flexibility in Households and Buildings," 2016.

[4] C. Martin, F. Starace, and J. P. Tricoire, "The Future of Electricity New Technologies Transforming the Grid Edge," *World Econ. Forum*, no. March, p. 32, 2017.

[5] Linear consortium, "Demand Response for Families," 2014.

[6] Berkeley Lab, "Welcome to DRRC | DRRC." [Online]. Available: https://drrc.lbl.gov/. [Accessed: 24-Aug-2018].

[7] International Energy Agency, "International Energy Agency Demand Side Management." [Online]. Available: http://www.ieadsm.org/. [Accessed: 24-Aug-2018].

[8] European Union, "Directive of 2009/72/EC," *Off. J. Eur. Union*, vol. L211, no. August, p. L 211/55-L 211/93, 2009.

[9] European Parliament, "Directive 2012/27/EU," 2012.

[10] European Commission, "Clean Energy for All Europeans," 2016. [Online]. Available: https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/clean-energy-all-europeans. [Accessed: 27-Aug-2018].

[11] SEDC, "Explicit Demand Response in Europe Mapping the Markets 2017," 2017.

[12] A. Conchado and P. Linares, "The Economic Impact of Demand-Response Program on Power Systems. A survey of the State of the Art," in *Handbook of Networks in Power Systems I*, 2012, pp. 281–301.

[13] Rocky Mountain Institute, "Demand Response: An Introduction – Overview of Programs, Technologies, & Lessons Learned," 2006.

[14] A. Farqui and R. Hledik, "The state of demand response in California. Prepared for California Energy Commision, final consultant report," 2007.

[15] International Energy Agency (IEA), *The power to choose - Demand Response in Liberalised Electricity Markets*. 2003.

[16] US Department of Energy, "Benefits of Demand Response in Electricity Markets and Recomendations for Achieving Them," 2006.

[17] DTE Energy, "Demand response overview and pilot concepts," 2007.

[18] B. J. Johnson, M. R. Starke, O. A. Abdelaziz, R. K. Jackson, and L. M. Tolbert, “A dynamic simulation tool for estimating demand response potential from residential loads,” *Innov. Smart Grid Technol. Conf. (ISGT), 2015 IEEE Power Energy Soc.*, no. Dlc, pp. 1–5, 2015.

[19] Z. Chen, L. Wu, and Y. Fu, “Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1822–1831, 2012.

[20] P. Du and N. Lu, “Appliance commitment for household load scheduling,” *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 411–419, 2011.

[21] M. Liu, F. Quilumba, and W. J. Lee, “A Collaborative Design of Aggregated Residential Appliances and Renewable Energy for Demand Response Participation,” *IEEE Trans. Ind. Appl.*, vol. 51, no. 5, pp. 3561–3569, 2015.

[22] P. Bronski *et al.*, “The Economics of Demand Flexibility: How ‘Flexiwatts’ Create Quantifiable Value for Customers and the Grid,” 2015.

[23] F. Sossan, A. M. Kosek, S. Martinenas, M. Marinelli, and H. Bindner, “Scheduling of domestic water heater power demand for maximizing PV self-consumption using model predictive control,” *2013 4th IEEE/PES Innov. Smart Grid Technol. Eur. ISGT Eur. 2013*, pp. 4–8, 2013.

[24] J. Munkhammar, P. Grahn, and J. Widén, “Quantifying self-consumption of on-site photovoltaic power generation in households with electric vehicle home charging,” *Sol. Energy*, vol. 97, pp. 208–216, 2013.

[25] S. Quoilin and A. Zucker, “Techno-economic evaluation of self-consumption with PV / battery systems under different regulation schemes.”

[26] J. Weniger, T. Tjaden, and V. Quaschning, “Sizing and grid integration of residential PV battery systems,” *8th Int. Renew. Energy Storage Conf. Exhib. (IRES 2013)*, pp. 1–15, 2013.

[27] A. Moreau, “Control strategy for domestic water heaters during peak periods and its impact on the demand for electricity,” *Energy Procedia*, vol. 12, pp. 1074–1082, 2011.

[28] S. Wong and S. Pelland, “Mitigate Minimum Generation Conditions,” 2013.

[29] J. Kondoh, N. Lu, and D. J. Hammerstrom, “An evaluation of the water heater load potential for providing regulation service,” *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1309–1316, 2011.

[30] E. C. Kara, M. D. Tabone, J. S. MacDonald, D. S. Callaway, and S. Kiliccote, “Quantifying flexibility of residential thermostatically controlled loads for demand response,” *Proc. 1st ACM Conf. Embed. Syst. Energy-Efficient Build. - BuildSys ’14*, no. October 2014, pp. 140–147, 2014.

[31] M. Ali, A. Safdarian, and M. Lehtonen, “Demand response potential of residential HVAC loads

considering users preferences," *IEEE PES Innov. Smart Grid Technol. Conf. Eur.*, vol. 2015–Janua, no. January, pp. 1–6, 2015.

[32] A. J. D. Rathnayaka, V. M. Potdar, T. Dillon, and S. Kuruppu, "Framework to manage multiple goals in community-based energy sharing network in smart grid," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 615–624, 2015.

[33] B. P. Koirala, E. Koliou, J. Friege, R. A. Hakvoort, and P. M. Herder, "Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 722–744, 2016.

[34] OMIE, "Price Report," 2016.

[35] OMIE, "Price Report," 2018.

[36] IRENA, "Global Atlas Gallery 3.0." [Online]. Available: https://irena.masdar.ac.ae/gallery/#map/871. [Accessed: 22-Aug-2018].

[37] I. Fraunhofer Institute for Solar Energy Systems, PSE Conferences, and Consulting GmbH, "Photovoltaics Report," no. August, 2018.

[38] EDP, "Tarifas de Média Tensão." [Online]. Available: https://www.edpsu.pt/pt/tarifasehorarios/Pages/TarifaMT.aspx. [Accessed: 22-Aug-2018].

[39] "Meteonorm: Irradiation data for every place on Earth." [Online]. Available: http://www.meteonorm.com/. [Accessed: 03-Aug-2018].

[40] R. Perez, R. Stewart, R. Seals, and T. Guertin, "The development and verification of the Perez Diffuse Radiation Model," 1988.

[41] R. Perez, R. Seals, P. Ineichen, R. Stewart, and D. Menicucci, "A new simplified version of the perez diffuse irradiance model for tilted surfaces," *Sol. Energy*, vol. 39, no. 3, pp. 221–231, 1987.

[42] R. Perez, P. Ineichen, R. Seals, J. Michalsky, and R. Stewart, "Modeling daylight availability and irradiance components from direct and global irradiance," *Sol. Energy*, vol. 44, no. 5, pp. 271–289, 1990.

[43] P. G. Loutzenhiser, H. Manz, C. Felsmann, P. A. Strachan, T. Frank, and G. M. Maxwell, "Empirical validation of models to compute solar irradiance on inclined surfaces for building energy simulation," *Sol. Energy*, vol. 81, no. 2, pp. 254–267, 2007.

[44] P. Cappers, C. Goldman, and D. Kathan, "Demand response in U.S. electricity markets: Empirical evidence," *Energy*, vol. 35, no. 4, pp. 1526–1535, 2009.

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6. Annexes

6.1. Economic Parameters Calculation

Following the assumption reported in Section 0, the yearly CF of the solar PV system and their related levelized values are reported in Table 6.1.

Table 6.1. Yearly cash flows and levelized values for the reference solar PV system

Year	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
CF	4,500.00	67.50	67.50	67.50	67.50	67.50	67.50	67.50	67.50	67.50	517.50	67.50	67.50
Levelized CF	4,500.00	63.08	58.96	55.10	51.50	48.13	44.98	42.04	39.29	36.72	263.07	32.07	29.97
Year	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*
CF	67.50	67.50	67.50	67.50	67.50	67.50	67.50	517.50	67.50	67.50	67.50	67.50	67.50
Levelized CF	28.01	26.18	24.47	22.86	21.37	19.97	18.66	133.73	16.30	15.24	14.24	13.31	12.44

Using the equation *(3.2)* it has been obtained a NPC of 5,631.66. Finally, with the equation *(3.3)* it has been obtained LC = 96.65.

6.2. Solar Photovoltaic System Technical Details

Sunmodule Pro-Series
SW 250 POLY (33mm frame)

SOLARWORLD

REAL VALUE

PERFORMANCE UNDER STANDARD TEST CONDITIONS (STC)*

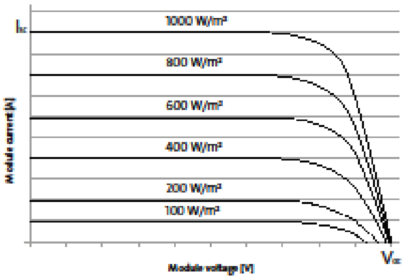
Maximum power	P_{max}	250 Wp
Open circuit voltage	V_{oc}	37.6 V
Maximum power point voltage	V_{mpp}	30.5 V
Short circuit current	I_{sc}	8.81 A
Maximum power point current	I_{mpp}	8.27 A
Module efficiency	η_m	14.91 %

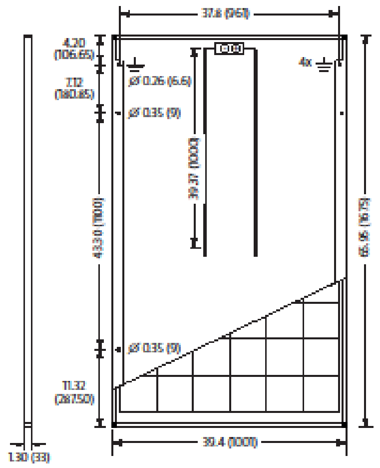
*STC: 1000 W/m², 25°C, AM 1.5

1) Measuring tolerance (P_{max}) traceable to TUV Rheinland: +/- 2% (TUV Power Controlled).

THERMAL CHARACTERISTICS

NOCT	46 °C
TC I_{sc}	0.081 %/°C
TC V_{oc}	-0.37 %/°C
TC P_{mpp}	-0.45 %/°C
Operating temperature	-40°C to 85°C





PERFORMANCE AT 800 W/m², NOCT, AM 1.5

Maximum power	P_{max}	185.4 Wp
Open circuit voltage	V_{oc}	34.2 V
Maximum power point voltage	V_{mpp}	27.8 V
Short circuit current	I_{sc}	7.24 A
Maximum power point current	I_{mpp}	6.68 A

Minor reduction in efficiency under partial load conditions at 25°C: at 200 W/m², 100% (+/-2%) of the STC efficiency (1000 W/m²) is achieved.

COMPONENT MATERIALS

Cells per module	60
Cell type	Poly crystalline
Cell dimensions	6.14 in x 6.14 in (156 mm x 156 mm)
Front	Tempered glass (EN 12150)
Frame	Clear anodized aluminum
Weight	39.7 lbs (18.0 kg)

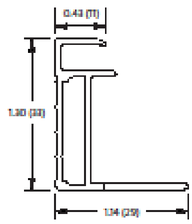
SYSTEM INTEGRATION PARAMETERS

Maximum system voltage SC II / NEC		1000 V
Maximum reverse current		25 A
Number of bypass diodes		3
*Design Loads**	*Two rail system*	113 psf downward 64 psf upward
*Design Loads**	*Three rail system*	178 psf downward 64 psf upward
*Design Loads**	*Edge mounting*	178 psf downward 41 psf upward

* Please refer to the Sunmodule installation instructions for the details associated with these load cases.

ADDITIONAL DATA

Power sorting¹	-0 Wp / +5 Wp
J-Box	IP65
Module leads	PV wire per UL4703 with H4 connectors
Module type (UL 1703)	1
Glass	Low iron tempered with ARC



- Compatible with both "Top-Down" and "Bottom" mounting methods
- Grounding Locations:
  – 4 locations along the length of the module in the extended flange.

All units provided are imperial. SI units provided in parentheses.
SolarWorld AG reserves the right to make specification changes without notice.

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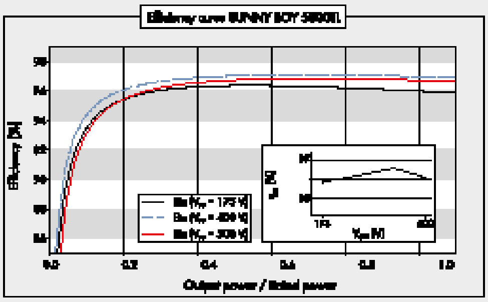

Accessory

[1] Does not apply to all national appendices of EN 50438
[2] 4600 VA according VDE-AR-N 4105 [3] 4825 W according to VDE-AR-N 4105
[4] Only SB 3600TL-21, SB 5000TL-21

Technical Data	Sunny Boy 4000TL	Sunny Boy 5000TL
Input (DC)		
Max. DC power (at cos φ = 1)	4200 W	5250 W[3]
Max. input voltage	750 V	750 V
MPP voltage range / rated input voltage	175 V to 500 V / 400 V	175 V to 500 V / 400 V
Min. input voltage / initial input voltage	125 V / 150 V	125 V / 150 V
Max. input current input A / input B	15 A / 15 A	15 A / 15 A
Max. input current per string input A / input B	15 A / 15 A	15 A / 15 A
Number of independent MPP inputs / strings per MPP input	2 / A:2; B:2	2 / A:2; B:2
Output (AC)		
Rated power (at 230 V, 50 Hz)	4000 W	4600 W
Max. AC apparent power	4000 VA	5000 VA[2]
Nominal AC voltage / range	220 V, 230 V, 240 V / 180 V to 280 V	220 V, 230 V, 240 V / 180 V to 280 V
AC power frequency / range	50 Hz, 60 Hz / −5 Hz to +5 Hz	50 Hz, 60 Hz / −5 Hz to +5 Hz
Rated power frequency / rated grid voltage	50 Hz / 230 V	50 Hz / 230 V
Max. output current	22 A	22 A
Power factor at rated power	1	1
Adjustable displacement power factor	0.8 lagging to 0.8 leading	0.8 lagging to 0.8 leading
Feed-in phases / connection phases	1 / 1	1 / 1
Efficiency		
Max. efficiency / European Efficiency	97 % / 96.4 %	97 % / 96.5 %
Protective Devices		
Input-side disconnection point	●	●
Ground fault monitoring / grid monitoring	● / ●	● / ●
DC reverse polarity protection / AC short-circuit current capability / galvanically isolated	● / ● / –	● / ● / –
All-pole sensitive residual-current monitoring unit	●	●
Protection class (according to IEC 62103) / overvoltage category (according to IEC 60664-1)	I / III	I / III
General Data		
Dimensions (W / H / D)	490 / 519 / 185 mm (19.3 / 20.4 / 7.3 inch)	
Weight	26 kg (57.3 lb)	
Operating temperature range	−25 °C to +60 °C (−13 °F to +140 °F)	
Noise emission (typical)	25 dB(A)	25 dB(A)
Self-consumption (at night)	1 W	1 W
Topology	Transformerless	Transformerless
Cooling method	Convection	Convection
Degree of protection (according to IEC 60529)	IP65	IP65
Climatic category (according to IEC 60721-3-4)	4K4H	4K4H
Maximum permissible value for relative humidity (non-condensing)	100 %	100 %
Features		
DC connection / AC connection	SUNCLIX / spring-cage terminal	SUNCLIX / spring-cage terminal
Display	Graphic	Graphic
Interfaces: RS485 / Bluetooth® / Speedwire/Webconnect	○ / ● / ●	○ / ● / ●
Multifunction relay / Power Control Module	○ / ○	○ / ○
Warranty: 5 / 10 / 15 / 20 / 25 years	● / ○ / ○ / ○ / ○	● / ○ / ○ / ○ / ○
Certificates and approvals (others available upon request)	AS 4777, C10/11, CE, CEI 0-21, EN 50438[1], G59/3, G83/2, IEC 61727, MEA[4], NEN-EN50438, NRS 097-2-1, PEA[4], PPC, PPDS, RD1699, RD 661, SI 4777, UTE C15-712, VDE-AR-N 4105, VDE0126-1-1, VFR 2013, VFR 2014	
● Standard features ○ Optional features – Not available, Data at nominal conditions		
Type designation	SB 4000TL-21	SB 5000TL-21

6.3. Photovoltaic System Production Calculation

To assess the production load curve of the reference solar PV system, the below Python code has been developed. The file *Martim_Longo-min.xlsx* has been gathered from Meteonorm as previously stated and it contains the meteorological data – air temperature, wind speed and global, direct and diffuse irradiation on an horizontal surface – from the chosen location. The effective irradiation hitting the tilted surfaces of the PV system and the simulated production have been calculated using the *PVlib* library.

```
import pandas as pd
import pvlib
from pvlib.pvsystem import PVSystem
from pvlib.modelchain import ModelChain
from pvlib.location import Location

# Location data for Martim Longo
latitude = 37.442
longitude = -7.771
tz = 'UTC'
altitude = 249
location = Location(latitude, longitude, tz=tz, altitude=altitude)

# Weather data from Meteonorm, 1 min resolution
df1 = pd.read_excel('Marim_Longo-min.xlsx')
df1['times'] = pd.date_range('1/1/2016', periods=525600, freq='min')
df1.index = df1['times']
df1.index.name = 'Time'

# Get the portion of data required:
# 1 week of March starting from the 14th
# 1 week of June starting from the 6th
# 1 week of September starting from the 12th
# 1 week of December starting from the 5th
df_march = df1.loc['20160314':'20160320']
df_june = df1.loc['20160606':'20160612']
df_september = df1.loc['20160912':'20160918']
df_december = df1.loc['20161205':'20161217']
frame = [df_march, df_june, df_september, df_december]
df = pd.concat(frame)

times = df['times']
d_weather = {'temp_air': df['Ta'],
             'wind_speed': df['FF'],
             'ghi': df['G_Gh'],
             'dni': df['G_Bn'],
             'dhi': df['G_Dh']}
weather_data = pd.DataFrame(d_weather)

# PV data
pv_db = pvlib.pvsystem.retrieve_sam('SandiaMod')
inverter_db = pvlib.pvsystem.retrieve_sam('cecinverter')
# print(list(pv_db))
# print(list(inverter_db))
pv_data = pv_db['SolarWorld_Sunmodule_250_Poly__2013_']  #
Hanwha_HSL60P6_PA_4_250T__2013_
inverter = inverter_db['SMA_America__SB5000TL_US_22__240V__240V__CEC_2013_']  #
'iPower__SHO_5_2__240V__240V__CEC_2018_'

# Production
system = PVSystem(surface_tilt=37, surface_azimuth=180, albedo=0.2,
                  surface_type=None, module_parameters=pv_data,
                  modules_per_string=10, strings_per_inverter=2,
                  inverter_parameters=inverter,
                  racking_model='open_rack_cell_glassback')
mc = ModelChain(system, location, orientation_strategy=None,
```

```
                clearsky_model='ineichen', transposition_model='perez',
                solar_position_method='nrel_numpy',
                airmass_model='kastenyoung1989',
                dc_model='sapm', ac_model=None, aoi_model='physical',
                spectral_model='no_loss', temp_model='sapm',
                losses_model='no_loss', name=None)

mc.run_model(times, None, weather_data)
power_ac = pd.Series(mc.ac)
power_ac.fillna(value=0, inplace=True)

# Summing up the energy produced each 15 min
energy_produced_min = power_ac / 60e3   # energy in kWh
energy_produced_15min = energy_produced_min.resample('15min').sum()

df_print = pd.DataFrame({'PV production': energy_produced_15min})

new_index = pd.date_range('2016/03/14 00:15', periods=26784, freq='15min')
df_print.index = new_index
df_print.to_csv('pv_production.csv', index_label='time')
```

6.4. Load Community Calculation

The LV profiles have been gathered from a timeframes' dataset – *Dados de Fev.xlsx* – provided by EDP with the following features: *Referência Equipamento* referring to the ID number of the client, *Potência Contratada (VA)* referring to the power contracted, *Data da leitura* indicating the date and the hour, *A+ (Total) kWh* showing the total energy (in kWh) consumed in the 15 minutes period. The below Python code has been developed to filter and select all the profiles' full week of consumption and, finally, to sum up the total LV profiles in single curve saved in the file *community_demand.csv*.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Open LV profiles csv file

df = pd.read_excel('Dados de Fev.xlsx', 'Raw')
df.index = df['Referência Equipamento']

reference = df['Referência Equipamento'].unique()
total_id = len(reference)
date = df['Data da leitura'].unique()
total_date = len(date)

final_consumption = np.zeros(672)

# Check if profiles have at least 7 days of data in a row
for i in range(0, total_id):
    df1 = df.loc[df['Referência Equipamento'] == reference[i]]
    count = 0
    for j in range(0, total_date):
        df2 = df1.loc[df1['Data da leitura'] == date[j]]
        check_row = df2.shape[0]
        if check_row == 96:
            count += 1
        else:
            count = 0
        if count == 7:
            # Condition satisfied // create a dataframe with the 7 days in a row
            for k in range(1, 7):
                df3 = df1.loc[df1['Data da leitura'] == (date[j] -
pd.Timedelta(days=k))]
                frames = [df3, df2]
```

```
                df2 = pd.concat(frames)

            # Order the dataframe from Monday to Sunday
            df2['Weekday'] = df2['Data da leitura'].dt.weekday
            df3 = df2.loc[df2['Weekday'] == 0]
            for z in range(1, 7):
                df4 = df2.loc[df2['Weekday'] == z]
                frames = [df3, df4]
                df3 = pd.concat(frames)

            # Sum the profile consumption to total final consumption
            final_consumption = final_consumption + df3['A+ (Total) kWh']
            final_consumption = np.asarray(final_consumption)       # in kWh!
            break

        # Drop values that doesn't have 7 days in a row from df to speed up the for
cycle
        if (total_date - 1) == j:
            df.drop(labels=reference[i], inplace=True)

times = pd.date_range('14/03/2016 00:15', periods=672, freq='15min')
df_print = pd.DataFrame({'final consumption winter': final_consumption})
df_print.index = times
df_print.to_csv('community_demand.csv', index_label='time')
```

Similarly, the dataset provided by Estabanell Energia has been treated with the below Python code to obtain the total MV profiles cluster profile curve, then saved into the file *MV_demand.csv*.

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Open file with MV profiles consumption data
df = pd.read_excel('CCH.xlsx')
df['DataLectura'] = pd.to_datetime(df['DataLectura'], yearfirst=True)
df.index = df['DataLectura']
reference_id = df['CUPS'].unique()
df['weekday'] = df['DataLectura'].dt.weekday

# Sum up all the consumption for the reference weeks for each quarter
consumption_hour_march = np.asarray([0 for x in range(169)])
consumption_hour_june = np.asarray([0 for x in range(169)])
consumption_hour_september = np.asarray([0 for x in range(169)])
consumption_hour_december = np.asarray([0 for x in range(169)])

total_id = len(reference_id)
for i in range(total_id):
    df1 = df.loc[df['CUPS'] == reference_id[i]]
    df_week_march = df1.loc['20180221230000':'20180228']
    df_week_june = df1.loc['201706132300':'20170620']
    df_week_september = df1.loc['201709112300':'20170918']
    df_week_december = df1.loc['201711042300':'20171111']    # get November instead
to avoid holidays

    # Order from Monday to Sunday
    df2_march = df_week_march.loc[df_week_march['weekday'] == 0]
    df2_june = df_week_june.loc[df_week_june['weekday'] == 0]
    df2_september = df_week_september.loc[df_week_september['weekday'] == 0]
    df2_december = df_week_december.loc[df_week_december['weekday'] == 0]
    for j in range(1, 7):
        df3_march = df_week_march.loc[df_week_march['weekday'] == j]
        df3_june = df_week_june.loc[df_week_june['weekday'] == j]
        df3_september = df_week_september.loc[df_week_september['weekday'] == j]
        df3_december = df_week_december.loc[df_week_december['weekday'] == j]

        frame_march = [df2_march, df3_march]
```

```
        frame_june = [df2_june, df3_june]
        frame_september = [df2_september, df3_september]
        frame_december = [df2_december, df3_december]

        df2_march = pd.concat(frame_march)
        df2_june = pd.concat(frame_june)
        df2_september = pd.concat(frame_september)
        df2_december = pd.concat(frame_december)

    consumption_hour_march = df2_march['ActivaImport'] / 1000 +
consumption_hour_march    # in kW
    consumption_hour_june = df2_june['ActivaImport'] / 1000 + consumption_hour_june
    consumption_hour_september = df2_september['ActivaImport'] / 1000 +
consumption_hour_september
    consumption_hour_december = df2_december['ActivaImport'] / 1000 +
consumption_hour_december

    consumption_hour_march = np.asarray(consumption_hour_march)
    consumption_hour_june = np.asarray(consumption_hour_june)
    consumption_hour_september = np.asarray(consumption_hour_september)
    consumption_hour_december = np.asarray(consumption_hour_december)

# Assume the reference week to be the selected one of the year 2016
new_index_march = pd.date_range('14/03/2016 0:15', periods=169, freq='H')
new_index_june = pd.date_range('06/06/2016 0:15', periods=169, freq='H')
new_index_september = pd.date_range('09/12/2016 0:15', periods=169, freq='H')
new_index_december = pd.date_range('12/05/2016 0:15', periods=169, freq='H')

consumption_hour_march = pd.Series(data=consumption_hour_march,
index=new_index_march)
consumption_hour_june = pd.Series(data=consumption_hour_june, index=new_index_june)
consumption_hour_september = pd.Series(data=consumption_hour_september,
index=new_index_september)
consumption_hour_december = pd.Series(data=consumption_hour_december,
index=new_index_december)

# get the energy each 15 min
power_15min_march =
consumption_hour_march.resample('15min').interpolate(method='linear')      # still
in kW
power_15min_june =
consumption_hour_june.resample('15min').interpolate(method='linear')
power_15min_september =
consumption_hour_september.resample('15min').interpolate(method='linear')
power_15min_december =
consumption_hour_december.resample('15min').interpolate(method='linear')

consumption_15min_march = power_15min_march * .25     # get the kWh
consumption_15min_june = power_15min_june * .25
consumption_15min_september = power_15min_september * .25
consumption_15min_december = power_15min_december * .25

consumption_15min_march.drop(consumption_15min_march.tail(1).index, inplace=True)
consumption_15min_june.drop(consumption_15min_june.tail(1).index, inplace=True)
consumption_15min_september.drop(consumption_15min_september.tail(1).index,
inplace=True)
consumption_15min_december.drop(consumption_15min_december.tail(1).index,
inplace=True)


df_print = pd.DataFrame({
    'final consumption march': consumption_15min_march,
    'final consumption june': consumption_15min_june,
    'final consumption september': consumption_15min_september,
    'final consumption december': consumption_15min_december
})
df_print.to_csv('MV_demand.csv', index_label='time')
```

The EWH profiles have been built with the following code that generates as well the probability vector in Figure 3.3. The profiles have been saved in the files *ewh_*.csv*, where * varies from 10 to 200 with a step equal 10. The final file contains not only the total EWHs cluster profile but also the individual ones with the related information to the usage as well as the electricity consumption.

```
import numpy as np
import pandas as pd
from scipy.stats import norm


def assign_with_probability(p):
    return np.random.choice(a=[1, 0], p=[p, 1 - p])


# Vectorize functions
v_assign_with_probability = np.vectorize(assign_with_probability)


def ewh_profile(peak_gap, morning_peak, evening_peak):
    # Create a vector with very low probability
    index_minutes = pd.date_range(start='22/06/2018', periods=24*60, freq='T')
    probability_vector = np.full(24 * 60, fill_value=0.001)
    probability_vector[(morning_peak * 60) - peak_gap:(morning_peak * 60) +
peak_gap] = \
        norm.pdf(np.linspace(norm.ppf(0.001),
                             norm.ppf(0.999), peak_gap * 2), scale=1)
    probability_vector[(evening_peak * 60) - peak_gap:(evening_peak * 60) +
peak_gap] = \
        norm.pdf(np.linspace(norm.ppf(0.001),
                             norm.ppf(0.999), peak_gap * 2), scale=1)

    probability_vector = pd.Series(probability_vector, index=index_minutes)
    probability_vector = probability_vector.resample('15T').mean()

    # Create a probability vector for 4 weeks
    probability_vector_week = np.tile(probability_vector.values, 7 * 4)
    # Create vector ewh_on vector using probability_vector
    return v_assign_with_probability(probability_vector_week)


number_ewh = 200
# Define consumption unit
P_nominal = 4.2   # Nominal power in kW
ewh_consumption = P_nominal * .25

#  Create MultiIndex DataFrame for EWH profiles
iterable = [np.array(range(number_ewh)),
            np.array(range(2688))]
index = pd.MultiIndex.from_product(iterable)
ewh_profiles = pd.DataFrame(index=index,
                            columns=['shower', 'consumption'])

for i in range(number_ewh):
    ewh_profiles.loc[i, 'shower'] = ewh_profile(300, 8, 19)

    for day in range(7*4):
        # Clean morning (from 0 till 47)
        n_drop = ewh_profiles.loc[i,
'shower'][day*96:(day*96+48)][ewh_profiles.loc[i, 'shower'] > 0].count() - 1

        if n_drop > 0:
            drop_indices = np.random.choice(ewh_profiles.loc[i,
'shower'][day*96:(day*96+48)]
                                            [ewh_profiles.loc[i, 'shower'] >
0].index, n_drop, replace=False)
```

```
            ewh_profiles.loc[i, 'shower'][drop_indices] = 0

        consumption_time = ewh_profiles.loc[i,
'shower'][day*96:(day*96+48)][ewh_profiles.loc[i, 'shower'] > 0]

        ewh_profiles.loc[i, 'consumption'][consumption_time.index + 1] =
ewh_consumption
        ewh_profiles.loc[i, 'consumption'][consumption_time.index + 2] =
ewh_consumption

        # Clean evening (from 48 till 95)
        n_drop = ewh_profiles.loc[i,
'shower'][(day*96+48):(day*96+96)][ewh_profiles.loc[i, 'shower'] > 0].count() - 1
        if n_drop > 0:
            drop_indices = np.random.choice(ewh_profiles.loc[i,
'shower'][(day*96+48):(day*96+96)]
                                            [ewh_profiles.loc[i, 'shower'] >
0].index, n_drop, replace=False)
            ewh_profiles.loc[i, 'shower'][drop_indices] = 0

        consumption_time = ewh_profiles.loc[i,
'shower'][(day*96+48):(day*96+96)][ewh_profiles.loc[i, 'shower'] > 0]

        if consumption_time.index >= 2685:
            ewh_profiles.loc[i, 'consumption'][2686] = ewh_consumption
            ewh_profiles.loc[i, 'consumption'][2867] = ewh_consumption

            ewh_profiles.loc[i, 'shower'][2685:2688] = 0
            ewh_profiles.loc[i, 'shower'][2685] = 1
        else:
            ewh_profiles.loc[i, 'consumption'][consumption_time.index + 1] =
ewh_consumption
            ewh_profiles.loc[i, 'consumption'][consumption_time.index + 2] =
ewh_consumption

    ewh_profiles.loc[i, 'shower'].replace(0, np.nan, inplace=True)
    ewh_profiles.loc[i, 'consumption'].fillna(value=0, inplace=True)

ewh_profiles.to_csv('ewh_%d.csv' % number_ewh)
```