SAPIENZA
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Ph.D. in Energy and Environment

A Mixed-Integer Linear Programming approach for the Optimization of Residential PV-Battery Energy Storage System

Francesca Lucchetta

Supervisor: Prof. Alessandro Corsini

Abstract

Europe´s electricity sector is facing a major historical turning point shifting away from fossil fuels towards more sustainable energy sources and moving from vertically integrated public monopolies into competitive private companies in unbundled and liberalized markets. In this scenario consumers are expected to play a fundamental role in realising the full potential of the European energy market; the EU energy strategy, with new policy and regulatory initiatives, in fact, recognizes consumers and communities as a key driver of this process, encouraging them to take full ownership of the energy transition and empowering them to actively participate in the electricity market by generating, consuming and selling electricity back to the grid and interacting with other energy market participants. Citizens are in fact no longer restricted to the role of passive end-use consumers, but they are asked to be energy producers, or 'prosumers', representing an important contribution to global sustainability and helping to decarbonize the electricity sector. Furthermore, as well as allowing to increase the amount of renewable energy generation, they have the potential to reduce the energy supply-demand gap and electricity system losses and to provide opportunities for demand-side management and for an active grid support increasing grid reliability flexibility, and resiliency. To this end, distributed energy storage systems at the residential level have been identified as a priority technology to open up new possibilities for local flexibility solutions and participation in demand response, leading the energy transition towards new energy configurations, such as self-generation and self-consumption schemes and peer-to-peer selling of the self-produced energy. Combining solar power generators and battery storage is one of the most common ways of reaching self-sufficiency in residential buildings by increasing the grid independence of individual households. Due to their cost and growth perspective, battery storage coupled to photovoltaic (PV) generation systems have reached a good level of competitiveness and market penetration in many European countries and they will increase as more such systems become available. In this thesis a battery energy storage systems (BESS) coupled with grid-connected rooftop-mounted residential photovoltaic

generation is analyzed. The multi apartment building is located in Civitavecchia (Rome), central Italy, with ten households living in rent at a subsidized price and it is covered by the energy retrofit intervention and building renovation plan set by "Civitavecchia SMART-A.T.E.R." project aiming to convert the old buildings in new Near Zero Energy Buildings (NZEBs) and to create energy communities. The aim of this thesis is to optimize the sizing and the operation of the battery energy storage system so as to maximize the households' self-consumption and minimize their electricity bill, whilst ensuring the correct charge-discharge cycles scheduling strategy in order to assure better performance and a longer lifetime of the batteries. To this end, a multi-objective mixed-integer linear programming (MILP) formulation is proposed and it is solved by CPLEX. The battery sizing and operational parameters, in terms of number of batteries and charging/discharging operation mode, are included in the optimization problem and a penalty coefficient is imposed to limit the number of batteries needed. Collected and estimated data of potential photovoltaic production and households' demand profiles are used to optimize the battery storage system using hourly dataset for different seasons.

Highlights

- Mixed-integer linear program based scheduling of a residential PV/storage system in a multi-apartment building.
- Applied to real consumption data of 10 residential families with a view to maximizing collective self-consumption.
- Mathematical formulation of the problem with specific constraints for optimal battery charging/discharging profile.
- Comparative analysis for different battery parameters and charging/discharging assumptions.
- Profitability assessment of the battery storage system comparing different scenarios.

Table of Contents

List of Figures

List of Tables

Introduction

The electricity market is a particularly complex system, both for the extreme diffusion and engineering variety of infrastructures and for the presence of a very delicate regulatory system, since it must maintain the balance between sources and uses of a precious resource such as energy. Furthermore, it is a system in which configurations and infrastructures are constantly evolving, they have undergone and continue to undergo profound transformations [1]. The recent changes in the national energy system resulting from the rapid widespread of renewable sources, primarily photovoltaic and wind power, are reflected today in the need to implement new "smart" management and operation methods that actively involve all phases of generation, distribution and consumption of energy, in order to ensure high reliability and safety standards. In particular, the growing impact of non-programmable renewable sources penetration has entailed a series of criticalities in short-term operational planning of the Italian power system [2]. Moreover, the gradual phase-out of fossil-fuel power plants, with a view to shutdown of each coal-fired power generating unit by 2025 [3], has the effect of reducing essential grid services such as the voltage and frequency regulations and congestion management services. There is therefore an obvious need for new decentralized, flexible and balanced energy systems. In particular, the decreasing cost of energy storage and the increasing penetration of renewable energy technologies as distributed generation embedded in the consumption centres is leading to fundamental changes in the role of energy consumers, giving rise to openings for new entrants to the electricity market, the so-called “prosumers”, because they both consume and produce electricity. The prosumers and their assets (decentralised production and storage systems, demand response, electric vehicles, etc.) have the potential to interact with each other and with the local distributor or the utility grid and to be aggregated forming a Local Energy Community (LEC) at distribution level [4]. In this context, residential districts can be considered as the first core for energy communities, aiming at providing active grid support by increasing grid reliability, flexibility, and resiliency, as outlined in the European

Directive 2018/2001 on the promotion of the use of energy from renewable sources [5]. Investments for the promotion of energy efficiency and the use of energy from renewable sources in buildings, on one hand, and the increasing deployment of customer-level energy storage systems equipped with Internet of Things (IoT) technologies, such as sensors and devices for smart metering, on the other, are therefore identified as the key factors in enabling the energy communities development [6]. Distributed smart storage systems in fact can be installed behind the meter in parallel to local loads; this allows to bring energy flexibility in a community by reducing average peak load and increasing self-consumption of local renewable energies not only at an individual household, but especially at an aggregated community level [7]. Moreover, the possibility of exploiting renewable energy sources and moving towards energy self-sufficiency at community level also represents a key measure to tackle energy poverty by ensuring a free access to the electricity market for all people within the community, including for example tenants of social housing or multiple-occupancy buildings.

In particular, in this thesis a multi apartment building with ten households living in rent at a subsidized price is considered as case study with the purpose of optimizing the battery storage coupled to photovoltaic generation system, both in terms of sizing and dispatching, with a view to maximizing the households' self-consumption.

The thesis is structured in the following way: Chapter 1 provides a detailed analysis of the current regulatory framework for energy self-consumption and gives a comprehensive overview of existing projects of energy storage system integration in residential buildings enabling residents of multi apartment buildings to commonly use electricity generated by a PV system. In Chapter 2 some preliminary concepts on optimization using Mixed-Integer Linear Programming are reported. Chapter 3 presents the state of the art on linear programming-based optimization for operational scheduling of energy storage systems and describes the reasons behind the application of the solution algorithm proposed in this work, with particular attention to formulating the batteries charging/discharging control strategy as the most important constraint to the optimization problem. Chapter 4 is focused on the application of the approach proposed in Chapter 3 to the case study. Finally, Chapter 5 investigates the benefits of energy storage system integration in residential buildings equipped with solar power generators from energetic and economic perspective.

Chapter 1

Background and motivation

1.1 The European energy transition

Energy systems in Europe are going through a process of profound transformation that will bring important changes to the way we fuel our cars, heat our homes and power our industries [8]. The growing share of renewable and decentralized generation, the progressive increase in energy efficiency along the whole energy value chain, the increasing need for flexibility in the energy system, the emergence of the consumers as active players in the energy system and the appearance of new network users are the main changes affecting the way in which energy producers, operators, regulators and consumers interact in an increasingly complex market towards a sustainable energy system with reduced greenhouse gas emissions, industrial development leading to growth and jobs and lower energy costs for the EU economy [9]. These ongoing changes are leading to an increased attention on energy storage systems across the entire energy value chain as illustrated in Figure 1 [10].

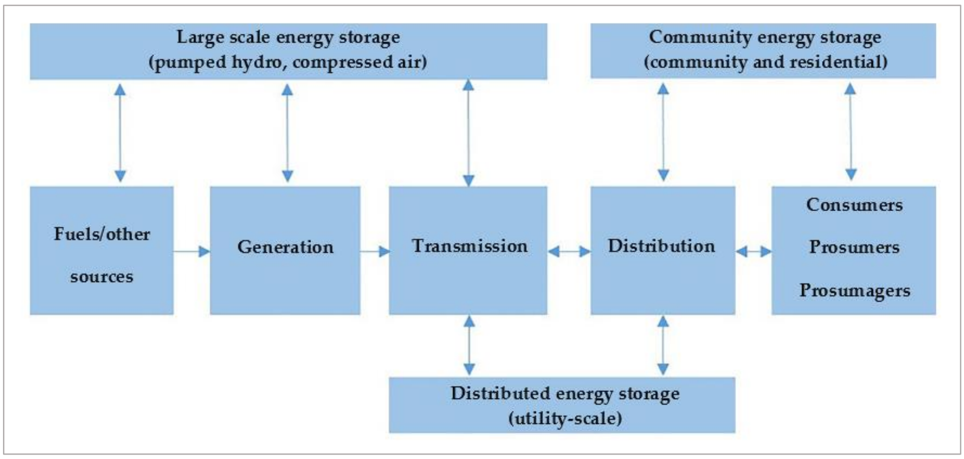


Figure 1 – Implementing energy storage at different scales in the energy system chain [10].

Among the several ways and scales energy storage systems can be implemented, the need for residential and community energy storage (CES) systems is expected to grow in the future in line with the increasing local energy initiatives and distributed energy resources (DERs) penetration as well as to meet increasing demand for flexibility and self-sufficiency of citizens and local communities [10]. On the other hand, the significative decreasing cost of worldwide residential PV systems over the last decade, as shown in Figure 2 [11], is expected to contribute positively towards self-consumption models and new cost-containment opportunities for energy consumers.

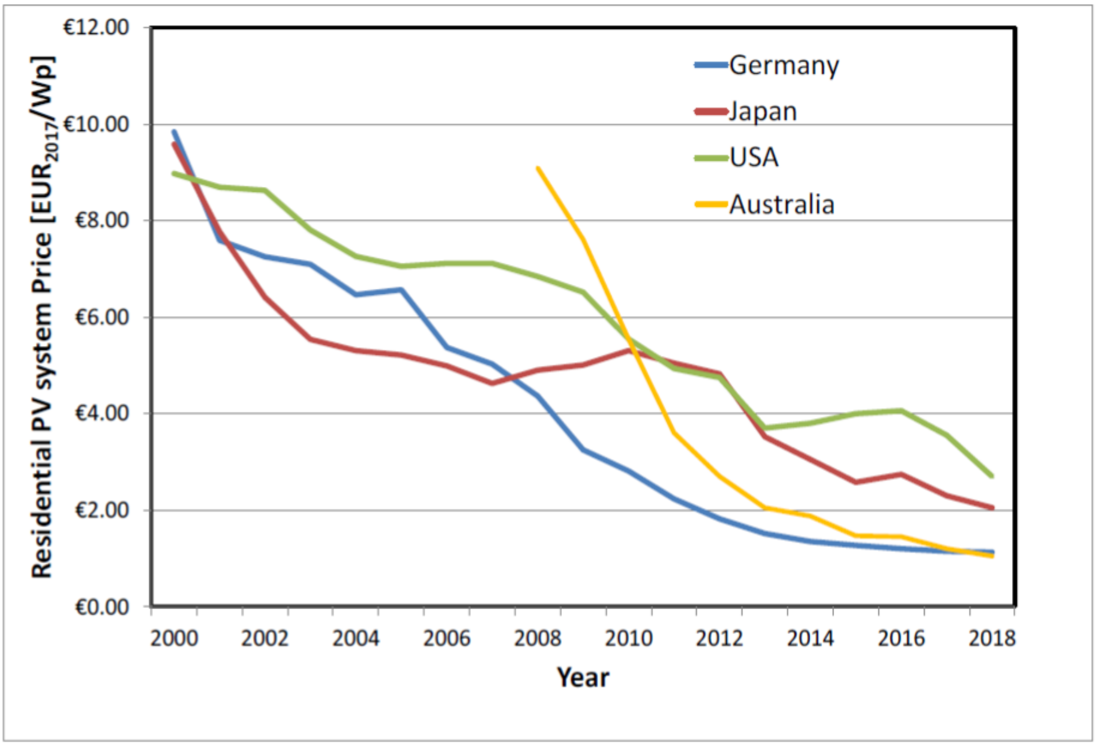


Figure 2 – Residential PV system price development over the last decade [11].

In particular, amongst residential consumers, new behavioural patterns are emerging ranging from rooftop solar PV coupled with battery energy storage systems owned by individual households or third parties, to collective self-consumption at building scale, up to Energy Communities [12].

1.2 Collective self-consumption and energy communities: overview of new and emerging approaches

With the “Clean Energy for all Europeans” package, published in November 2016, the European Union has introduced new provisions on the energy market design and frameworks for new energy initiatives. Specifically, the renewable energy and the electricity market directives open the way for new types of energy initiatives aiming at, in particular, the empowerment of smaller actors in the energy market as well as an increased decentral renewable energy production and consumption (“presumption”) through new concepts of collective self-consumption and energy communities, allowing citizens to collectively organize their participation in the energy system [13]. Basing on the objectives set by the Clean Energy Package, different new self-consumption scenarios can be imagined overcoming the individual self-consumption concept, such as [14]:

- *Collective self-consumption at building and block scale:* collective self-consumption at building scale has been developed as an alternative to the self-consumption at consumer scale for buildings with a large number of users, such as large multi-apartment buildings or office buildings with many different companies, in order to make several electricity consumers located in one single building benefit from the electricity produced by a common PV system. Self-consumption at building scale requires no specific system design as this does not require the connection of several small PV systems to each single private electricity grid, as in the case of individual self-consumption, but only one single PV system with consumption data split among several electricity consumers. This split of consumption data among users is called “Virtual Metering” meaning that, in this case, physical infrastructures such as wires and meters are replaced by data. Figure 3 shows the self-consumption scheme at building scale, where blue indicates the PV system, green the private low voltage grid and red the public distribution grid.

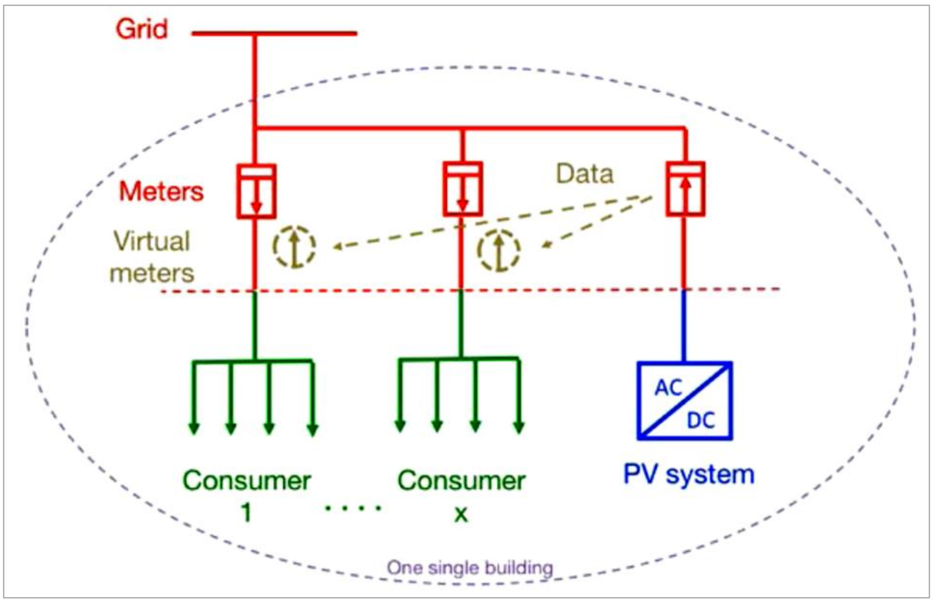


Figure 3 – Collective self-consumption at building scale [14].

Two possible configurations are delineated in this case for the system: the direct connection to the public distribution grid or the connection to a private grid. In the former case, all energy consumers and the PV system are directly connected to the public distribution grid with a meter installed and controlled by the local Distribution Network Operators (DNO). The local DNO is in charge of reading the PV production meter and splitting the energy production data among energy consumers of the building. Each energy consumer has its own conventional energy supplier that bills an amount of energy corresponding to the energy consumption measured by the physical meter of the DNO minus the share of the energy production indicated by the virtual meter provided by the DNO. In the latter case, instead, each energy consumer and the PV system are connected to a private grid (building micro-grid) with private sub-meters. This micro-grid is also connected to the public distribution grid at one single point with one specific meter installed and controlled by the local DNO. Viewed from the grid, the building is therefore considered as one single grid user. In this option, the facility manager is in charge of billing each energy consumer for their energy consumption, which is composed of PV energy and energy supplied to the micro-grid by a conventional energy supplier [14]. Figure 4 illustrates in detail the two connection schemes.

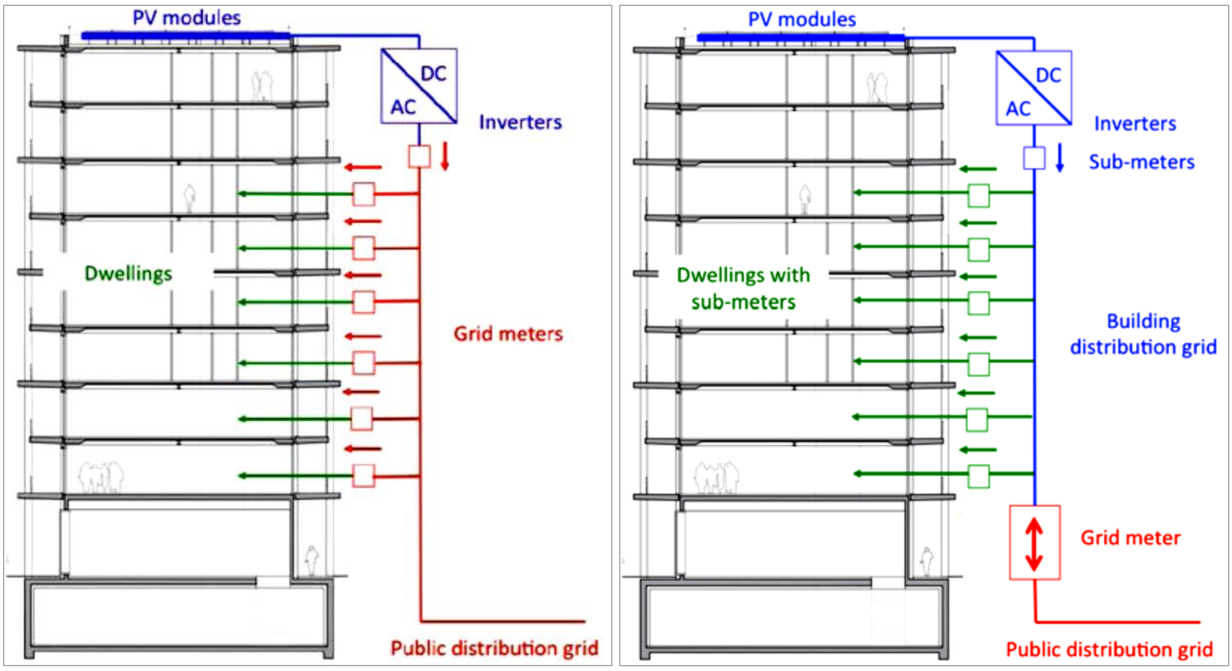


Figure 4 –Self-consumption at building scale with public (left) and private grid (right) [14].

Similarly, the considerations given for the collective self-consumption at building scale can be extended to a block scale: here the area is enlarged to more than one building (including neighbouring buildings via direct lines) and correspondingly more actors are involved [13].

- *Energy communities:* the Clean Energy Package has introduced energy communities concept into European legislation. Behind the different definitions listed in the european directive for *closed distribution systems*, *community energy storage*, *renewable energy communities* and *energy communities of citizens* [15], the main idea is that a group of consumers may join and cooperate together in the form of integrated community energy systems, providing environmental, economic or social community benefits for the members or for the local areas where they operate, rather than financial profits. In particular, the members of the energy community will participate in the generation of energy from renewable sources, storage, distribution and supply of electricity with significant cost savings and providing different energy services for the system operators, such as balancing and flexibility. As illustrated in Figure 5, the households are the basic units of these energy communities [16].

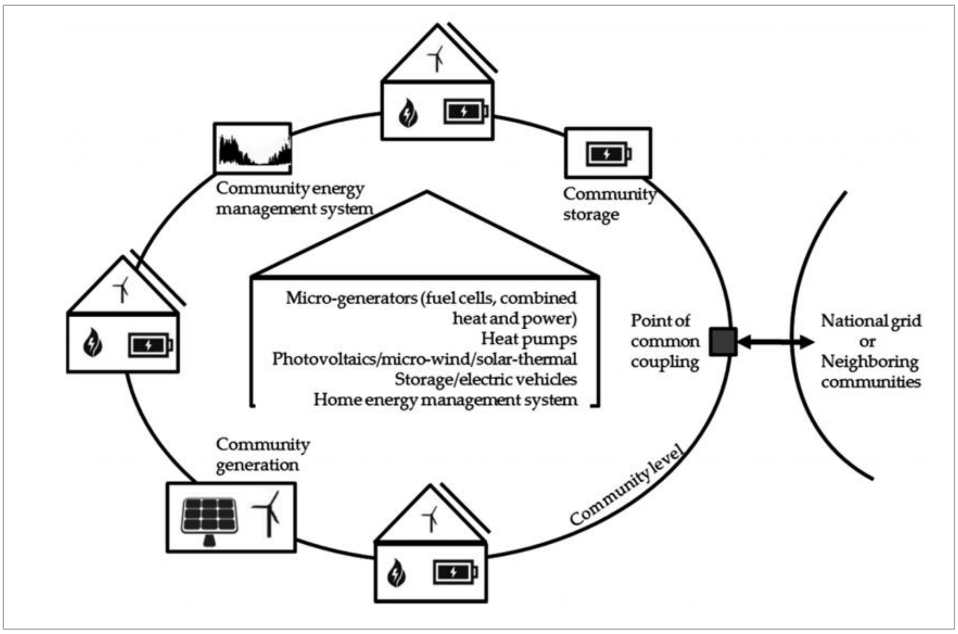


Figure 5 – Conceptual design of an integrated community energy system [15].

Any energy deficit or surplus at the community level can be purchased or sold to other communities or market agents through the national grid. Different options exist for energy sharing, such as peer-to-peer (P2P) exchanges through blockchain technology, in order to improve the community self-consumption. P2P energy sharing provides options for prosumers to trade energy within the neighbourhood through local buying and selling. Figure 6 shows the architecture of P2P energy sharing in a community, with N customers NB of which have individual PV battery systems installed. An entity named "P2P Energy Sharing Coordinator (ESC)" is used to achieve an aggregated control of the individual battery systems, i.e. managing batteries from a community's perspective so that the self-consumption of the aggregated generation is maximized. The P2P ESC also coordinates between customers and provides P2P sharing services, i.e. assuring the power balance and payment balance. When the community has insufficient energy, the P2P ESC purchases electricity from the grid, and when the community has surplus energy, the P2P ESC sells electricity to the main grid [17].

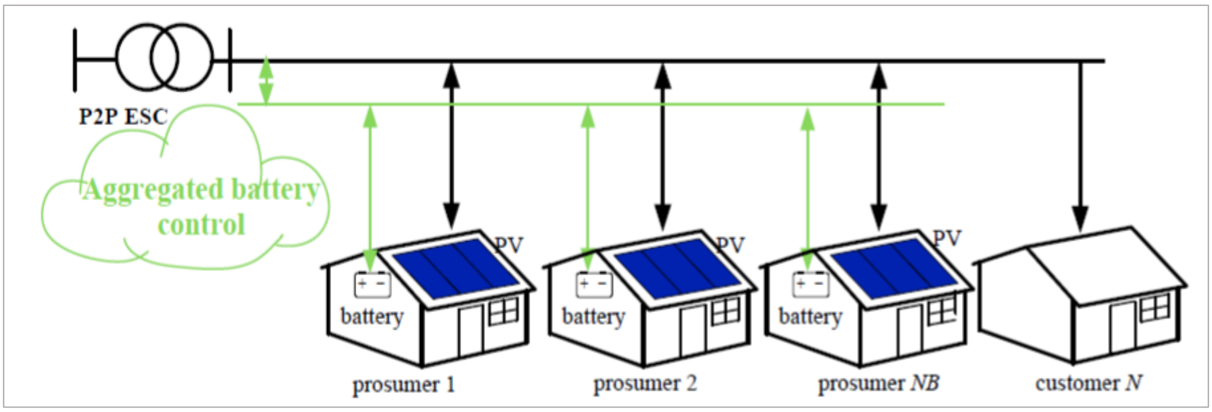


Figure 6 – P2P energy sharing in a community managed by an ESC [17].

1.3 Overview of European regulatory framework

On 21 December 2018 a substantial part of the long-awaited Clean Energy Package (CEP) has been published in the Official Journal of the European Union, notably the EU Renewable Energy Directive 2018/2001 (the "RED II"), the Energy Efficiency Directive 2018/2002 as well as the EU Climate Action Governance Regulation 2018/1999. These directives establish a common framework of measures to promote energy efficiency within the European Union in order to ensure that the Union's 2020 headline targets on energy efficiency of 20% and its 2030 headline targets on energy efficiency of at least 32,5% are met and pave the way for further energy efficiency improvements beyond those dates. New concepts, such as 'jointly acting renewables self-consumer' or 'prosumers', together with 'renewable energy communities', have been addressed for the first time in EU legislation with the objective of facilitating the involvement of (household) consumers in renewable energy deployment. In particular, Article 21 and Article 22 of EU Directive 2018/2001 promote and facilitate the development of renewables self-consumption and renewable energy communities, respectively. End customers are now explicitly entitled to become 'prosumers', which means that they can generate, store and consume renewable energy as well as sell the excess production and participate in the applicable support scheme, without losing their rights and obligations as end customers connected to the grid and without being faced with discriminatory or disproportionate procedures and charges. Prosumers must also be entitled to engage jointly and create energy communities. In several countries, a regulatory framework according to the Clean Energy Package is under discussion or preparation or in very early stage, while in some EU member states the discussion and first implementation of collective self-consumption and energy communities schemes is ongoing. Table 1 describes the legislative framework on collective self-consumption for different European countries [15], [16].

European Legal Frameworks for Collective Self-Consumption
Austria
Collective self-generation has been introduced into the Austrian Green Electricity Act and the Austrian Electricity Act in 2017. **Key points:** A collective self-generation system produces electricity to cover the energy demand of a group of jointly acting renewable self-consumers, precondition are smart meters. Excess electricity is fed into the grid based on a contract signed with an energy supplier. Each participant can choose his/her own supplier to cover the demand that is not met by the self-generation system and each customer is billed separately for the energy consumed from the grid.
France
With the Ordinance n° 2016-1019 of 27 July 2016 relative to the self-consumption of electricity, the system of self-consumption has been reformed introducing also the concept of collective self-consumption. Following a consultation process, the Commission de Regulation de l'Energie adopted a decision regulating network tariffs for collective self-consumption. **Key points:** The law allows collective self-generation of customers situated under the same MV/LV transformer. The possibility to increase this perimeter is currently under debate in parliament. The law states that all participants must be part of a same legal person, that represents the community. The law does not specify what this legal entity should be. In practice, it is often an ad hoc association. The

community is in charge of attributing the energy produced locally to each participant. Consumption is then billed on an individual basis. The part that is not self-produced is billed the standard way by the supplier, taxes included, and the part that is self-produced is paid for according to the contract that links the self-consumers together, taxes included. Each supplier also recovers the network bill of its own customers, including the part for the use of the local network by locally produced energy.
Germany
In July 2017 the tenant electricity model (in German, also translated as 'landlord-to-tenant electricity supply model') was formalised by the German government with a dedicated subsidy framework for this model set out in an amendment to the German renewable Energy Act (EEG) 2017. **Key points:** Landlords who have photovoltaic installations on the roofs of their buildings receive remuneration when they sell the electricity thus generated to their tenants. However, as no grid fees need to be paid for this electricity, the remuneration is much lower than when the electricity is fed into the grid. This new rule increases the supply of landlord-to-tenant electricity and bring the energy transition into the cities. Tenants will still be able to freely choose their electricity suppliers.
Greece
The new law 4513 has been voted by the Greek Parliament and published on January 23rd, 2018. Citizens, municipalities and small and medium-sized local businesses are encouraged to directly participate in energy projects, with priority being given to Renewable Energy Sources. **Key points:** The law defines 'energy communities' as civil law partnerships with the exclusive aim of promoting the social economy, encouraging solidarity and innovation in energy, responding to energy needs, promoting energy sustainability in the production, storage, self-consumption, distribution and supply of energy and increasing energy efficiency in final consumption on the local and regional level.

Members of energy communities may be individuals, public and private law legal entities and/or local authorities of the seat of an energy community or its plant. The law, regulates, that energy communities are, as a rule, non-profit organizations, but will be entitled to receive certain financial incentives and distribute profit if they have at least 15 members, or 10 in case of islands with population below 3.100 inhabitants, 50% of which are individuals.
Luxembourg
Proposed modification of the electricity markets law is currently under debate in parliament. **Key points:** The draft law foresees two types of communities: local communities, consisting of customers and generators situated behind the same MV/LV transformer and "virtual communities", consisting of any final customers and generators. The legal form is not specified, only that it needs to be a moral person specifically created for this purpose. This is to ensure that the participation is truly voluntary.
Spain
The Royal Decree 244/2019 was published on 6th of April; it regulates the administrative, technical and economic conditions of self-consumption of electrical energy and implies a profound reform of self-consumption in Spain. **Key points:** According to this new law, several consumers will be able to join the same generation installation and communicate individually to the distributor as the person in charge of the reading, the same agreement signed by all the participants that collects the criteria for the distribution of self-consumption.
Switzerland
In January 2018 Switzerland has introduced an innovative regulatory framework for collective self-consumption which could be applied to any distributed energy technology. **Key points:** The new legislation improves significantly the possibilities for collective self-consumption and requires every DSO to approve it. It will be allowed to extend

self-consumption to neighbouring buildings, as long as their land is contiguous and that the public grid is not used (one single grid connection). The consumers that group together will be treated as one single consumer (internal metering will be under the responsibility of the group) for the DSO and can have access to the free electricity market (additional strong incentive).

Table 1 - Reference legislative framework for collective self-consumption in European countries [15], [18].

1.4 Collective PV self-consumption in multi-apartment buildings best practices

Heidelberg Energiegenossenschaft eG (Germany)

Heidelberger Energiegenossenschaft eG (HEG) is a student energy cooperative founded in 2010. Currently HEG has 200 cooperative members and has invested over 1.000.000 € in 12 citizen owned solar-power plants for a total power of 700 kW_P. HEG has managed to successfully develop an innovative collective self-consumption scheme that allows tenants of apartment buildings to purchase electricity cheaper than what they would pay for purchasing electricity from the grid. This is achieved via a combination of on-site production of energy with PV, self-consumption of this energy and supply of residual energy from the grid. This innovative business model has been tested with 116 tenants of the “Neue Heimat” Cooperative Family Home, situated in Nußloch in Germany near Heidelberg with 7 PV systems for a total power of 445 kW_P [14]. The metering infrastructure implemented in cooperation with the local DNO is shown in Figure 7 for the measure of:

▪ Energy produced by the PV system (regular meter owned by HEG - blue circle in Figure 7);

▪ Energy consumed by each energy consumer (regular meter owned by HEG - green circles in Figure 7);

▪ Residual energy supplied by HEG from the grid or the excess of energy injected into the grid by HEG (two-way meter owned by the local DNO - green rectangle in Figure 7).

▪ Energy consumed by energy consumers that do not want to be supplied by HEG but by any another energy supplier (regular meters owner by the local DNO and "virtual" meters located at the grid connection point with consumption data subtracted from the total energy consumed by HEG - black circles in Figure 7).

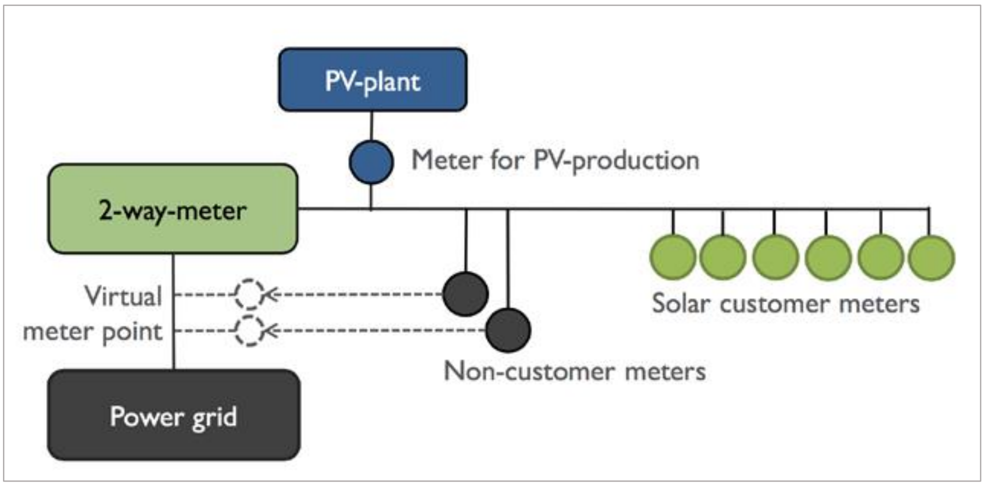


Figure 7 - Innovative metering infrastructure used by HEG for the collective self-consumption of PV [14].

The total investment cost supported by HEG for the PV system was 525.000 € (1,18 €/W_P). Tenants can choose to buy the energy from HEG at a rate of 25.4 c€/kWh plus a monthly fee of 6.95 € given that this price is guaranteed for 20 years. This energy is a mix of the energy produced by the PV system (30%) and the energy imported from the grid (70%). The excess of energy produced is injected into the local grid and sold at a feed-in tariff. In this case, HEG becomes a real small-scale utility, which requires specialized expertise such as meters management and maintenance and energy billing to costumers.

Apartment building in der Lavaterstraße, Wien (Austria)

The recent amendment to the Austrian national energy law has opened the way for collective self-consumption in apartment buildings. The apartment building in der Lavaterstraße represents one of the first examples of collective self-consumption, in which the electricity generated by the photovoltaic plant is addressed to the consumers according to their energy needs. Users who have chosen to purchase solar electricity (this option, in fact, does not constitute an obligation for the consumers) pay 11 c€/kWh, with a saving of around 30% compared to network tariffs. These advantageous tariffs have made it possible to convince as many as 47 apartments out of 69, thus equal to 70% of the families in the building, to join the purchase of photovoltaic electricity. It is an even more interesting result when you consider that they are only tenants. The scheme adopted is dynamic: PV production is divided among the families according to their instantaneous needs, in order to maximize the self-consumption rate. In the example in Figure 8 the energy destined to consumer 4 that, at the moment does not have any need, is therefore redistributed between the users 2 and 3, thus allowing to have a 100% self-consumption [19].

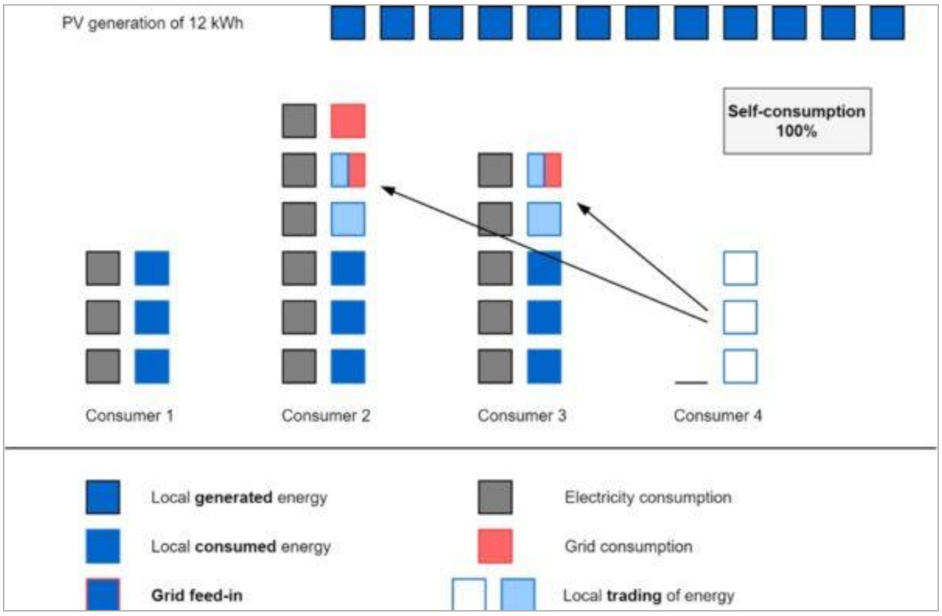


Figure 8 – Collective self-consumption dynamic scheme [19].

The CommUNITY project in Brixton, London (United Kingdom)

Residents of a block of flats in Brixton are pioneering a community energy trading project that will enable them to trade solar energy with each other. In February 2019, in fact, Energy's Research & Development department of French electric utility EDF with Repowering London and UCL's Energy Institute have launched an energy sharing project in the U.K., with the aim to increase residents' consumption of local low-carbon energy while reducing their overall costs. The CommUNITY project will enable Brixton residents at Elmore House to access electricity generated from a solar PV system on the block's roof, store it in a battery and trade with one another (peer-to-peer) using blockchain technology. The platform, managed via an app, allows residents in urban areas to source their energy from local renewables and either use their own allocation of energy or trade it with their neighbours. Under current regulations, customers cannot buy from, or sell to, other consumers but delivery of the project has been made possible as part of a special regulatory sandbox, which allows the consortium to work outside the current regulatory framework [20].

1.5 Towards the lifting of legal barriers in the Italian context

The existing legislation in the Italian framework is characterized by the current absence of specific regulation on prosumers and energy communities as the competences on production, transmission and distribution of energy are shared between the state and the regions [21]. At the moment self-consumption between third parties based on sub-metering and energy exchange is forbidden. Therefore, it is not possible to share electricity within an energy cooperative and to set up a renewable energy community in the same multi-apartment building. Buildings, in fact, may own local electricity generation plants dedicated to supply only shared areas loads, such as elevator and lighting of common areas. This is a barrier not just to solar on multi-family residential buildings but also shopping centres, multi occupancy office buildings and business parks [22]. However, there seems to be a strong political will to better enable collective forms of prosumerism in the near future. By the end of 2019, in fact, national governments are expected to deliver their national energy and climate plans (NECPs) containing objectives, policies and measures showing how they aim to meet their 2030 renewables, energy efficiency and greenhouse gas targets. These have to include objectives, policies and measures to support collective self-consumption and renewable energy communities [23]. On the other hand, in Italy there are historical cooperatives, which have their own grid and function as autonomous systems. Their existence provides a 'case study' of collective forms of self-consumption and inspiration for future communities [21]. In particular, good practice examples of legislative proposals foreseeing that residential consumers living in a single apartment block or located in the same commercial or shared services site should be considered as being an individual prosumer, are coming from different Italian regions, as discussed in detail in the next paragraph. In such a context, financial incentives policies for solar PV energy and the widespread roll out of smart meters for the accurate metering and billing of the solar electricity, will represent a key enabler for future multi-occupancy PV business models. In this thesis a building with several different consumption points is expected to turn out to be a best practice of collective self-consumption in the social housing context. The connection with the public grid will be through just one meter and the families will be equipped with smart meters.

1.6 Regional regulations on collective self-consumption and energy communities

Piedmont Region

Piedmont is the first Italian Region to have energy communities by law. The Regional Law 12/2018, that represents the first regional law for the constitution of energy communities in Italy, has been presented on 24th July 2017 and unanimously approved on July 25th, 2018 by the Commission for Economy, Industry and Energy of the Regional Council [24]. The law in question is based on the Italian National Law 28th December 2015, n. 221 "Environmental law to promote green economy measures and to limit excessive use of natural resources" which assumes that "as part of their sectoral legislation, the regions regulate the organization of the Oil Free Zones, with particular regard to the technological innovation applied to electricity generation from renewable energy sources and to sustainable development through low environmental impact systems" [25]. The Regional Law 12/2018 identifies energy communities as homogeneous territorial areas that, in order to overcome the use of fossil fuels, produce and exchange energy generated from renewable sources, promoting measures of energy efficiency and energy savings. Energy communities can enter into agreements with the national electricity, gas and water authority in order to optimize the management, use and costs of energy distribution; they must also draw up an energy balance and an energy plan that identifies actions for the reduction of energy consumptions [26]. Despite the lack of regulation in this field, there are already some Italian cases of energy communities and cooperatives, mostly in the Alpine territory, that benefit from the local production of energy from renewable sources and from the energy exchange between stakeholders, but they don't have the authorisation by Terna, the Italian leading electricity transmission grid operator, to constitute themselves as a distributor, and they are also quite small (about 15 thousand users or less). The new Piedmontese energy community, on the other hand, includes 25 towns surrounding Pinerolo (Torino) and it stretches for over one thousand three hundred square kilometres with a population of around 150,000; the aim of the project is to meet the energy needs of the territory by exploiting solar, hydroelectric and biomass/waste-sourced energy and it could become a pilot project for other Italian regions as well. However, the project still has many technical and regulatory obstacles to overcome, first of all the development of an agreement with the Italian Regulatory Authority for Energy, Networks and Environment (ARERA) allowing the access to and use of the national electricity transmission system for the energy distribution within the community.

Apulia Region

Apulia is the first Italian region to establish the "regional energy income". The Regional Law n. 42, approved on August 9th, 2019, provides that the Region is responsible for the purchase and installation of renewable energy production systems supplied as loan for use to poor families and multi-apartment buildings, with the dual purpose of promoting renewable energy sources and combatting poverty [27]. The selection criteria for the beneficiaries are the following:

- With regard to the households, firstly the neediest families, the most numerous families and young couples shall be favoured;

- With regard to the condominium buildings, a specific score will be assigned depending, for example, on the number of housing units in the building.

The energy produced from renewable sources can be self-consumed by the users for their own energy needs, while the surplus will be fed into the national grid and the proceeds will be invested in the installation of new PV plants.

Furthermore, following the example of Piedmont Region, Apulia has adopted the Regional Law n. 45 in order to economically support the development of energy communities by granting financial contributions depending on the specific features of the different territories in order to give preference to the most disadvantaged areas. Both public and private entities can participate in the energy community by adopting generation from renewable sources and storage systems such as to ensure a minimum 60% of energy produced annually from renewable sources for self-consumption.

Lombardy Region

In April 2019 Lombardy Region launched the pilot project, supported by the Electric System Research (RSE) on a mandate from the Ministry of Economic Development, to establish the first 100% Renewable Energy Community (REC) in the municipality of Tirano (Sondrio). The community consists of 192 prosumers and produces both electric and thermal energy from solar and woody biomass plants [28].

However, the most significant initiative undertaken by the Lombardy Region will begin in 2020 in collaboration with RSE and with the involvement of ARERA and TERNA [29]. The idea is to aggregate the existing residential PV battery systems, including the extra-small plants, to create a “virtual” power plant that can participate and enable secondary regulation in the Dispatching Services Market (MSD). Lombardy has the highest percentage of installed solar energy systems, approximately 15,2% of all 822.000 PV systems installed in Italy (data from GSE, 2018). It is estimated that 2.700 residential users with small PV and storage systems will be part of the project, and their number is about to grow thanks to the financing measures promoted by the Region in favour of citizens installing storage systems. Each plant will be supplied with a smart gateway that uses artificial intelligence algorithms to properly exploit the advantages of the residential batteries for balancing the network in real-time, without additional costs or changes in consumption habits from the users. In particular, it will be essential the presence of an "aggregator" with the task of aggregating the small plants until they reach 1 MW of power so that they are eligible to participate in the Dispatching Services Market. TERNA will provide a refund of € 30.000/MW·year in favour of the aggregator, which can pay back the investment required and share the profits with the users. The project can be considered as a first step towards the Aggregate Virtual Mixed Units (UVAM) in the residential sector, that are expected to become a key factor in grid services provision.

Chapter 2

Optimization problems and Linear Programming techniques

2.1 Introduction to Optimization

For almost all the human activities there is a desire to deliver the most, seen as the maximum profit or the maximum efficiency, with the least, in terms of minimum initial investment and operational cost. The concept of optimization has therefore great significance in both human affairs and the laws of nature which is the inherent characteristic to obtain the best or most favorable (minimum or maximum) result under given circumstances [30]. In particular, optimization is one of the most powerful tools in design and process integration. Therefore, the study of design optimization is of essential help in the human activity to create optimum design of products, processes and systems, subject to various mathematical, physical, environmental and technical restrictions, such as material and energy balances, process modeling equations, thermodynamic requirements, etc. [31]. For example, in design, construction, and maintenance of any engineering system, engineers have to take many technological and managerial decisions at several stages. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, *optimization* can be defined as the process of finding the conditions that give the maximum or minimum value of a function. It can be seen from Figure 9 that if a point x^* corresponds to the minimum value of function $f(x)$, the same point also corresponds to the maximum value of the negative of the function, $-f(x)$. Thus without loss of generality, optimization can be taken to mean minimization since the maximum of a function can be found by seeking the minimum of the negative of the same function [32].

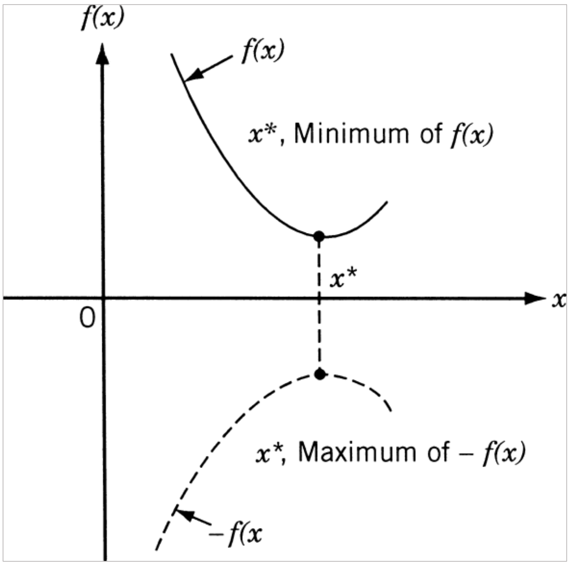


Figure 9 - Minimum of $f(x)$ is same as maximum of $-f(x)$ [32].

In addition, the following operations on the objective function will not change the optimum solution x^* as shown in Figure 10:

1. Multiplication (or division) of $f(x)$ by a positive constant c.

2. Addition (or subtraction) of a positive constant c to (or from) $f(x)$.

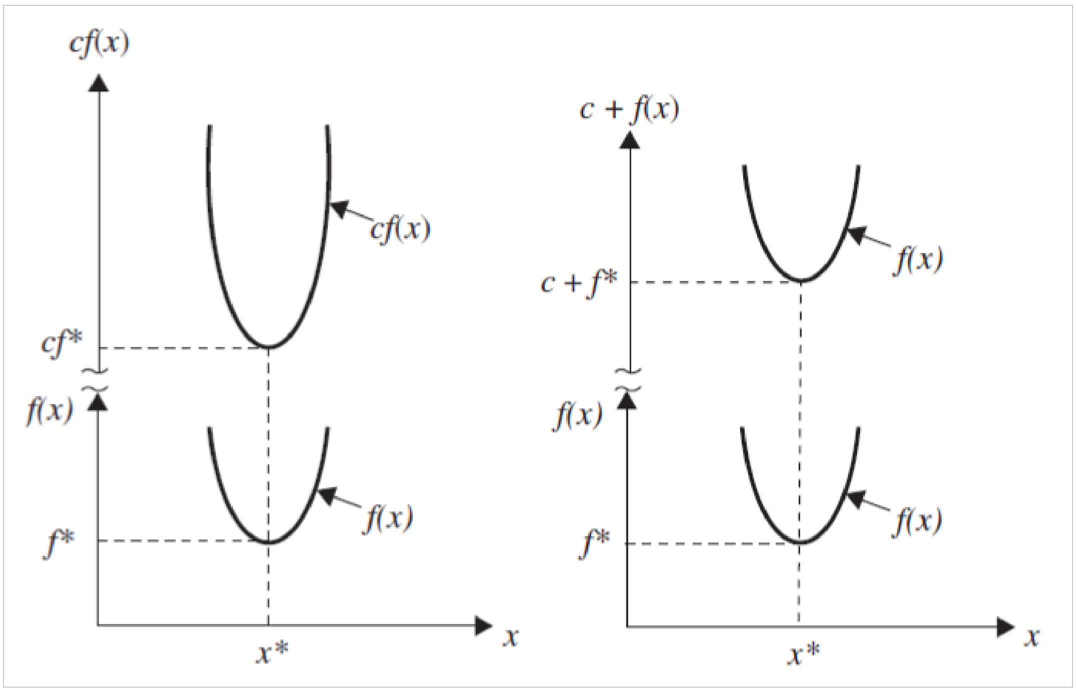


Figure 10 - Optimum solution of $cf(x)$ or $c + f(x)$ same as that of $f(x)$ [32].

The constraints are inherent part of the real world problems and they have to be satisfied to ensure the acceptability of the solution. There are always numerous requirements and constraints imposed on the designs of components, products, processes or systems in real-life engineering practice, just as in all other fields of design activity. Therefore, creating a feasible design under all these diverse requirements/constraints is already a difficult task, and to ensure that the feasible design created is also 'the best' is even more difficult [30].

There is no single method available for solving all optimization problems efficiently. Hence a number of optimization methods have been developed for solving different types of optimization problems. The optimum seeking methods are also known as *mathematical programming techniques* and are generally studied as a part of operations research. *Operations research* is a branch of mathematics concerned with the application of scientific methods and techniques to decision making problems and with establishing the best or optimal solutions. The beginnings of the subject of operations research can be traced to the early period of World War II. During the war, the British military faced the problem of allocating very scarce and limited resources (such as fighter airplanes, radars, and submarines) to several activities (deployment to numerous targets and destinations). Because there were no systematic methods available to solve resource allocation problems, the military called upon a team of mathematicians to develop methods for solving the problem in a scientific manner. The methods developed by the team were instrumental in the winning of the Air Battle by Britain. These methods, such as linear programming, which were developed as a result of research on (military) operations, subsequently became known as the methods of operations research [32].

2.2 Applications of optimization to industrial engineering problems

The ever-increasing demand to lower production costs and to minimize wastes of time, materials, energy, and other resources, has prompted researchers and industry to look for rigorous methods of decision making, such as optimization methods, to design and produce products both economically and efficiently in a highly competitive economic environment

[32]. For such reason, optimization, as a powerful modelling and problem solving methodology, has become of substantial importance for the competitiveness of any industrial system and nowadays represents a basic research and decision making tool successfully applied in a wide range of practical problems arising in virtually any sphere of human activities, including sciences, biomedicine, engineering, energy management, aerospace research, telecommunications and finance [33]. Optimization is the process of choosing the tradeoffs between different factors in the "best" way, in order to achieve desirable outcomes. The notion of 'different factors' means that there are different possible solutions, and the notion of 'achieving desirable outcomes' means that there is an objective of seeking improvement on how to find the best solution. In fact, in an optimization problem, different candidate solutions are compared and contrasted, which means that solution quality is fundamental [33]. The application of optimization in engineering has a very long history. In particular, two special classes of optimization problems, linear least squares and linear optimization problems, have been widely used in a tremendous number of application areas, such as transportation, production planning, design and data fitting. Since 1990, the appearance of algorithms and software for convex optimization has motivated people to apply convex optimization models in several new areas, such as automatic control systems, signal processing, communications and networks, product and shape design, electronic circuit design, data analysis and modelling, statistics and financial engineering [34]. The application of convex optimization in engineering enables engineers to design and solve problems more efficiently. In recognition of the contribution of optimization to engineering, S.S. Rao wrote: "Optimization is now viewed as an indispensable tool of the trade for engineers working in many different industries, especially the aerospace, automotive, chemical, and manufacturing industries." [32]. In particular, optimization theory finds ready application in all branches of engineering in four primary areas [35]:

1. Design of components or entire systems

2. Planning and analysis of existing operations

3. Engineering analysis and data reduction

4. Control of dynamic systems

A broad range of engineering problems can be defined as optimization problems, such as production planning, resources allocation, process design, process synthesis and analysis, transportation, logistics, production scheduling, telecommunications networks, energy systems integration, etc. Figure 11 highlights some prominent fields of applications including electrical engineering, defence related application, civil engineering related applications, automation, medical, industry, surveillance and agriculture [36].

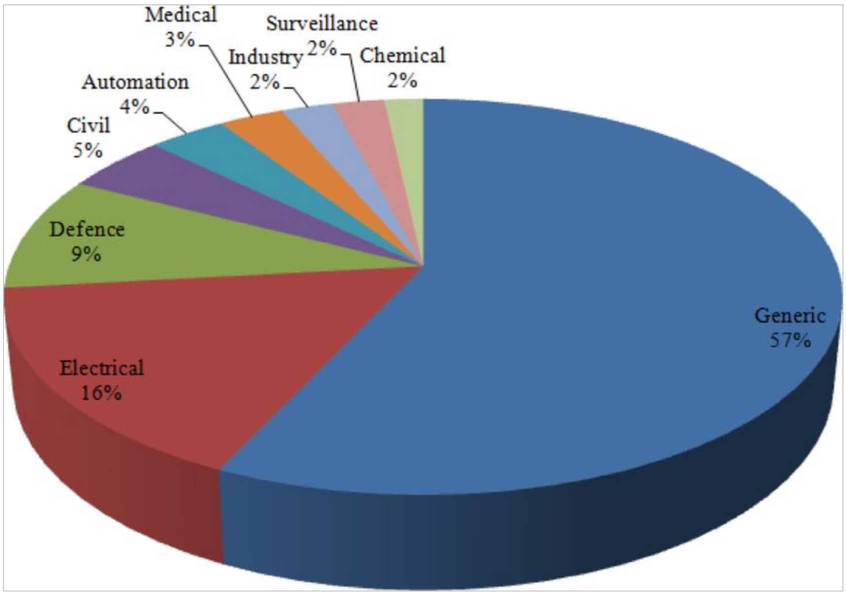


Figure 11 - Trend with respect to engineering application [36].

As concerns the energy sector, modern energy grid systems incorporate not only traditional electrical systems but also renewables such as wind and solar photovoltaic. In order to optimize the electric load requirements, generators, transmission and distribution lines, and storage must be taken into account. At the same time, costs must remain sustainable for profits. In such a context, mathematical programming, especially linear programming, provides a method to optimize the electric power system design and can be used to optimize load-matching or to optimize cost. It allows for matching the electric load in the shortest total distance between the generation of the electricity and its demand over time [37]. Linear programming, in fact, because of its rigorousness, flexibility and extensive modeling capability, has become one of the most widely explored methods for energy scheduling problems, providing a valuable tool to the energy industry [38].

2.3 Statement of an Optimization Problem

All optimization problems can be presented by some standard form. In particular, each optimization problem contains an objective function *f(x)* that needs to be minimized. An optimization problem can be stated as follows [39].

Find

$$x = (x^1, x^2, \ldots., x^n)$$

which minimizes

$$f(x)$$

subject to the constraints

$$g_j(x) \leq 0$$

for *j = 1, ….., m*, and

$$l_j(x) = 0$$

for *j = 1, ….., p*.

The variable x is called the design vector, $f(x)$ is the objective function, $g_j(x)$ are the inequality constraints and $l_j(x)$ are the equality constraints. The number of variables n and the number of constraints $p + m$ need not be related. If $p + m = 0$ the problem is called an unconstrained optimization problem.

Various terms are in general used for optimization problems [40], these are:

Decision variables and design vector

Any real-world system can be described by a set of variables that control the output of the system. Some of these quantities are imposed by the *environment* and can be viewed in the optimization process as preassigned parameters, while others are variables over which the decision maker has control. The latter are usually input to the model and can be changed by the decision maker with the aim of revising the response of the system. They are called design or decision variables and are collected in the design vector x.

Identifying and prioritizing key decision variables

The objective function generally depends on lots of variables. However, all variables are not equally important during the optimization process. Based on the Pareto ranking of effects on objective function, the key decision variables are chosen. The sensitivity of the objective function to changes in the variables is the key factor for deciding important variables. Variables with high sensitivity may be considered as decision variables, whereas less sensitive variables may be ignored.

Limits of decision variables

Every decision variable has some upper and lower limits. Theoretically, some variables may reach infinity (e.g., time, length); however, in the optimization process, it is possible to limit them to certain practicable values.

Design Constraints

Constraints are additional relations between the decision variables and process parameters other than the objective function. In practice, the decision variables cannot be selected arbitrarily, but have to satisfy certain requirements and limits. These restrictions are called design constraints. Design constraints may represent limitation on the performance or behavior of the system or physical limitations and can be expressed in the form of equality or inequality. Consider, for example, an optimization problem with only inequality constraints, i.e. $g_j(x) \leq 0$. The set of values of x that satisfy the equations $g_j(x) = 0$ forms a hypersurface in the design space, which is called constraint surface. In general, if n is the number of decision variables, the constraint surface is an $n - 1$ dimensional surface. The constraint surface divides the design space into two regions: one in which $g_j(x) < 0$ and one in which $g_j(x) > 0$. The points x on the constraint surface satisfy the constraint critically, whereas the points x such that $g_j(x) > 0$, for some j, are infeasible, i.e. are unacceptable, as shown in Figure 12.

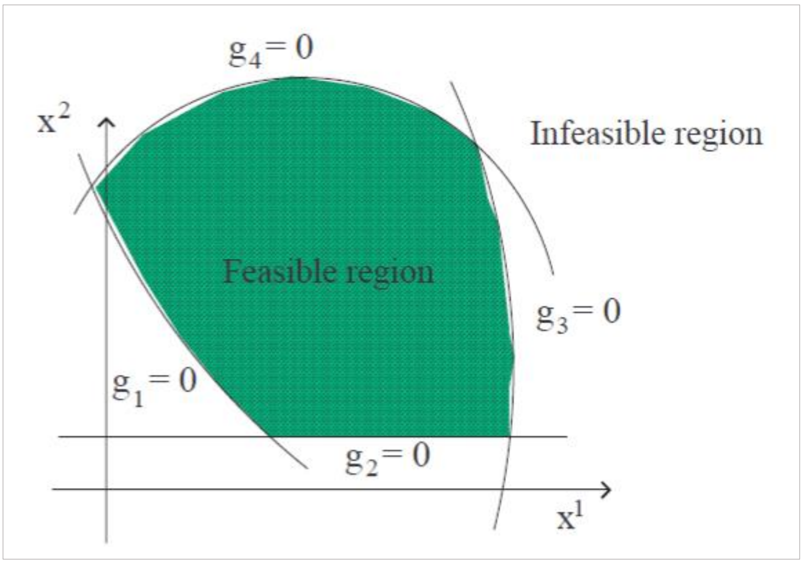


Figure 12 - Feasible region in a two-dimensional design space. Only inequality constraints are present [39].

Objective function

The classical design procedure aims at finding an acceptable design, i.e. a design which satisfies the constraints. In general, there are several acceptable designs that satisfy the constraints, and the purpose of the optimization is to single out the best possible design. Thus, a criterion has to be selected for comparing different designs. This criterion, when expressed as a function of the design variables, is known as objective function. Objective function (also known as "cost function") is therefore the mathematical expression, describing the correlation between the decision variables and process parameters, that must be optimized. There are many types of objective functions, often specified by physical or economical considerations, like profit from the process, cost of production, error during curve fitting/parameter estimation, minimization of environmental impact etc. However, the selection of an objective function is not trivial, because what is the optimal design with respect to a certain criterion may be unacceptable with respect to another criterion. Typically there is a trade off performance–cost, or performance–reliability, hence the selection of the objective function is one of the most important decisions in the whole design process. If more than one criterion has to be satisfied it will become a multiobjective optimization problem, that may be approximately solved considering a cost function which is a weighted sum of several objective functions.

Given an objective function $f(x)$, the locus of all points x such that $f(x) = c$ forms a hypersurface. For each value of c there is a different hypersurface. The set of all these surfaces are called objective function surfaces. Once the objective function surfaces are drawn, together with the constraint surfaces, the optimization problem can be easily solved, at least in the case of a two-dimensional decision space, as shown in Figure 13. If the number of decision variables exceeds two or three, this graphical approach is not viable and the problem has to be solved as a mathematical problem.

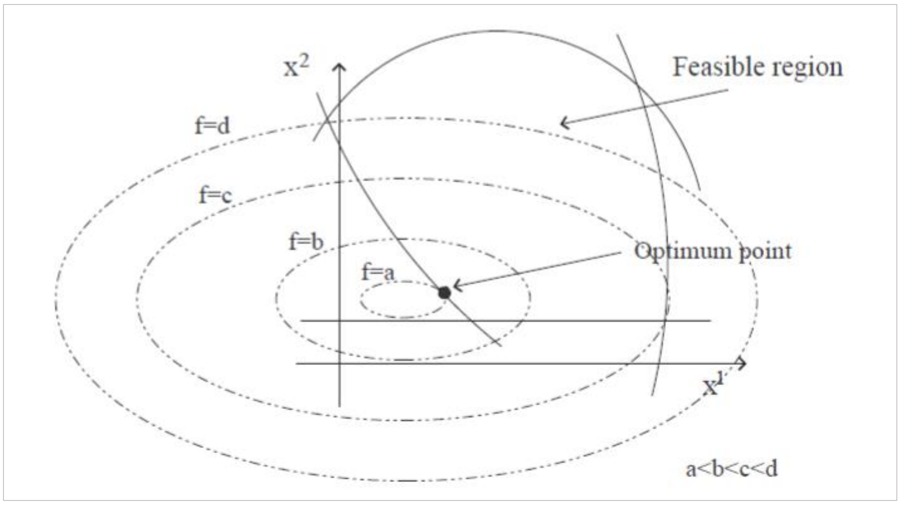


Figure 13 - Design space, objective functions surfaces, and optimum point [39].

2.4 Classification of Optimization Techniques

Optimization problems can be classified in several ways [32]. Some possible classification schemes can be made based on:

• **Existence of constraints**: Under this category optimizations problems can be classified into two groups:

(i) *Constrained optimization problems*, which are subject to one or more constraints.

(ii) *Unconstrained optimization problems*, in which no constraints exist.

• **Nature of the design variables**: There are two broad categories in this classification:

(i) *Parameter or static optimization problems*, in which the objective is to find a set of design parameters that makes a prescribed function of these parameters minimum or maximum subject to certain constraints.

(ii) *Trajectory or dynamic optimization problems*, in which the objective is to find a set of design parameters that are all continuous functions of some other parameter that minimizes an objective function subject to a set of constraints.

• **Physical structure of the problem**: Based on the physical structure, optimization problems are classified as:

(i) *Optimal control problems*, which are mathematical programming problems involving a number of stages, where each stage evolves from the preceding stage in a prescribed manner. They are defined by two types of variables: the control or design and state variables. The control variables define the system and controls how one stage evolves into the next. The state variables describe the behavior or status of the system at any stage. The problem is to find a set of control variables such that the total objective function (also known as the performance index, PI) over all stages is minimized, subject to a set of constraints on the control and state variables.

(ii) *Non-optimal control problems*, which are not optimal control problems.

• **Nature of the equations involved**: This classification is very useful from a computational point of view since many predefined special methods are available for effective solution of a particular type of problem. Based on the nature of equations for the objective function and the constraints, optimization problems can be classified as:

(i) *Linear programming problems*, in which the objective function and all the constraints are 'linear' functions of the design variables.

(ii) *Nonlinear programming problems*, in which one or more functions among the objectives and constraint functions are nonlinear. This is the most general form of a programming problem and all other problems can be considered as special cases of the nonlinear programming problems.

(iii) *Geometric programming problems*, in which the objective function and constraints are expressed as polynomials.

(iv) *Quadratic programming problems,* which are the best behaved nonlinear programming problems with a quadratic objective function and linear constraints and are concave (for maximization problems). They can be solved by suitably modifying the linear programming techniques.

• **Admissible values of the decision variables**: Depending upon the values permitted for the design variables, optimization problems can be classified as:

(i) *Integer programming problems*, when some or all of the design variables are restricted to take only integer (or discrete) values.

(ii) *Real-valued programming problems*, in which it is sought to minimize or maximize a real function by systematically choosing the values of real variables from within an allowed set that contains only real values.

• **Deterministic nature of the variables**: Under this classification, optimization problems can be classified as:

(i) *Stochastic programming problems*, when some or all the design variables are expressed probabilistically (non-deterministic or stochastic).

(ii) *Deterministic programming problems*, in which all the design variables are deterministic.

• **Separability of the functions**: Based on this classification, optimization problems can be classified as:

(i) *Separable programming problems*, when the objective function and the constraints are separable. A function is said to be separable if it can be expressed as the sum of *n* single-variable functions.

(ii) Non-separable programming problems, when the objective function and the constraints are not separable.

• **Number of objective functions**: Under this classification, objective functions can be classified as:

(i) *Single-objective programming problems*, in which there is only a single objective function.

(ii) *Multi-objective programming problems*, in which there are more objective functions to be minimized simultaneously.

Table 2 lists some of the most common traditional optimization methods among the mathematical programming, stochastic and statistical techniques, respectively, together to the more recent ones. As regards the latter, the modern optimization methods, also sometimes called nontraditional optimization methods, have emerged as powerful and popular methods for solving complex engineering optimization problems in recent years. These methods include genetic algorithms, simulated annealing, particle swarm optimization, ant colony optimization, neural network-based optimization, and fuzzy optimization. The genetic algorithms are computerized search and optimization algorithms based on the mechanics of natural genetics and natural selection. The simulated annealing method is based on the mechanics of the cooling process of molten metals through annealing. The particle swarm optimization algorithm mimics the behavior of social organisms such as a colony or swarm of insects, a flock of birds, and a school of fish. The ant colony optimization is based on the cooperative behavior of ant colonies, which are able to find the shortest path from their nest to a food source. The neural network methods are based on the immense computational power of the nervous system to solve perceptional problems in the presence of massive amount of sensory data through its parallel processing capability. The fuzzy optimization methods were developed to solve optimization problems involving design data, objective function, and constraints stated in imprecise form involving vague and linguistic descriptions [32].

Mathematical programming or optimization techniques	Stochastic process techniques	Statistical methods
Calculus methods	Statistical decision theory	Regression analysis
Calculus of variations	Markov processes	Cluster analysis, pattern recognition
Nonlinear programming	Queueing theory	Design of experiments
Geometric programming	Renewal theory	Discriminate analysis (factor analysis)
Quadratic programming	Simulation methods	
Linear programming	Reliability theory	
Dynamic programming		
Integer programming		
Stochastic programming		
Separable programming		
Multiobjective programming		
Network methods: CPM and PERT		
Game theory		
Modern or nontraditional optimization techniques		
Genetic algorithms		
Simulated annealing		
Ant colony optimization		
Particle swarm optimization		
Neural networks		
Fuzzy optimization		

Table 2 - Methods of Operations Research [32].

In this thesis a scheduling problem is addressed by the applying the Mixed-Integer Linear Programming technique.

2.5 Linear Programming and Mixed Integer Linear Programming problems

A general Linear Programming (LP) problem has the following formulation [41]:

$$min \sum_{j=1}^{n} c_j x_j$$

$$\sum_{j=1}^{n} a_{ij}x_j \geq b_i \qquad i = 1 \ldots . m_1$$

$$\sum_{j=1}^{n} a_{ij}x_j = b_i \qquad i = m_1 + 1 \ldots m$$

$$x_j \geq 0 \qquad j = 1 \ldots n_1$$

Where n, n_1, m, m_1, are known constant scalars; $c = c_j \in \mathbb{R}^n$ and $b = b_i \in \mathbb{R}^m$ are known vectors; $A = a_{ij} \in \mathbb{R}^{m*n}$ is a known matrix. While the vector $x = x_j \in \mathbb{R}^n$ represents the decision variables for which an optimal value needs to be found. For LP problems variables are supposed to be *continuous* and they can assume every value within a continuous interval. This formulation can be used for every optimization problem with a linear objective function and where constraints are expressed by linear equations or inequalities.

An Integer Linear Programming problem (ILP) is a variation of the Linear Programming problem (LP) which contains a further constraint that imposes that every variable will be an integer one.

$$x_j \ integer$$

$$j = 1 \ldots . n$$

A Mixed Integer Linear Programming problem (MILP) is a generalization of LP and ILP where just a subset of variables are restricted to be integers while other variables are allowed to be non-integers.

$$x_j \ integer$$

$$j \in S$$

$$S \subseteq \{1 \ldots n\}$$

A special case is the 0-1 Integer Linear Programming, in which variables are binary.

$$x_j \in \{0,1\}$$

$$j = 1 \ldots . n$$

Both ILP and MILP problems can be solved and they are practically solved by using *branch–and–bound* algorithms where a continuous relaxation of the problem is iteratively solved by removing the integer constraints. The idea is to subdivide the whole problem into a set of sub-problems of progressively decreasing dimensions that can be more easily solved, according to a *divide-and-conquer* strategy. In particular, the original problem is splitted into branches of sub-problems as a rooted tree, as illustrated in Figure 14. Each node in the rooted tree is considered as a new integer linear programming optimization problem. Based upon the upper and lower estimated bounds of the optimal solution, each branch is checked. The branch will be discarded in case of not producing a better solution than that found by the algorithm in the previous step [42].

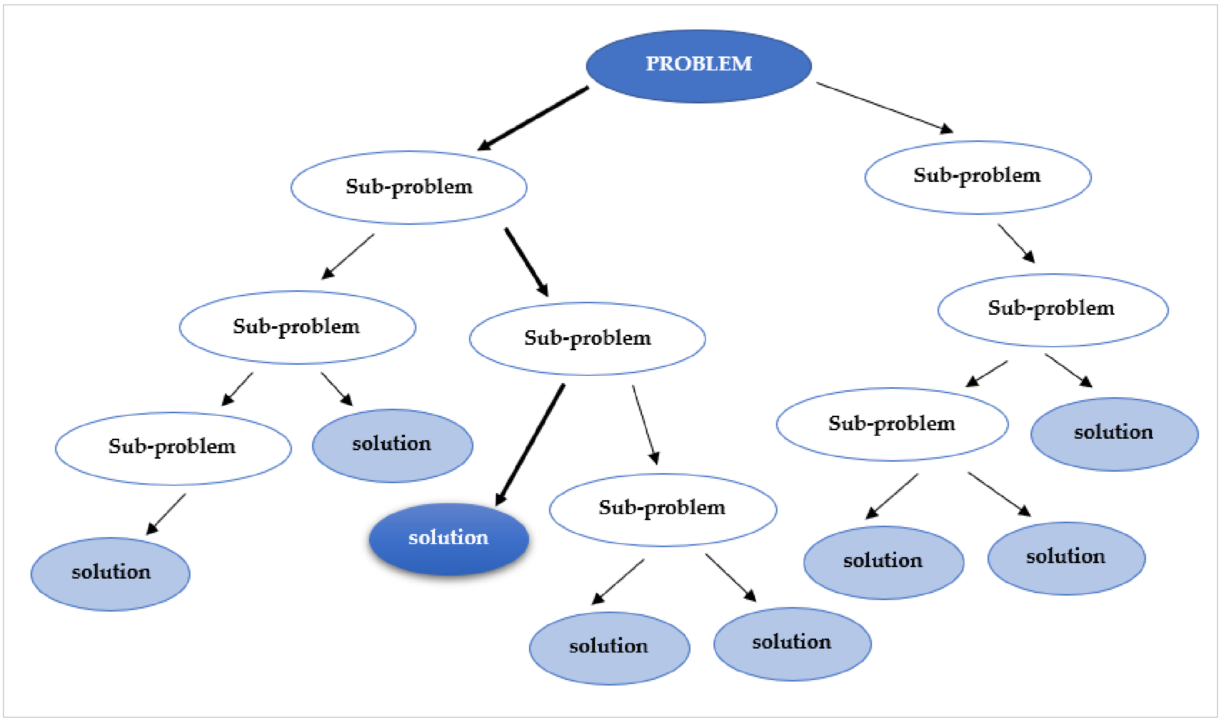


Figure 14 - Diagram explaining the main concept of branch-and-bound algorithm [42].

Throughout more than 50 years of existence, Mixed Integer Linear Programming theory and practice have been significantly developed, and MILP is now an indispensable tool in business, engineering and management science for supporting managerial decisions [43]. Through allowing for the use of integer or binary variables, a wide range of problems can be modeled as MILP in many application areas, such as [44]:

- **Capital Budgeting:** in a typical capital-budgeting problem, the investment decisions might be to choose among possible plant locations, to select a configuration of capital equipment, or to settle upon a set of research-and-development projects. Often the problem can be modeles as a go–no-go integer program, where the decision variables are taken to be $x_j = 0\ or\ 1$, if the jth investment is rejected or accepted, respectively.
- **Warehouse Location**: in modeling distribution systems, decisions must be made about tradeoffs between transportation costs and costs for operating distribution centers. In such cases generally binary variables $y_i = 0\ or\ 1$ are applied in order to, for example, identify if warehouse i is opened or not.
- **Scheduling:** the entire class of problems referred to as sequencing, scheduling, and routing are inherently integer programs. In particular, the energy sector offers a wide range of applied problems where ILP and MILP can be successfully applied to facilitate the decision making process and to analyze the state of the art of some technologies, making sensitivity analyses on the most interesting parameters involved. The most important problems that can be studied through ILP and MILP in the energy sector are related to energy production and energy dispatching, such as the optimal plants management, scheduling and location and the optimal energy distribution along optimized energy networks [41].

2.6 Non-Linear Programming problems

Although numerous applications can be treated as linear programs, there are many examples of nonlinear systems in the real-world applications in which nonlinearities, in the form of either nonlinear objective functions or nonlinear constraints, are crucial for representing an application properly as a mathematical program [45].

A general Non-Linear Programming problem (NLP) aims at finding the optimal values of $x = (x_1, x_2 \dots x_n)$ in such a way that:

$$\min f(x)$$

$$g_i(x) \leq b_i \qquad \forall i = 1 \dots m$$

$$x \geq 0$$

Where $f(x)$ and $g_i(x)$ are known functions of the n decision variables [41].

There are many different classes of nonlinear programming problems, depending on the characteristics of the $f(x)$ and $g_i(x)$ functions, such as [46]:

- Unconstrained optimization problems: they have *no* constraints, so the objective is simply to maximize $f(x)$ over *all* values of $x = (x_1, x_2 \dots x_n)$.
- Linearly constrained optimization problems: characterized by constraints that completely fit linear programming, so that *all* the $g_i(x)$ constraint functions are linear, but the objective function $f(x)$ is nonlinear.
- Quadratic programming: a special case of linearly constrained optimization problems; they again have linear constraints, but now the objective function $f(x)$ must be *quadratic*.
- Convex programming: it covers a broad class of problems that actually encompasses as special cases all the preceding types when $f(x)$ is a concave function to be maximized. The assumptions are that $f(x)$ is a concave function and each $g_i(x)$ is a convex function. These assumptions are enough to ensure that a local maximum is a global maximum. If the objective were to *minimize* $f(x)$ instead, the first assumption would change to requiring that $f(x)$ must be a *convex* function, since this is what is needed to ensure that a local minimum is a global minimum.
- Separable Programming: it is a special case of convex programming with additional assumption that *all* the $f(x)$ and $g_i(x)$ functions are separable functions. A separable function is a function where *each term* involves just a *single variable*, so that the function is separable into a sum of functions of individual variables.

- Nonconvex Programming: it encompasses all nonlinear programming problems that do not satisfy the assumptions of convex programming. In this case there is no assurance that a *local maximum* also will be a *global maximum*.
- Geometric Programming: the objective function and constraint functions are of the form of: $g(x) = \sum_{i=1}^{N} c_i P_i(x)$, where $P_i(x) = x_1^{a_{i1}} x_2^{a_{i2}} \dots x_n^{a_{in}},\ \ for\ i = 1, 2, \dots, N$. In such cases, the c_i and a_{ij} typically represent physical constants, and the x_j are design variables. When *all* the c_i coefficients in each function are strictly positive, the functions are *generalized positive polynomials* now called *posynomials* and the objective function is to be minimized by applying a convex programming algorithm.
- Fractional Programming: the objective function is in the form of a ratio of two functions: $maximize\ f(x) = \frac{f_1(x)}{f_2(x)}$. The most straightforward approach to solving a fractional programming problem is to transform it into a linear programming problem, when $f(x)$ has the linear fractional programming form: $f(x) = \frac{cx+c_0}{dx+d_0}$, where c and d are row vectors, x is a column vector, and c_0 and d_0 are scalars.

In general, non-linear problems are intrinsically more difficult to solve and there is no standard method available for solving these problems; hence ad hoc algorithms have been created and are used for different types of nonlinear problems. In particular, some of the greatest criticalities in solving nonlinear problems are [47]:

- it is hard to distinguish a local optimum from a global optimum;
- the optimal solution is not restricted to extreme points, but it can occur at an interior point of the feasible region, on the boundary of the feasible region, which is not an extreme point, or at an extreme point of the feasible region;
- there may be multiple disconnected feasible regions;
- different starting points may lead to different final solutions;
- it may be difficult to find a feasible starting point;
- it is difficult to satisfy equality constraints and to keep them satisfied;
- there is no definite determination of the outcome;

- there is a huge body of very complex mathematical theory and numerous solution algorithms;
- it is difficult to determine whether the conditions to apply a particular solver are met;
- different algorithms and solvers arrive at different solutions and outcomes for the same formulation;
- different but equivalent formulations of the model given to the same solver may produce different solutions and outcomes;
- using the available non-linear solvers can be complex.

The most common way of dealing with nonlinear programming problems is to try to linearize the problem by applying some linear approximation techniques and then use one of the many available linear programming solvers [48].

2.7 Linear reformulation of nonlinear programming problems

In the last decades the research carried out to solve more and more complex problems has followed two main directions: first, an improvement of the solvers and algorithms, taking also into account the increasing power of computers. Second, the way to model problems [49]. Concerning the formulation of the problems, several different formulations may share the same numerical properties (feasible region, optima) though some of them are easier to solve than others with respect to the most efficient available algorithms [50]. Therefore, in cases that the formulation of a problem is not the best for a given solver, starting from the first formulation, one tries to modify it in order to obtain an alternative model, called reformulation, which is better in terms of possibility of exploiting alternative and more efficient solvers and computational time needed to obtain the optimal solution. For instance, if a nonlinear problem can be reformulated as a linear one, one may take advantage of powerful solvers which are usually more robust than the nonlinear ones [49]. Being able to cast the problem in the best possible formulation is therefore a crucial aspect of any solution process [50].

In the literature, different definitions of reformulation are presented, such as [49]:

- Sherali's reformulation [51]: *A reformulation of an optimization problem P (with objective function f_P) is a problem Q (with objective function f_Q) such that there is a pair (σ,τ) where σ is a bijection between the feasible region of Q and that of P, and τ is a monotonic univariate function with $f_Q = \tau(f_P)$.*

This definition is really strict, excluding from the class of reformulations all the cases where there does not exist a bijection *σ* between the feasible region of the reformulated problem *Q* and that of the original one *P*.

- Audet's reformulation [52]: *Let P_A and P_B be two optimization problems. A reformulation B(·) of P_A as P_B is a mapping from P_A to P_B such that, given any instance A of P_A and an optimal solution of B(A), an optimal solution of A can be obtained within a polynomial amount of time.*

In this case the definition excludes nonpolynomial time reformulations, which could be carried out in a reasonable amount of time, and it includes all the polynomial time reformulations even if very slow in practice. Moreover, there is no guarantee of preserving local or global optima.

- Liberti's reformulation (also called *auxiliary problem*) [53]: *Any problem Q that is related to a given problem P by a computable formula f(Q, P) = 0 is called an auxiliary problem (or reformulation) with respect to P.*

Starting from the latter definition, reformulations can be classified in four different types [49], [50]:

- <u>exact</u> or <u>opt-reformulations</u>: *Q is an exact reformulation (or opt-reformulation) of P if each local optimum $l \in L(P)$ corresponds to a local optimum $l' \in L(Q)$ and each global optimum $g \in G(P)$ corresponds to a global optimum $g' \in G(Q)$.*

  Opt-reformulations are auxiliary problems that preserve all optimality properties. They are defined by considering local and global optima. A local reformulation transforms all optima of the original problem into optima of the reformulated problem, although more than one reformulated optimum may correspond to the same original optimum. A global reformulation transforms all global optima of the original problem into global optima of the reformulated problem, although more than one reformulated global optimum may correspond to the same original global optimum. Opt-reformulations can be chained (i.e. applied in sequence) to obtain other opt-reformulations.

- narrowings: *Q is a narrowing of P if each global optimum $g' \in G(Q)$ corresponds to a global optimum $g \in G(P)$.*

  Narrowings are auxiliary problems that preserve at least one global optimum. They come in specially useful in presence of problems exhibiting many symmetries: it may then be the huge amount of global optima that is preventing a search from being successful. All opt-reformulations are a special case of narrowings; narrowings can be chained to obtain more complex narrowings. Chaining an opt-reformulation and a narrowing results in a narrowing.
- relaxations: *Q is a relaxation of P if $F(P) \subseteq F(Q)$, and considering minimization problems P and Q where f_P and f_Q are respectively their objective functions, then $\forall x \in F(P)$, $f_Q(x) \leq f_P(x)$.*

  In other words, a problem *Q* is a relaxation of *P* if both the feasible region of *P* is contained into the feasible region of *Q* and the objective function of *Q* provides better (or equal) value than the objective function of *P* when evaluated in the points of the feasible region of *P*. Loosely speaking, a relaxation of a problem *P* is an auxiliary problem of *P* with fewer constraints. Relaxations are useful because they often yield problems which are simpler to solve yet they provide a bound on the objective function value at the optimum. The "fundamental theorem" of relaxations states that relaxations provide bounds to the objective function. Opt-reformulations and narrowings are special types of relaxations. Relaxations can be chained to obtain other relaxations; chaining of relaxations with opt-reformulations and narrowings results in other relaxations. There are different kinds of relaxations. For instance the elimination relaxation takes place when we simply drop some constraints (as in the continuous relaxation for integer problems, where the integrality constraints on the variables are dropped). In the surrogate relaxation a set of constraints is replaced by a linear combination of them. In the Lagrangian relaxation a set of constraints is removed from the model but the objective function is modified in order to penalize solutions which does not respect these constraints.

- <u>approximations</u>: *Q is an approximation of P if there is a countable sequence of problems* Q_k *(for* $k \in N$*), a positive integer* k' *and an auxiliary problem* Q^* *of P such that: (a)* $Q = Q_{k'}$*; (b) for all expression trees* $f^* \in O(Q^*)$ *there is a sequence of expression trees* $f_k \in O(Q_k)$ *that represent functions converging uniformly to the function represented by* $f^*(c)$ *for all* $c^* = (e^*, s^*, b^*) \in C(Q^*)$ *there is a sequence of constraints* $c_k = (e_k, s_k, b_k) \in C(Q_k)$ *such that: (i) the functions represented by* e_k *converge uniformly to the function represented by* e^**; (ii)* $s_k = s^*$ *for all k; (iii)* b_k *converges to b.*

  Approximations are auxiliary problems dependent on a numerical parameter, which approximate as closely as desired other auxiliary problems for some limiting value of the parameter. Since approximations can be defined for all types of auxiliary problems, we can have approximations to opt-reformulations, narrowings, relaxations and approximations themselves. In general, approximations have no guarantee of optimality, i.e. solving an approximation may give results that are arbitrarily far from the optimum. In practice, however, approximations manage to provide solutions of good quality. Opt-reformulations, narrowings and relaxations are special types of approximations. Chaining approximations and other auxiliary problems yields an approximation.

In general, not all reformulations are equally good; some desirable properties are: using a small number of auxiliary variables, having a small number of positive quadratic terms (as an empirical measure of sub-modularity) or capturing the underlying structure of the original nonlinear problem [54].

In this thesis some different linearization techniques are used in the development of solution procedure for the purpose of constructing an equivalent linear mixed integer representation of the problem. They are described in more detail in Chapter 4.

Chapter 3

Linear Programming applications in residential storage systems: a case study

3.1 Literature review on LP and MILP applications for battery storage systems optimization

Optimization methods in the field of energy efficiency and energy management is a popular research area. A vast number of publications address the topic of optimization of PV and storage systems focusing on two main aspects: component sizing and operation strategies [55]. In this context applications of linear mixed integer linear programming are important since they provide an efficiently-solvable model for these complex problems [56]. With regard to the sizing problem, for example, [57] proposes a mixed integer programming formulation to obtain the optimal capacity of the battery energy storage system in a power system, minimizing the cost of battery in the first case investigated and the imported power in the second case. Similarly, in [58] and [59] an optimal approach for sizing of an integrated hybrid system including PV panels, wind turbine, and battery is presented, using as the most important criterion the unit cost of electricity energy and different operational costs such as maintenance, emission and battery costs, respectively. On the other hand, lots of works have been published on batteries scheduling and operation strategies using LP and MILP techniques. [60] and [61] use linear programming to define an improved dispatch operation for PV/energy storage system in a group of households and in a microgrid of multiple buildings, respectively, with the aim to reduce the overall costs by minimizing the individual amount of power purchased from the grid, while [62] obtains the best storage operation patterns considering a trade-off between not only energy purchase, but also feed-in remuneration and battery aging. Also, in [63] and [64] a MILP optimization model has been developed to maximize FiT revenue streams for a grid connected PV generation system considering different electricity pricing schemes and Net-Energy-Metering (NEM) policies. In a more complex residential system with different energy conversion units, such as a cogeneration fuel cell, a heat pump, a boiler, photovoltaic panels and solar thermal collectors combined with energy storage devices, consisting of a battery and a hot water tank, a linear program is developed to determine the optimal investment and drive down total yearly energy costs and CO_2 emissions while meeting space heat, hot water and electricity needs [65]. Similarly, in [66] the optimal operation of a wind turbine, a solar unit, a fuel cell and a storage battery is searched by a mixed-integer linear programming, including the maintenance, operation cost and the generation measurement and control. On a larger scale, [67] and [68] propose a LP optimization method to solve the optimal scheduling problem and dispatch the distributed energy resources within a microgrid including a battery energy storage system with the dual objective function of economics and peak-shaving in the first case and operating costs minimization and self-consumption promotion in the second case. Furthermore, some works, such as [69], [70] and [71] develop LP models considering battery degradation processes and battery state of health, respectively, to derive suitable charging patterns to prolong battery lifetime. For further information reference should be made to review of literature on optimal sizing and operation of energy storage systems in [72] and [73]. In this thesis the optimization of a PV/BESS operation is addressed with the purpose of minimizing energy imported from and exported to the grid while focusing on the mathematical formulation of the most important batteries constraints, such as depth of discharge requirements, state of charge limitations, charge and discharge rates, and charging/discharging optimal profiles.

3.2 Degradation of battery lifetime and need for optimal management

An important question, especially in applications with long system lifetimes, like PV systems, and where the battery share of the overall systems' life cycle cost is significant, is to maximize the battery lifetime as much as possible, by properly managing its charging and discharging schedule [74]. In general, the overall lifetime of a battery can be approximated based on two parameters, the calendar lifetime L_B^{cal} and the maximum number of full battery cycles until decommissioning L_B^{cyc}, differing depending on the battery chemistry (lead-acid, lithium-ion, nickel-based, sodium-based, saltwater, flow batteries, etc.). A full cycle refers to a sequence of discharge-charge operations that starts and ends with a fully charged battery [70]. Calendar lifetime tends to dominate in systems where batteries are used infrequently or at very low currents, whereas cycle life is often used for regularly cycled applications. In addition, another metric can be used: the total amp-hours (Ah) of charge processed is a useful measure of life when batteries are used frequently but with irregular or incomplete cycles [75]. The battery lifetimes are depending on a variety of environmental and operation parameters, such as chemical substances and therefore battery type, temperature, depth of discharge (DOD), charging and discharging rate, state of charge when stored, etc. In particular, some impact factors on battery performance and aging can be influenced by the operation strategy and especially by the charge conditions. In engineering and design, experts are working to get a better understanding of usage patterns causing battery degradation with the aim to improve battery management systems and thermal control, increasing cycle life and allowing deeper discharge, thus decreasing the cost per usable kWh [76]. It is found that each battery type has a specific set of restraints and conditions related to its charging and discharging optimal regime. For example, nickel cadmium batteries should be nearly completely discharged before charging, while lead acid batteries should never be fully discharged. Furthermore, the voltage and current during the charge cycle will be different for each type of battery. Various phenomena, in fact, take place at the electrode/electrolyte level during charging and the method in which a battery is charged can significantly alter its efficiency and safety [77]. Therefore, it is important to select the battery type according to the specific application field. Some of the most common battery technologies for household applications are [78], [79]:

- **Lead-acid (LA) batteries:** lead-acid chemistry uses a lead-based grid submerged in an acidic electrolyte. LA batteries are one of the oldest forms of energy storage and are known for being dependable and inexpensive, with low self-discharge and relatively low capital cost, which are their most prominent benefits when compared to other cells. However, LA batteries suffer from limited cycle life and are inefficient when it comes to charge and discharge when compared to other chemistries. LA batteries can be flooded cell type or valve regulated type. In flooded batteries the electrodes are completely submerged in the electrolyte. During charging of flooded batteries to full state of charge, hydrogen and oxygen gases produced from water by the chemical reaction at negative and positive plates passes out through vents of the battery. Flooded batteries need to be refilled regularly as the electrolytes evaporate during charging. The Valve Regulated Lead-Acid (VRLA) batteries can be "sealed" and use valves to regulate off-gassing. They can be further separated into two categories: absorbed glass mat (AGM) and gel. AGM batteries hold the electrolyte in its glass mats and use only enough liquid to keep the grid wet. Gel batteries use a thick silica-based gel as its electrolyte base. AGM batteries perform better in colder temperatures, while gel batteries work better in warmer temperatures when there's less chance for the thick paste to freeze.

- **Sodium-based batteries:** these batteries use salt—sometimes saltwater—to produce long-duration power. Salt-based cells can be completely drained to zero charge without damaging the system. Sodium batteries are not flammable or explosive and can function in a wide temperature range.
- **Nickel-cadmium (Ni-Cd) batteries**: in Ni-Cd batteries positive electrode is made up of cadmium and the negative electrode by nickel hydroxide separated by nylon separators immersed in potassium hydroxide electrolyte. These batteries are characterized by higher energy and power density, and better cycle life than lead-acid batteries and are temperature tolerant. Ni-Cd batteries present memory effect, which degrades the battery capacity according to its usage, and high values of self-discharge. Memory effect is the process of remembering the depth of discharge in the past. If the battery is discharged to 25% repeatedly, it will remember it, and if the discharge is greater than 25%, the cell voltage will drop as shown in figure 15. To

recover the full capacity the battery, it should be reconditioned by fully discharging and then fully charging once in few months.

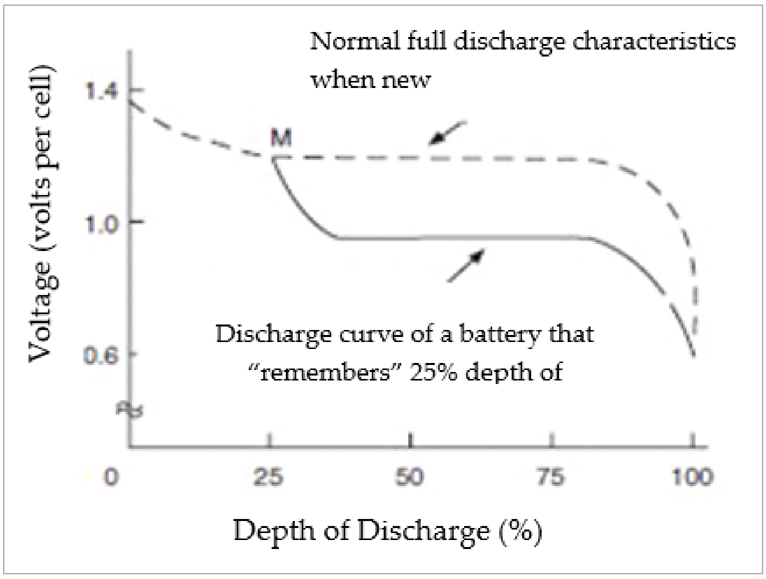


Figure 15 - Memory effect of Ni-Cd battery [78].

- **Nickel-metal hydride (Ni-MH) batteries**: they are considered an improvement over the Ni-Cd batteries, safer and less susceptible to memory effect issues. Additionally, they have a higher energy and power density than Ni-Cd. Despite these advantages, they are expensive than Ni-Cd and overcharging damages the batteries easily. Also, they suffer from high self-discharge and low coulombic efficiencies.

- **Lithium-ion (Li-ion) batteries:** Lithium-based energy storage systems are overwhelmingly the most common storage technology used within the solar market. These batteries are characterized by the transfer of lithium ions between electrodes during charge and discharge reactions. In particular, the lithium electrode reacts with the electrolyte creating a passivation film during every discharge and charge operation, with damages for the battery in case of overcharging. This is compensated by the usage of thick electrodes. Because of this fact and their need for battery management systems to monitor voltage and temperature, lithium-ion batteries are more expensive than other chemistries. The benefits of lithium-ion, though, include long cycle life, greater energy density, high charge and discharge efficiency and wider operating temperature range over conventional lead acid batteries and Ni-Cd, but they are prone to self-discharge. There are many different types of lithium ion batteries that are primarily distinguished by their cathode materials. Even with the same cathode types, the choice of anode materials, electrolyte solvents, separators and nanomaterial additives strongly influences performance. The most common lithium-based battery types are: lithium polymer (PLiON), lithium cobalt oxide (LCO), lithium manganese oxide (LMO), lithium iron phosphate (LFP), lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA) and lithium titanate (LTO).

Table 3 summarizes the main characteristics, while Figure 16 compares in detail the energy densities of the different solar rechargeable battery types [80], [81].

Type	**Energy Density (Wh/kg)**	**Energy Efficiency (%)**	**Power Density (W/Kg)**	**Cycle Life (Cycles)**	**Self Discharge (%/Month)**
Lead-Acid	30 - 40	70 - 90	180	200 - 2000	3 - 4
Li-Ion	100 - 250	75 - 90	1800	500 - 2000	5 - 10
Li Polymer	130 - 200	70	3000	>1200	4 - 8
Ni-MH	30 - 80	70	250 - 1000	500 - 100	30
Ni-Cd	40 - 60	60 - 90	140 - 180	500 - 2000	10 - 15
NaS	150	80 - 90	120 - 150	2500	-

Table 3 - Comparison of key characteristics of different rechargeable battery technologies [80].

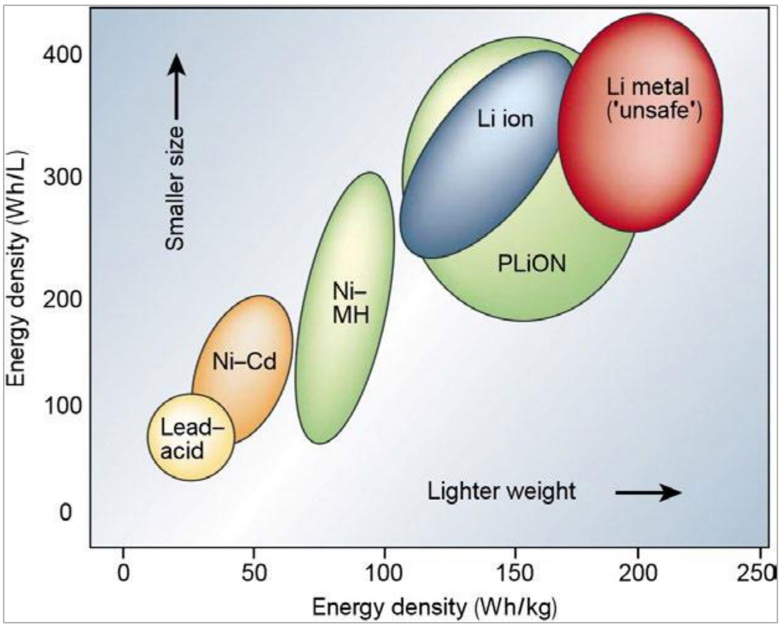


Figure 16 - Comparison of energy densities and specific energy of different rechargeable batteries [81].

Furthermore, numerous chemistries and novel technologies are being developed for the solar storage, such as silicon-based, room-temperature sodium sulfur (RT-NaS), proton, graphite dual-ion, aluminum-ion, nickel-zinc, potassium-ion, salt-water, paper-polymer and magnesium batteries.

Depending on the reactions of electrochemical processes, performances and lifetime of the different battery chemistries can be more or less seriously affected by several factors. In general, battery performance highly depends mainly on [82]:

- Temperature: while most manufacturers designate a large operating temperature margin from -30 ˚C to +55 ˚C, the optimal operating temperature is much smaller and pronounced life fade can be experienced at the extremes. For lithium-ion batteries high temperatures accelerate aging side reactions within a battery cell. Conversely, low temperatures cause lithium plating to occur on the anode while charging the battery, as shown in Figure 17. Additionally, cell temperature affects battery power output at extreme points such that high powered charging or discharging at very high or low temperatures would generate a diminished response. An optimal operating temperature which minimizes degradation of both of these effects can be found, however it is chemistry specific.

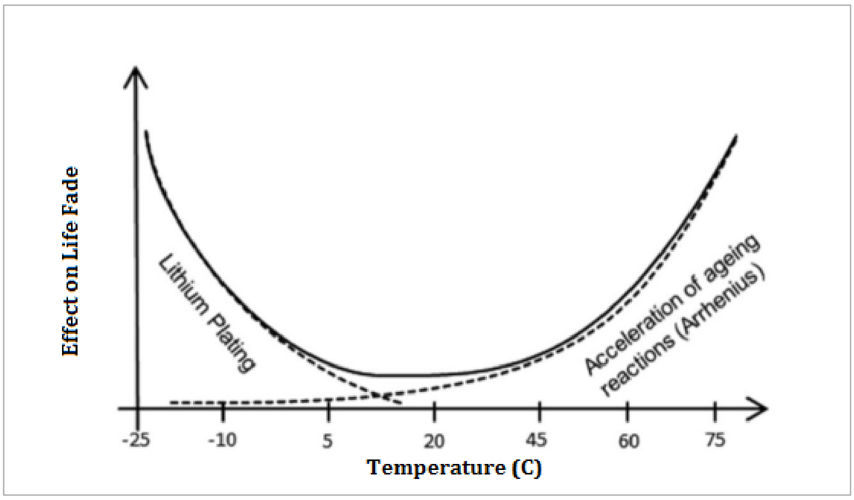


Figure 17 - Generalized thermal effects for lithium-ion batteries [82].

- State of Charge (SOC) and Depth of Discharge (DOD): the state of charge indicates battery charge as a fraction of the initial capacity, while the depth of discharge refers to the capacity discharged as a fraction of the initial capacity and it is treated as a complement of SOC, as shown in Figure 18.

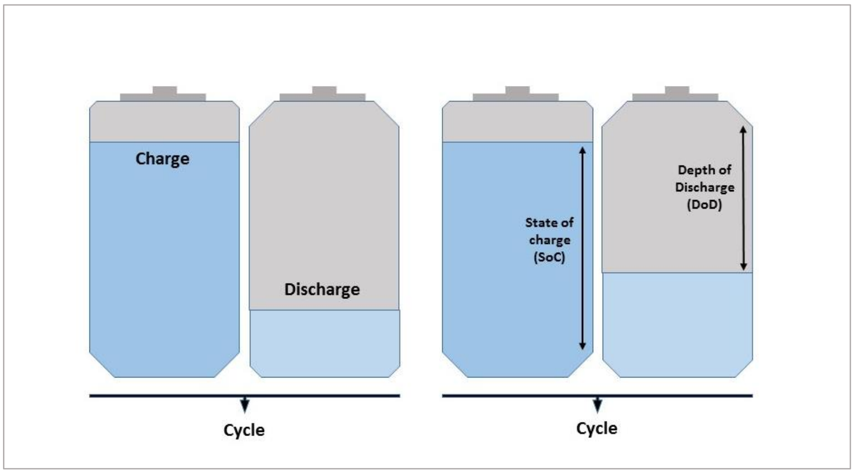


Figure 18 - The battery cycle working principle, SOC and DOD [83].

Lithium ion batteries show a strong dependency on the absolute state of charge and cycle life is mainly determined by how deeply the battery is used, i.e., DOD. In particular, the higher the SOC of the cell, the higher the Li ion concentration at the surface of the anode and, therefore, the higher the rate of the side reaction. Furthermore, high states of charge cause a change in volume of the active material and therefore mechanical stress. From this understanding it is clear that cycling from a lower average SOC will cause less degradation than cycling at a higher average SOC. This is important when considering DOD effects as well since cycling the battery with identical cycle depth ΔSOC but at different cycling regimes (e.g. between 100% SOC and 20% SOC or between 80% SOC and 0% SOC) can lead to deviations in lifetime by a factor of 3 and more. Higher DOD cycling results, in fact, in greater mechanical stresses applied to the cell due to volumetric changes which cause cracking of the Solid Electrolyte Interface (SEI) layer, i.e. the passivating layer on the anode surface formed by the reaction between the anode and electrolyte, lithium exfoliation, isolation of active electrode material, and contact loss at each current collector. The cyclic aging is typically defined by means of a Woehler diagram that correlates the number of performable cycles to the ΔSOC of the cycle. It gives the maximum number of cycles a cell can drive till the end of life, given the cycle depth. An example of such a Woehler diagram is shown in Figure 19. The Woehler diagram is usually given by the cell manufacturer [74].

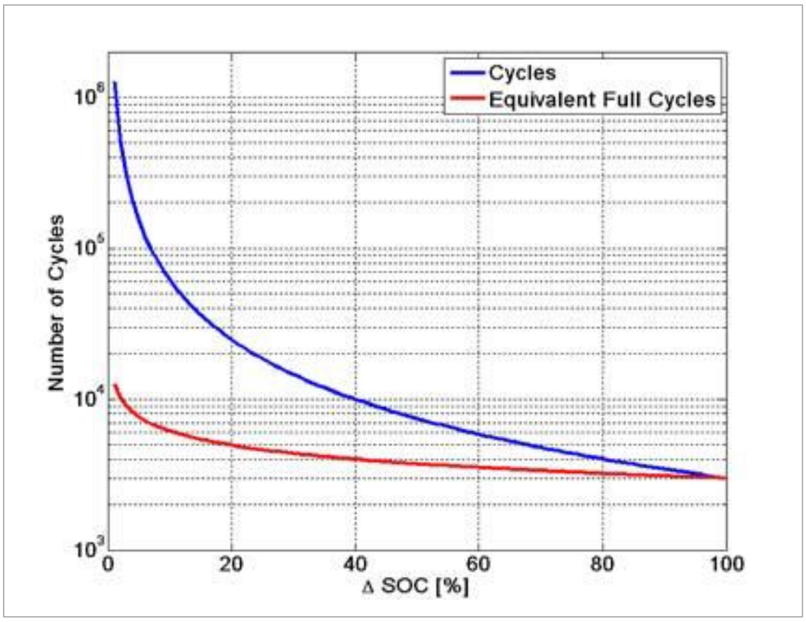


Figure 19 - Example of Woehler Curve [74].

- Charge Rate (C-rate): The C-rate is an expression of charge or discharge current which is normalized to battery capacity. In lithium-ion batteries high currents contribute to an increased SEI layer growth at the anode, which both decreases actively available lithium and increases resistive behavior. Furthermore, high C-rates can cause SEI mechanical fracture due to particle cracks during battery cycling especially at low temperatures. Additionally, high currents generate more ohmic heating which in turn increases battery temperature and contributes to the resultant temperature effects. The amount of ohmic heating will also depend on the cell internal impedance. Finally, C-rate is known to affect charge efficiency with lower C-rates being more efficient following a non-linear trend.

Figure 20 provides a general overview of various degradation mechanisms for lithium-ion batteries depending on the main factors influencing battery degradation (temperature, SOC, C-rate, DOD) [82].

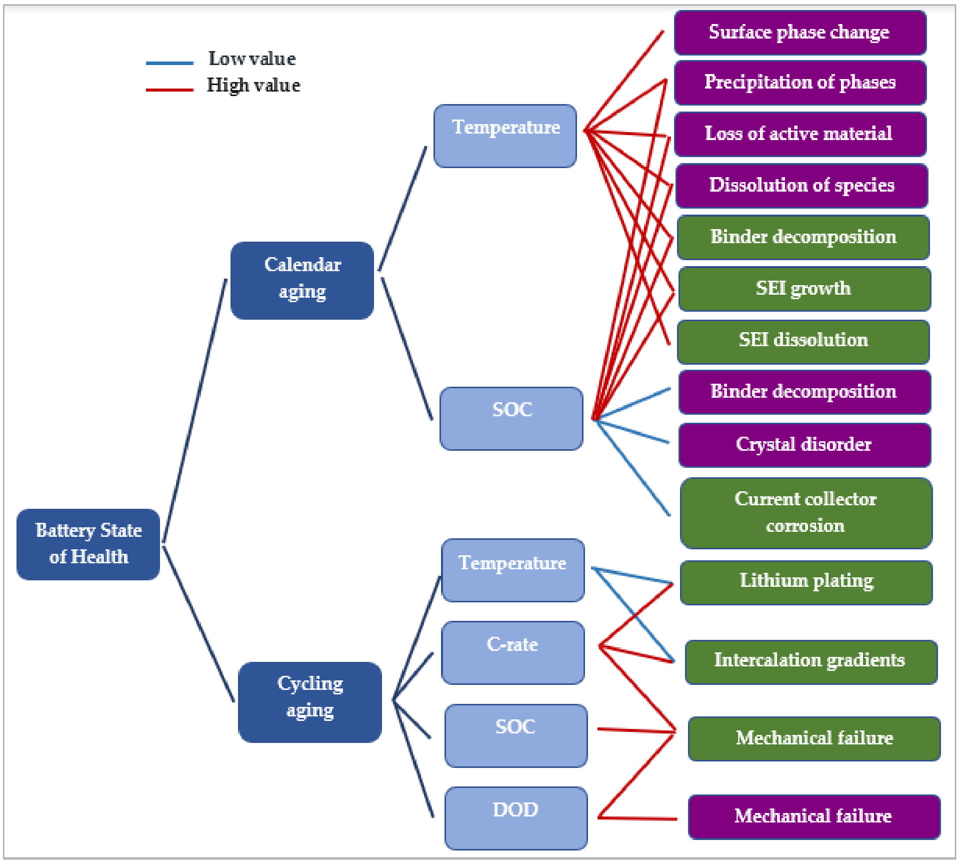


Figure 20 - Degradation mechanisms for lithium-ion batteries acting at the cathode (purple boxes) and anode (green boxes) [82].

In this thesis the above key factors impacting battery degradation have been considered by imposing constraints on model parameter values. In particular, the charging and discharging processes for a generic battery energy storage system have been formulated given the following constraints:

- The state of charge of each battery must be respected to its upper and lower limitations, SOC_{max} and SOC_{min} respectively, to protect the storage system from overcharging and overdischarging, that represent prominent degradation mechanisms reducing battery capacity in day to day activities and causing early cell failure. Therefore, the model has been formulated so that when the battery SOC reaches SOC_{min}, it stops discharging, and similarly, when the battery SOC reaches SOC_{max}, it stops charging.
- Each battery is forced to follow a full charging/discharging profile between SOC_{min} and SOC_{max}, i.e. it can not be discharged until it reaches SOC_{max} and vice versa. This constraint is intended to avoid partial cycles and the superposition of micro cycles with frequent changes of the direction of the battery current. Actually, for some battery chemistries, such as floaded lead acid batteries, cycling a battery between two partial states-of-charge soon can have a negative impact on the battery wear and lifetime, causing sulfate crystal formation and severe electrolyte stratification [70].
- The two constraints above stated ensure that for each battery the recommended DOD for optimal performance is respected.
- Finally, a specific constraint forces each battery to respect the recommended maximum continuous charge/discharge rate in order to avoid high charge and discharge currents.

3.3 "SMART-A.T.E.R." project for Civitavecchia municipality

The agency for public residential buildings (Azienda Territoriale per l'Edilizia Residenziale Pubblica, A.T.E.R.) is a public body involved in public residential housing and working on promoting and restoring buildings in the municipality of Civitavecchia, province of Rome. "SMART-A.T.E.R." project has the objective to develop the first national smart community within the public residential housing, mainly through, firstly, exploiting renewable energy sources. In particular, the energy produced by renewable sources will be fed into the grid and drawn depending on the energy needs of the different users within the community. The aim is to comply with European legislation promoting the renewable energy sources and the regional law on urban regeration and building recovery [84], but it is also and above all to guarantee environmental and economic benefits for the less well-off households. Indeed it has been estimated that a family living in A.T.E.R. rental housing pays on average 630-900 €/year electricity bill, compared to approximately 93 €/year for the apartment rental, as shown in Figure 21 (data elaborated by A.T.E.R. Civitavecchia).

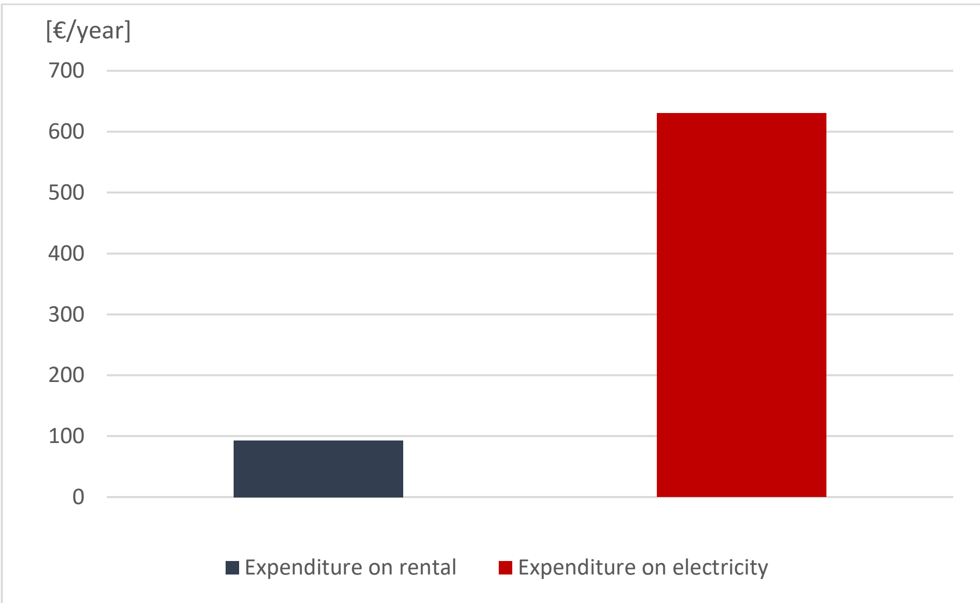


Figure 21 – Annual expenditure on apartment rental and electricity for an average family in Civitavecchia (data elaborated by A.T.E.R. Civitavecchia).

Within the real estate owned by A.T.E.R. Civitavecchia 40 buildings, for a total of 493 residential units, have been selected for the project.

In particular, the project aims at developing a micro energy community for each residential complex by creating a smart interconnected network for power and information data transmission employing innovative technological solutions and advanced systems for renewable-source energy production and distributed energy storage. Specifically, at building level, each apartment can be considered as a node of the network and the key components of the whole system are:

1. **Renewable energy sources**: photovoltaic systems will be installed on the common areas of the building, such as terrace, rooftop and shelters.
2. **Storage systems**: battery energy storage systems will be situated in appropriate technical rooms and other common areas of the building.
3. **Home energy devices**: each apartment will be equipped with smart meter load disaggregation systems, allowing to extract individual power signatures for different appliances and monitor consumption data in real time in order to create an energy profile for each user.
4. **Management and control system**: the platform will process data coming from all the nodes, forecast the power demand of each user and consequently regulate the flow of energy.

Similarly, the individual building will be interconnected to the others to create a larger energy community. The project, besides securing cost savings for the families by increasing energy self-sufficiency, will led to increase the profitability of ATER by selling the surplus energy to the grid, and it is therefore candidate to become a best practice case at national level. Further details on the project can be found in Appendix A.

3.4 System layout

As part of the more far-reaching "Civitavecchia SMART A.T.E.R." project, this thesis focuses on the application example of collective self-consumption in the multi-apartment building located in Via Navone 23, Civitavecchia. The proposed case study investigates, in fact, an optimization method for sizing and scheduling the battery energy storage system for solar

PV system integration in the building, with the purpose of maximizing the collective self-consumption for the families living in it and ensuring the correct charge-discharge cycles scheduling strategy for the batteries. Table 4 summarizes the main parameters and specifications describing the key elements of the systems, i.e. the PV plant, the batteries and the users, respectively. In particular, a 20 kW_P solar rooftop PV system has been considered, as provided for in the proposed project for the building in question. A storage system has been proposed consisting of more batteries with 4 kWh of rated capacity each. Initially, 10 generic rechargeable batteries have been assumed and subsequently corrected in accordance with the optimization model results; in fact, a penalty coefficient is imposed within the model in order to maximize the households' self-consumption with the lowest number of batteries. Lastly, households' demand profiles have been estimated for typical days in different seasons for the ten families living in the building.

PV system parameters	
Site	Civitavecchia (Rome)
PV peak power	20 kW_P
Installation type	residential grid-connected solar rooftop
PV technology	crystalline silicon cells
Installation parameters	Plane tilt 35°, Azimuth 0° (facing South)
Average annual sum of global irradiation	1990 kWh/m^2
Average annual electricity production	28400 kWh
Battery storage system parameters	
Battery capacity	4 kWh
Number of batteries (initial assumption)	10
Battery chemistry	Lithium-ion
Battery minimum state of charge (SOC_{min})	20%
Battery maximum state of charge (SOC_{max})	80%
Initial state of charge	3,2 kWh
Depth-of-discharge (DOD)	80%
Charge rate	2 kW/h
Discharge rate	2 kW/h
Cycle lifetime	3000 cycles
Households' consumption data	
Number of families	10
Total Annual electricity consumption	39 MWh
Maximum demand power during Summer	10,3 kW

Table 4 – Summary of technical input parameters for the optimization model.

More details on collected and estimated data of hourly potential PV production, and typical households' demand profiles are provided in the next paragraphs, respectively. For the purposes of simplicity, the inverter has been assumed to be lossless, therefore it is not shown in the table. The main battery specifications are based on literature data; the roundtrip efficiency in the simulation has been taken as 100% in order to reduce the computational complexity of the model, while still providing acceptable results.

The logic of operation of the model is the following: the solar PV power is utilized onsite to meet the variable households' power demand at every moment. When there is excess power, it is prioritized by storing the power in the batteries first, until the batteries reach the maximum state of charge (SOC_{max}). In particular, among the different batteries inside the battery pack, only the batteries that are charging or are at the minimum state of charge (SOC_{min}) can contribute to storing the excess power. Lastly, any surplus PV power is then exported to the grid. Similarly, the batteries are employed to backup to meet the demand, if the demand is not met by the PV system. Therefore, when PV power is not sufficient for meeting the households' power demand, the batteries are used to supplement the power requirements. In particular, among the different batteries inside the battery pack, only the batteries that are discharging or are at the maximum state of charge (SOC_{max}) can contribute to provide the required power. Lastly, when the SOC of the batteries falls below SOC_{min}, the required power is imported from the grid. Schematic of the system is shown in Figure 22.

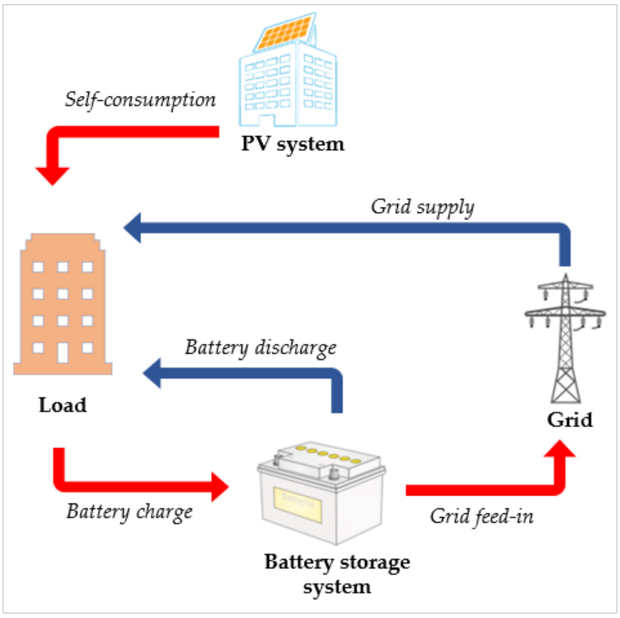


Figure 22 – Overall schematic of the system illustrating the direction of the power flows.

The implemented charging/discharging control strategy of batteries aims to prolong their lifetime; missing or inadequate battery management, in fact, may seriously affect the health of the batteries by shortening their lifetime. There are lots of stress factors, such as the "memory effect", that have a negative impact on the batteries performance and lifetime; they can vary dependent on battery types, but in general, the depth of discharge (DOD) represents one of the most important parameters influencing a battery lifespan and it should be adequately taken into account. Therefore, an optimal management system is urgently needed.

3.5 Data collection

3.5.1 Solar electricity generation estimation

To simulate the operation behaviour of PV systems, time series of meteorological data are required. For this investigation measurements from the European Commission Joint Research Centre - Photovoltaic Geographical Information System (PVGIS), located in Ispra, Italy, are used [85]. The measured values refer to Civitavecchia, a central-Italy town located on the Tyrrhenian Sea, 60 kilometres north-west of the center of Rome, as illustrated in Figure 23 [86].

Figure 23 - Location of Civitavecchia in Italy [86].

The measurement data of solar irradiation on the horizontal and 35° inclined plane, as well as the air temperature, are available as one hour average values from the year 2007 until 2016; monthly averages values are reported in Table 5 [85].

Month	H_h	H_{opt}	$H(35)$	DNI	I_{opt}	D/G	T_D	T_{24h}	N_{DD}
Jan	1830	3180	3150	2820	64	0.47	9.9	9.7	296
Feb	2960	4630	4600	4240	58	0.38	9.5	9.1	253
Mar	4360	5630	5610	4870	45	0.40	11.8	11.3	199
Apr	5680	6300	6300	6040	30	0.33	14.4	13.8	83
May	6980	6840	6870	7260	17	0.30	17.3	16.8	7
Jun	7720	7140	7190	8320	8	0.26	21.6	21.0	2
Jul	7850	7460	7500	8870	12	0.22	24.5	24.0	0
Aug	6840	7270	7290	7970	25	0.24	24.9	24.3	1
Sep	5080	6280	6270	6000	40	0.32	22.0	21.4	5
Oct	3530	5100	5080	4460	53	0.40	18.6	18.2	63
Nov	2150	3620	3590	3210	62	0.44	15.0	14.6	213
Dec	1660	3100	3070	2850	67	0.46	11.4	11.2	269
Year	4730	5550	5550	5580	36	0.31	16.8	16.3	1391

H_h: Irradiation on horizontal plane (Wh/m²/day)
H_{opt}: Irradiation on optimally inclined plane (Wh/m²/day)
$H(35)$: Irradiation on plane at angle: 35deg. (Wh/m²/day)
DNI: Direct normal irradiation (Wh/m²/day)
I_{opt}: Optimal inclination (deg.)
D/G: Ratio of diffuse to global irradiation (-)
T_D: Average daytime temperature (°C)
T_{24h}: 24 hour average of temperature (°C)
N_{DD}: Number of heating degree-days (-)

Table 5 - PVGIS estimates of long-term monthly averages solar irradiation [85].

Basing on the data above, the estimation of the hourly power output from a given PV installation can be calculated; it is estimated for a fixed PV system with a nominal power of 20.0 kW. The main information about the installation is available in Table 6 [85].

PV system data
Location: 42°06'00" North, 11°48'0" East, Elevation: 0 m a.s.l.
Solar radiation database used: PVGIS-CMSAF
Nominal power of the PV system: 20.0 kW
PV technology: crystalline silicon cells
Inclination: 35°
Orientation: 0° (South)
Mounting position: building integrated
Estimated losses due to temperature and low irradiance: 14.3% (using local ambient temperature)
Estimated loss due to angular reflectance effects: 2.6%
Other losses (cables, inverter, dirt, etc.): 14.0%
Combined PV system losses: 28.2%

Table 6 – PV system specifications and calculation parameters [85].

The average electricity production values aggregated on monthly basis are shown in Table 7 and Figure 24 [85].

Month	E_d	E_m	H_d	H_m
Jan	46.80	1450	3.07	95.2
Feb	68.20	1910	4.56	128
Mar	80.80	2510	5.51	171
Apr	89.90	2700	6.23	187
May	94.70	2940	6.69	207
Jun	98.00	2940	7.03	211
Jul	101.00	3150	7.37	229
Aug	97.90	3040	7.10	220
Sep	86.30	2590	6.17	185
Oct	71.20	2210	4.95	154
Nov	52.90	1590	3.57	107
Dec	45.40	1410	3.03	93.9
Yearly average	**77.8**	**2370**	**5.45**	**166**
Total for year		**28400**		**1990**

E_d: Average daily electricity production from the given system (kWh)
E_m: Average monthly electricity production from the given system (kWh)
H_d: Average daily sum of global irradiation per square meter received by the modules of the given system (kWh/m^2)
H_m: Average sum of global irradiation per square meter received by the modules of the given system (kWh/m^2)

Table 7 – PVGIS estimates of average monthly solar electricity generation [85].

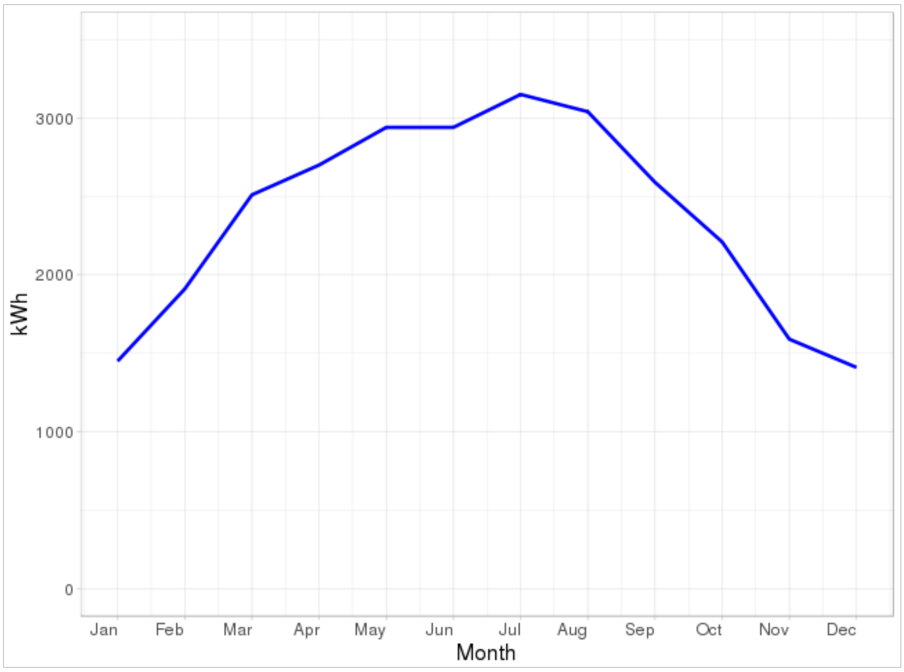


Figure 24 - Average monthly electricity production from the given PV system (kWh) [85].

3.5.2 Electricity consumption data

For the demand data in this study, the electricity bills for the past three years have been exploited for each family in order to estimate typical values of expected average consumption level. Table 8 shows annual electricity consumption for the ten households, calculated as the average over the period 1st January 2016–31st December 2018, with the detail of the distribution for different time slots. In particular, Time slot F1 runs from 8 A.M. to 7 P.M., from Monday to Friday, excluding national holidays; Time slot F2 runs from 7 A.M. to 8 A.M. and from 7 P.M. to 11 P.M., from Monday to Friday and from 7 A.M. to 11 P.M. on Saturday; Time slot F3 runs from midnight to 7 A.M. and from 11 P.M. to midnight, from Monday to Saturday and all day on Sunday and national holidays, as defined by the Italian Regulatory Authority for Energy, Networks and the Environment (ARERA) [87].

Household	F1 [kWh]	F2 [kWh]	F3 [kWh]	TOTAL [kWh]
n. 1	1509	1369	1593	4472
n. 2	714	1224	996	2934
n. 3	974	1166	1750	3890
n. 4	1281	1356	2466	5103
n. 5	1366	1868	1978	5212
n. 6	1029	1047	1211	3287
n. 7	656	1283	1300	3239
n. 8	2258	1307	1245	4810
n. 9	1016	1153	1401	3570
n. 10	443	1076	1291	2810

Table 8 - Annual electricity consumption by household expressed in kWh. Average values for the period 2016-2018, with the detail of Time Slots F1, F2, F3. Data resulting from electricity bills.

Table 9 reports the monthly average electricity consumption data by household and time slot and Figure 25 is a graphical representation of monthly totals for the whole building, calculated as the sum of the individual household consumption.

Household	January			February			March			April			May			June		
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
n. 1	150	120	129	153	129	140	116	129	118	78	80	118	97	97	101	97	102	115
n. 2	51	105	87	39	96	75	42	126	69	45	114	87	48	93	75	48	90	75
n. 3	84	75	123	77	78	116	88	98	143	74	89	144	83	107	146	74	110	144
n. 4	111	95	218	93	101	170	105	114	201	81	83	174	104	98	185	126	147	227
n. 5	120	184	226	112	190	148	140	178	158	104	144	176	120	142	156	108	134	140
n. 6	98	92	105	83	83	80	76	92	87	67	76	95	77	77	88	70	60	94
n. 7	46	112	104	44	98	84	40	116	108	54	106	122	60	110	118	60	109	96
n. 8	213	107	114	213	123	94	235	139	93	195	114	122	229	130	104	120	61	90
n. 9	95	98	126	87	99	104	86	105	111	70	85	114	82	90	108	70	87	111
n. 10	62	102	140	42	100	112	27	88	113	21	76	103	19	73	99	16	74	106

Household	July			August			September			October			November			December		
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
n. 1	225	196	255	157	139	190	85	90	108	91	92	76	120	95	117	140	101	128
n. 2	75	90	84	105	93	102	60	93	84	72	114	78	63	111	72	66	99	108
n. 3	86	132	189	93	117	189	75	108	146	83	101	123	86	84	131	75	69	158
n. 4	137	177	285	141	159	264	111	126	209	107	101	174	83	77	165	84	81	197
n. 5	150	142	164	102	80	78	98	134	120	102	184	184	130	188	206	80	168	222
n. 6	123	105	119	123	122	133	80	90	111	69	84	83	85	83	88	78	84	129
n. 7	70	104	116	70	104	116	64	104	108	60	110	96	38	112	96	50	98	136
n. 8	120	61	90	200	114	107	126	91	90	211	122	102	211	122	102	184	125	139
n. 9	99	110	146	98	103	127	70	93	105	83	98	101	93	94	110	83	91	137
n. 10	16	86	113	18	88	74	19	95	76	49	99	101	93	98	111	60	99	144

Table 9 - Monthly electricity demands by household and time slot, expressed in kWh. Data resulting from electricity bills.

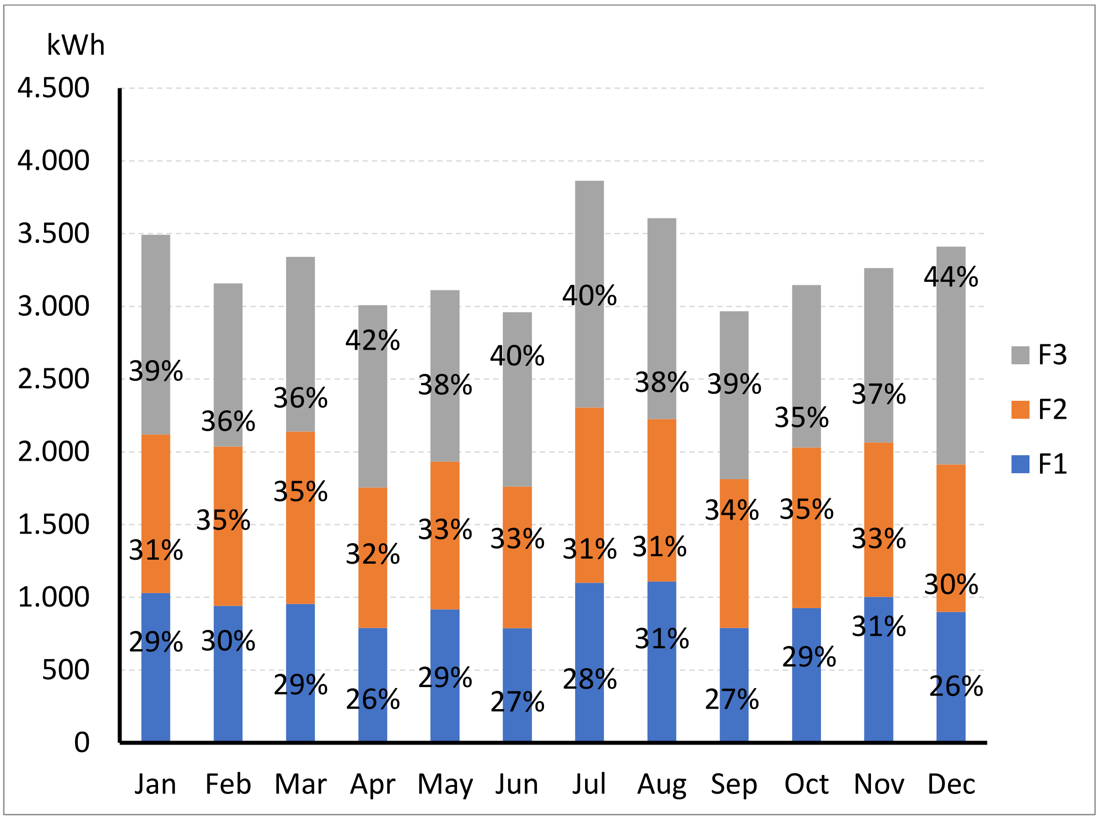


Figure 25 - Monthly total electricity demands of the building by time slot, expressed in kWh. Data calculated from electricity bills.

Based on monthly consumption data it has been possible to calculate daily values and then estimate average hourly demand profiles for weekdays and weekends during the four seasons. In particular, for the evaluation of the hourly profiles, statistical data based on literature reports and dwellings characteristics have been considered. In fact, instantaneous power demand for a single house can greatly vary through time and it can be very different for different families depending on households' lifestyle and habits. There is, however, evidence of common patterns in electricity load profiles throughout residential sector. Figure 26, for example, shows average hourly demand profile for a typical working day and weekend in different seasons. These data have been collected from a research study conducted by Electric System Research (Ricerca sul Sistema Energetico - RSE), on a sample of 1.200 Italian families statistically significant for number and stratification, monitored over a period of 2 years [88].

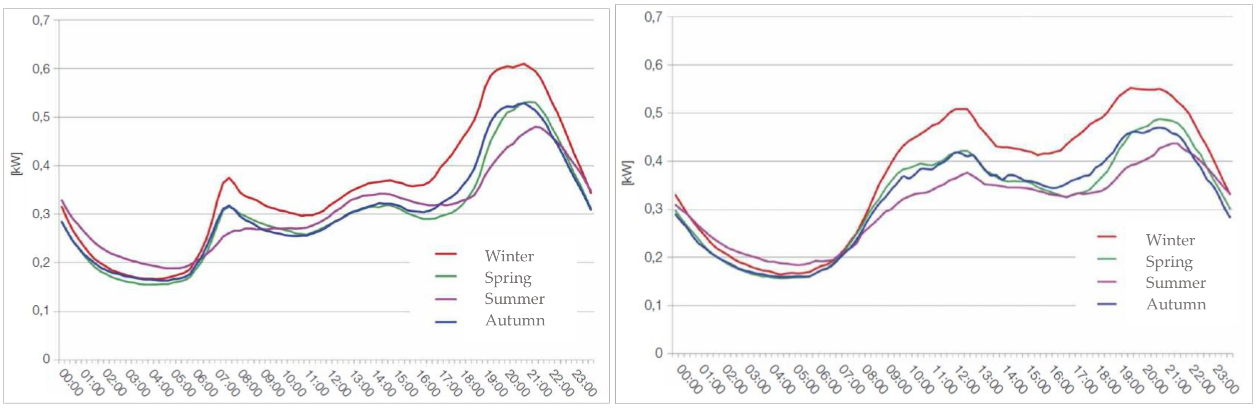


Figure 26 – Average hourly demand profiles in kW for a working day (left) and weekend (right) for a typical Italian family. Data resulting from a RSE research study [88].

It may, in general, be noted that the graphic representation of a domestic electricity load profile is mainly defined by its morning load, its evening load and its mid-day loads. The over-night load shape is defined by the low level of use in this period, as most occupants are inactive during their sleeping hours [89]. In many cases, though, the electricity load profile may differ from the typical domestic trend because of the impact of variable tariffs on the energy behaviour of individual end-consumers, that are incentivized to shift appliance operation to the late evening or the weekend when the electricity costs are more advantageous (Time Slot F2 and F3, respectively). The effect of these behavioural trends can be observed in Figure 25 that shows the percentage of energy consumption for different time slots. In the case of this study, in fact, most families have variable-price electricity contracts, as shown in Table 10, that provides the most important dwellings and households characteristics.

Household	**Dwelling type**	**Household type**	**Number of occupants**	**Occupancy pattern**	**High energy-consuming appliances**	**Electricity supply contract**
n. 1	Flat	Family with two teenage children	4	Always occupied	Air conditioner	Fixed tariff
n. 2	Flat	Young couple without children	2	Evenings, weekends	-	Variable tariff
n. 3	Flat	Single person under 65	1	Evenings, weekends	Electric water heater	Variable tariff
n. 4	Flat	Family with one children	3	Always occupied	Air conditioner	Variable tariff

n. 5	Flat	Family with two children	4	Always occupied	Electric water heater	Variable tariff
n. 6	Flat	Family with one teenage children	3	Always occupied	Air conditioner	Variable tariff
n. 7	Flat	Young couple without children	2	Evenings, weekends	-	Variable tariff
n. 8	Flat	Family with grandparents	4	Always occupied	Electric water heater, Air conditioner	Fixed tariff
n. 9	Flat	Couple over 65 without children	2	Always occupied	Air conditioner	Variable tariff
n. 10	Flat	Single person under 65	1	Evenings, weekends	-	Variable tariff

Table 10 - Dwellings and households characteristics for the case study considered.

Therefore, the estimates of the hourly demand profiles have been made on the basis of typical literature trends appropriately adjusted in accordance with the real consumption data for the different time slots, for every family and for every month. Figure 27 shows the resulting hourly demand profile, aggregated for all the families investigated, for a typical weekday and weekend throughout the four seasons.

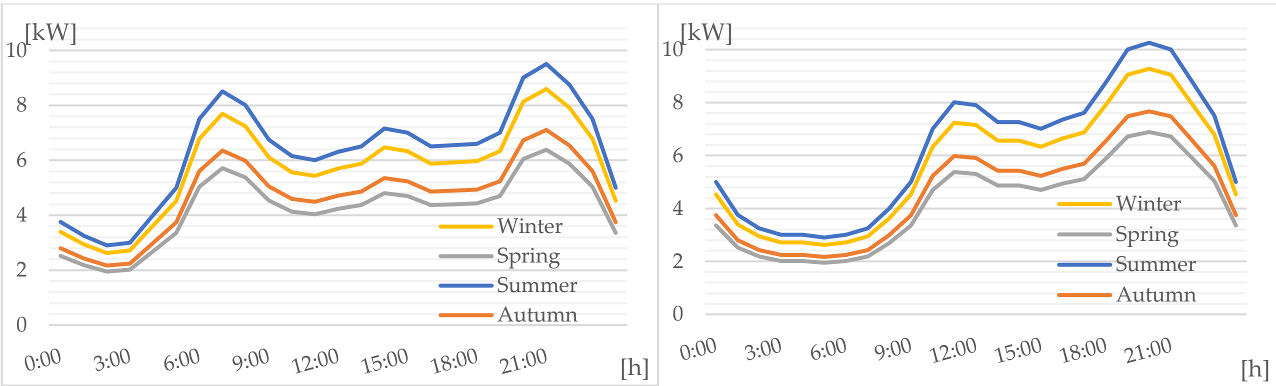


Figure 27 – Resulting hourly demand profile in kW for a working day (left) and weekend (right), aggregated for all the families, throughout the four seasons.

Chapter 4

Mathematical Formulation of the problem

4.1 Decisional Variables

Two sets of continuous non-negative variables $\alpha(t) \geq 0$ and $\beta(t) \geq 0$ $\forall t \epsilon T$ are defined to represent the amount of energy respectively bought and sold in each time slot t. In order to identify how many batteries have to be installed, a set of the binary variables $y_i(t) \in \{0, 1\}$ $\forall i \epsilon B$ is introduced, equal to 1 if battery i is used and 0 otherwise. Two additional sets of continuous non-negative variables $\delta_N^i(t) \geq 0$ and $\delta_P^i(t) \geq 0$ $\forall t \epsilon T, \forall i \epsilon B$ represent the quantity of energy respectively got from each battery i, to satisfy the energy demand in each time slot t, and gave to each battery i utilized in the system to recharge it. Moreover the binary variables $c^i(t) \in \{0, 1\}$ $\forall t \epsilon T$, $\forall i \epsilon B$ are defined to describe the state of each battery i in each time slot t, equal to 1 if the battery can be recharged at time slot t and 0 otherwise. The set of continuous non-negative variables $\lambda^i(t) \geq 0$ $\forall t \epsilon T, \forall i \epsilon B$ represent the energy level of each battery i in each time slot t. Moreover, the two sets of binary variables $f^i(t)$ and $F^i(t)$ for each time slot t and for each battery i are used to define the minimum and maximum battery level state: $f^i(t)$ is equal to 1 if battery i at time slot t is not at minimum energy level and 0 otherwise, $F^i(t)$ is equal to 1 if battery i at time slot t is not at the maximum energy level and 0 otherwise. Finally, the sets of binary variables $z_1^i(t)$ and $z_2^i(t)$ are introduced to correctly define the number of batteries recharging cycles represented by the integer variable Nc^i for each battery i. In particular, variable $z_1^i(t)$ for each battery i and each time slot t is equal to 1 if between time slot *t-1* and t the battery reaches the minimum energy level and 0 otherwise; variable $z_2^i(t)$ for each battery i and each time slot t is equal to 1 if between time slot *t-1* and t the battery reaches the maximum energy level and 0 otherwise.

4.2 Parameters

The input parameters of the model are represented by: (i) the set T of time slots in which the time window under consideration is divided, (ii) the demand of energy $d(t)$ in each time slot t, (iii) the solar panel energy $p(t)$ in each time slot t, (iv) the minimum energy level for each battery $\Lambda_{min,}$ (v) the maximum energy level for each battery $\Lambda_{max,}$ (vi) the maximum energy amount of recharge in each time slot t for each battery i, Δ_{max} , (vii) the maximum number of recharging cycles for each battery Nc_{max} and (viii) the penalty k related to number of used batteries.

4.3 Objective Function

The objective function of the problem is the minimization of: (i) the total amount of energy bought and sold during the time window under consideration and (ii) the number of batteries used in the system, multiplied by an appropriate penalty factor empirically determined. Indeed, the goal is maximizing the households' self-consumption but taking into account also the sizing problem of the battery system.

$$min \sum_{t \in T} \big(\alpha(t) + \beta(t)\big) + k \sum_{i \in B} y_i \tag{1}$$

4.4 Problem constraints

In each time slot t in which the energy demand is greater than or equal to the solar panel energy availability, the potential deficit of energy is the amount $\delta_N^i(t)$ that will be required to the batteries, as defined by constraints (2). Similarly, in each time slot t in which the energy demand is less than the solar panel energy availability, the surplus of energy is the amount $\delta_P^i(t)$ usable for recharging the batteries, as stated by constraints (3).

$$\sum_{i \in B} \delta_N^i(t) \leq d(t) - p(t) \quad \forall t \in T : d(t) \geq p(t) \tag{2}$$

$$\sum_{i \in B} \delta_P^i(t) \leq p(t) - d(t) \quad \forall t \in T : d(t) < p(t) \tag{3}$$

Constraints (5) and (4) impose that the potential deficit and the surplus of energy are equal to zero respectively when the demand is less than and when the demand is greater than or equal to the solar panel energy availability.

$$\delta_N^i(t) = 0 \quad \forall i \in B, \forall t \in T : d(t) < p(t) \tag{4}$$

$$\delta_P^i(t) = 0 \quad \forall i \in B, \forall t \in T : d(t) \geq p(t) \tag{5}$$

Always distinguishing between time slots in which the energy demand is greater than or equal to the solar panel energy availability and slots in which, on the contrary, the energy demand is less than the solar panel energy availability, equations (6) and (7) define the relation between demand *d(t)*, solar panel energy availability *p(t)* and, respectively, energy taken from the batteries $\delta_N^i(t)$, if available, and energy given for recharging the batteries $\delta_P^i(t)$, if they can be recharged. Indeed, as introduced in Section 4.1, the variables $c^i(t)$ represent the state of each battery *i* in each time slot *t* and they are equal to 1 if the battery can be recharged at time slot t and 0 otherwise.

$$d(t) = p(t) + \alpha(t) + \sum_{i \in B} \delta_N^i(t) \cdot (1 - c^i(t)) \quad \forall t \in T : \ d(t) \geq p(t) \tag{6}$$

$$d(t) = p(t) - \beta(t) - \sum_{i \in B} \delta_P^i(t) \cdot c^i(t) \quad \forall t \in T : \ d(t) < p(t) \tag{7}$$

Obviously, as the aim is maximizing the self-consumption, the quantity of energy sold is equal to 0 if the solar panel production is not sufficient to satisfy the demand, constraints (8), and the quantity of energy bought is equal to 0 if the demand can be completely satisfied with the solar panel production, constraints (9).

$$\beta(t) = 0 \quad \forall t \in T : \ d(t) \geq p(t) \tag{8}$$

$$\alpha(t) = 0 \quad \forall t \in T : \ d(t) < p(t) \tag{9}$$

Constraints (10) and (11) set the initial status of the battery system: the energy level of each battery at time slot 0 is equal to the maximum energy level Λ_{max} and thus, the initial value of the binary variable $c^i(t)$, representing the state of each battery (if it can be recharged or not), is equal to 0.

$$\lambda^i(0) = \Lambda_{max} \quad \forall i \in B \tag{10}$$

$$c^i(0) = 0 \quad \forall i \in B \tag{11}$$

Moreover constraints (12) and (13) guarantee that the energy level of each battery ranges between the minimum and maximum energy level.

$$\lambda^i(t) \geq \Lambda_{min} \quad \forall i \in B, \qquad t \in T : \ t > 0 \tag{12}$$

$$\lambda^i(t) \leq \Lambda_{max} \quad \forall i \in B, \qquad t \in T : \ t > 0 \tag{13}$$

It is also assumed that the recharge and the discharge of each battery is not instantaneous but there is a maximum amount of energy that the battery can take from or give to in one time slot, constraints (14) and (15).

$$\lambda^i(t) - \lambda^i(t-1) \leq \Delta_{max} \quad \forall i \in B, \qquad t \in T : \ t > 0 \tag{14}$$

$$\lambda^i(t) - \lambda^i(t-1) \geq -\Delta_{max} \quad \forall i \in B, \qquad t \in T: \ t > 0 \tag{15}$$

Logic constraints (16) and (17) permit to correctly set the values of the binary variable y_i for each battery i: if the energy level of a battery becomes less than the maximum level Λ_{max}, at least once, this implies that the battery is used in system.

$$M \cdot y_i \geq \sum_{t \in T} (\Lambda_{max} - \lambda^i(t)) \quad \forall i \in B \tag{16}$$

$$y_i \leq \sum_{t \in T} (\Lambda_{max} - \lambda^i(t)) \quad \forall i \in B \tag{17}$$

The energy level of each battery i in each time slot t is expressed by means of constraints (18), (19) and (20). More in details, if the energy demand is less than the solar panel energy availability, the battery level at time slot t is equal to the battery level at the previous time slot plus the amount of energy gained recharging, if the battery can be recharged. Indeed, it is assumed that each battery can be recharged only if it reached the minimum energy level. On the contrary, if the energy demand is greater than the solar panel energy power, the battery level at time slot t is equal to the battery level at the previous time slot minus the energy given to satisfy the residual demand, if the battery can be used. Indeed, it is assumed that a battery can be used to give energy to the households only if it is not recharging. Finally, if the energy demand is equal to the solar panel energy availability, the battery level does not change.

$$\begin{gathered} \lambda^i(t) = \lambda^i(t-1) + \delta_P^i(t) \cdot c^i(t-1) \\ \forall i \in B, \qquad t \in T: \ t > 0 \ \wedge \ d(t) < p(t) \end{gathered} \tag{18}$$

$$\begin{gathered} \lambda^i(t) = \lambda^i(t-1) - \delta_N^i(t) \cdot (1 - c^i(t-1)) \\ \forall i \in B, \qquad t \in T: \ t > 0 \ \wedge \ d(t) > p(t) \end{gathered} \tag{19}$$

$$\lambda^i(t) = \lambda^i(t-1) \quad \forall i \in B, \qquad t \in T: \ t > 0 \ \wedge \ d(t) = p(t) \tag{20}$$

In order to correctly set the values of the binary variables $f^i(t)$ and $F^i(t)$ as function of the energy level of the batteries $\lambda^i(t)$, the logic constraints (21)-(24) have been added to the formulation.

$$f^i(t) \leq (\lambda^i(t) - \Lambda_{min}) \quad \forall i \in B, \qquad t \in T \tag{21}$$

$$(\lambda^i(t) - \Lambda_{min}) \leq M \cdot f^i(t) \quad \forall i \in B, \qquad t \in T \tag{22}$$

$$F^i(t) \leq (\Lambda_{max} - \lambda^i(t)) \quad \forall i \in B, \qquad t \in T \tag{23}$$

$$(\Lambda_{max} - \lambda^i(t)) \leq M \cdot F^i(t) \quad \forall i \in B, \qquad t \in T \tag{24}$$

The additional logic constraints (25)-(30) are then introduced to set the values of the binary variables $c^i(t)$ as function of the binary variables $f^i(t)$ and $F^i(t)$.

$$c^i(t) \leq c^i(t-1) + \left(2 - f^i(t) - F^i(t)\right) \quad i \in B, \qquad t \in T: t > 0 \tag{25}$$

$$c^i(t) \geq c^i(t-1) - \left(2 - f^i(t) - F^i(t)\right) \quad i \in B, \qquad t \in T: t > 0 \tag{26}$$

$$c^i(t) \geq 1 - f^i(t) \quad i \in B, \qquad t \in T: t > 0 \tag{27}$$

$$c^i(t) \leq 1 + f^i(t) \quad i \in B, \qquad t \in T: t > 0 \tag{28}$$

$$c^i(t) \geq -F^i(t) \quad i \in B, \qquad t \in T: t > 0 \tag{29}$$

$$c^i(t) \leq F^i(t) \quad i \in B, \qquad t \in T: t > 0 \tag{30}$$

Moreover, logic constraints (31)-(38) permit to explicit the binary variables $z_1^i(t)$ and $z_2^i(t)$, as function of the binary variables $f^i(t-1)$ and $F^i(t-1)$, introduced to count the number of batteries cycles.

$$(1 - f^i(t)) - (1 - f^i(t-1)) \leq z_1^i(t) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{31}$$

$$(1 - F^i(t)) - (1 - F^i(t-1)) \leq z_2^i(t) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{32}$$

$$z_1^i(t) \leq f^i(t) + f^i(t-1) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{33}$$

$$z_1^i(t) \leq 1 + (f^i(t-1) - f^i(t)) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{34}$$

$$z_1^i(t) \leq 2 - (f^i(t-1) + f^i(t)) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{35}$$

$$z_2^i(t) \leq F^i(t) + (F^i(t-1) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{36}$$

$$z_2^i(t) \leq 1 + (F^i(t-1) - F^i(t)) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{37}$$

$$z_2^i(t) \leq 2 - (F^i(t-1) + F^i(t)) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{38}$$

Constraint (39) defines the number of battery cycles for each battery i as the half of the times in which the battery reaches the maximum and the minimum energy level. Indeed, it is assumed that a battery cycle consists in one complete discharge and one complete recharge.

$$Nc^i = \sum_{t \in T:\, t>0} \left(z_1^i(t) + z_2^i(t) \right) / 2 \quad \forall i \in B \tag{39}$$

Finally, constraint (40) imposes that the number of battery cycles for each battery i is not greater than a given maximum number of cycles Nc_{max}.

$$Nc^i \leq Nc_{max} \quad \forall i \in B \tag{40}$$

4.5 Linearization of the non-linear constraints

The formulation presented in Section 4 is a mixed integer non-linear programming model due to the presence of the constraints (6), (7), (18) and (19). Non-linear constraints increase the model complexity making the problem challenging to be solved. Thus, to overcome this issue, the procedure to linearize the product between a continuous and a binary variable (Adams1990) can be adopted. In order to perform the linearization of constraints (6), (7), (18) and (19), for each $i \in B$ and for each $t \in T : t > 0$, the following two continuous variables can be defined:

$$v^i(t) = \delta_N^i(t) \cdot (1 - c^i(t-1)) \text{ and } w^i(t) = \delta_P^i(t) \cdot c^i(t-1)$$

By means of these new variables, constraints (6), (7), (18) and (19) can be write in the equivalent form:

$$d(t) = p(t) + \alpha(t) + \sum_{i \in B} v^i(t) \quad \forall t \in T : \ d(t) \geq p(t) \tag{41}$$

$$d(t) = p(t) - \beta(t) - \sum_{i \in B} w^i(t) \quad \forall t \in T : \ d(t) < p(t) \tag{42}$$

$$\begin{gathered} \lambda^i(t) = \lambda^i(t-1) + w^i(t) \\ \forall i \in B, \qquad t \in T : \ t > 0 \ \wedge \ d(t) < p(t) \end{gathered} \tag{43}$$

$$\begin{gathered} \lambda^i(t) = \lambda^i(t-1) - v^i(t) \\ \forall i \in B, \qquad t \in T : \ t > 0 \ \wedge \ d(t) > p(t) \end{gathered} \tag{44}$$

with the additional constraints

$$v^i(t) \leq M \cdot c^i(t-1) \quad \forall i \in B, \qquad t \in T : \ t > 0 \tag{45}$$

$$v^i(t) \leq \delta_N^i(t) \quad \forall i \in B, \qquad t \in T : \ t > 0 \tag{46}$$

$$v^i(t) \geq \delta_N^i(t) - (1 - c^i(t-1)) \cdot M \quad \forall i \in B, \qquad t \in T : t > 0 \tag{47}$$

Constraints (45), (46) and (47) guarantee that $v^i(t)$ is equal to 0 if $c^i(t-1)$ is equal to 1 and that $v^i(t)$ is equal to $\delta_N^i(t)$ if $c^i(t-1)$ is equal to 0.

$$w^i(t) \leq M \cdot c^i(t-1) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{48}$$

$$w^i(t) \leq \delta_P^i(t) \quad \forall i \in B, \qquad t \in T : t > 0 \tag{49}$$

$$w^i(t) \geq \delta_P^i(t) - (1 - c^i(t-1)) \cdot M \quad \forall i \in B, \qquad t \in T : t > 0 \tag{50}$$

Analogously constraints (48), (49) and (50) state that $w^i(t)$ is equal to 0 if $c^i(t-1)$ is equal to 0 and that $w^i(t)$ is equal to $\delta_P^i(t)$ if $c^i(t-1)$ is equal to 1.

Chapter 5

Results and discussion

5.1 Experimental results under different scenarios

In this section the obtained results for a selection of different scenarios are summarized. In particular, the optimization model has been run on typical weekly energy consumption and PV electricity production data during different seasons comparing two different configurations, specifically with or without constraints for batteries charging/discharging.

5.1.1 Autumn

During a typical Autumn week, the total electricity consumption of the ten families living in the building has been estimated to be 792,7 kWh, with a solar PV electricity generation of 590,5 kWh. Two configurations have been considered: in the former the constraints force the batteries to charge and discharge between SOC_{min} = 20% = 0,8 kWh and SOC_{max} = 80% = 3,2 kWh with a charge/discharge rate of 0,5C = 2 kWh and preventing the battery can be discharged until it reaches SOC_{max} and vice versa; in the latter, on the other hand, the constraints are removed, so that the batteries can charge and discharge between SOC_{min} = 0% = 0 kWh and SOC_{max} = 100% = 4 kWh with a charge/discharge rate of 1C = 4 kWh without forcing them to follow any specific charge/discharge profile. Table 11 summarizes the most significant results in the two cases investigated.

Case a): charging/discharging constraints Case b): no charging/discharging constraints	**Case a)**	**Case b)**
Total energy demand by families	792,7 kWh	792,7 kWh
Total energy produced by PV system	590,5 kWh	590,5 kWh
Number of batteries needed	6	9
Average number of charge/discharge cycles	7	5,6
Total self-consumed PV energy	327 kWh	327 kWh
Total energy from batteries discharge	115,2 kWh	262,4 kWh
Total energy to batteries charge	100,8 kWh	226,4 kWh
Total energy imported from the grid	350,5 kWh	203,3 kWh
Total energy exported to the grid	162,7 kWh	37,14 kWh
Share of PV to self-consumption	55,37%	55,37%
Share of PV to batteries charge	17,06%	38,33%
Share of PV to the grid	27,55%	6,29%
Share of demand met by PV	41,25%	41,25%
Share of demand met by batteries	14,53%	33,10%
Share of demand met by the grid	44,21%	25,65%

Table 11 – Autumn week main results.

The comparison between case a) and case b) reveals that the model tends to use more batteries when the charging/discharging constraints are removed because the use is more convenient. It can be observed, in fact, that in case b) the total energy from batteries discharge and to batteries charge increases more than proportionally with increasing number of batteries than in the case a). The reason for this is that the increasing number of batteries provides greater benefits in terms of energy imported from and exported to the grid, significantly exceeding the penalty coefficient added to the model in order to minimize the number of batteries. Figure 28 shows the most important resulting power profiles and battery charging/discharging scheduling, comparing the two different cases; the plot focuses only on 48 hours for a better visualization.

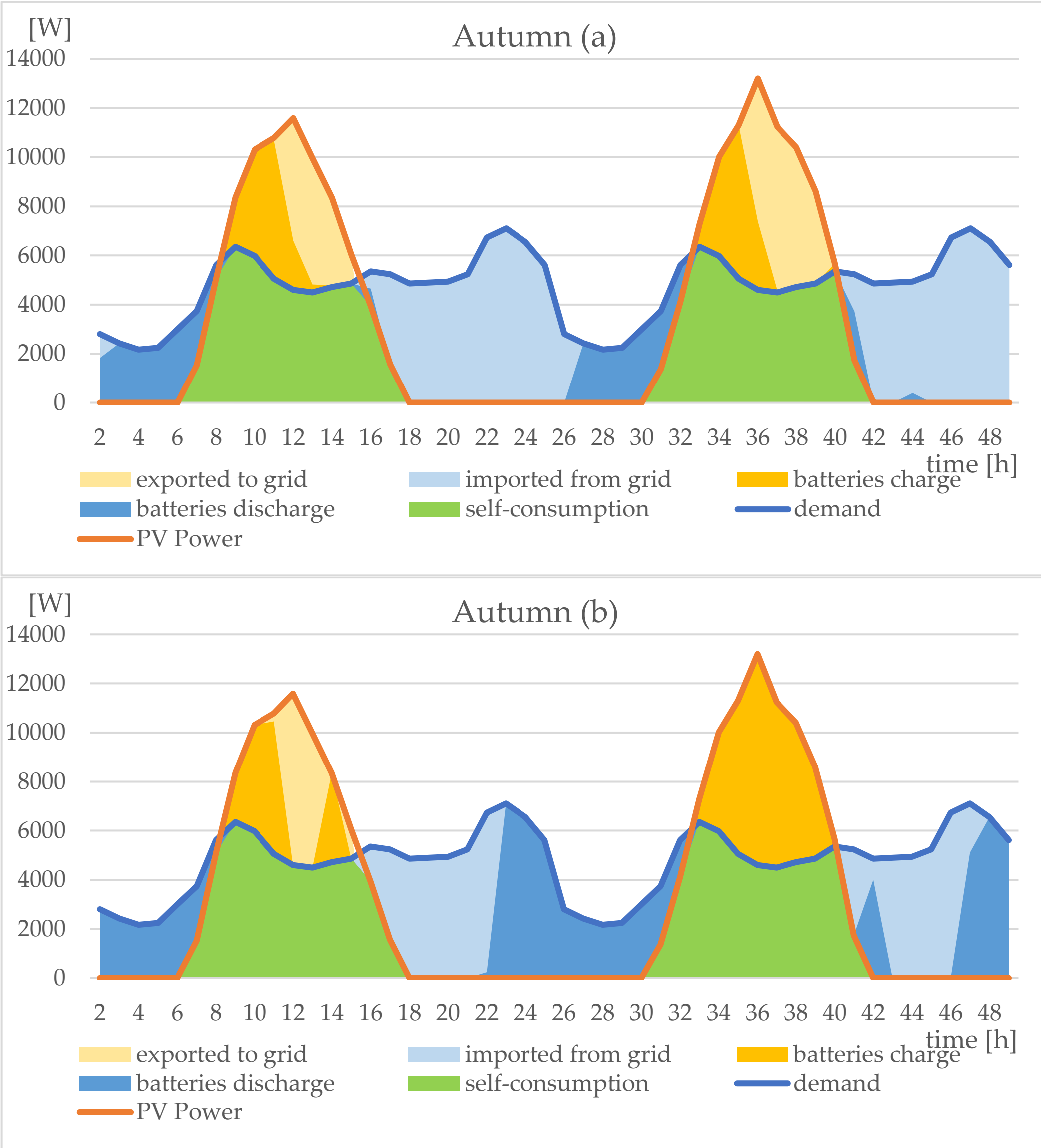


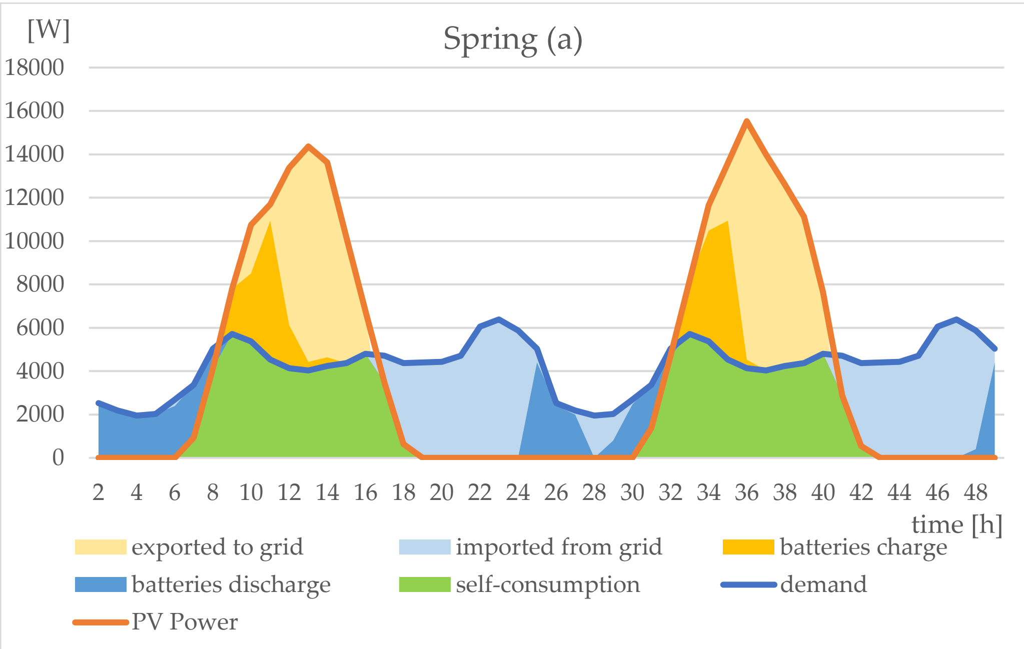
Figure 28 – Autumn power profiles and battery charging/discharging scheduling results.

5.1.2 Spring

Results obtained for the Spring week are very similar to the Autumn results. In this case the energy produced by PV system is higher while the families energy demand is lower than the Autumn case, ensuring a higher share of demand met by PV. The number of batteries needed is equal to the Autumn case, as well as the total energy from batteries discharge and the total energy to batteries charge, corresponding to a full exploitation of the storage system capacity with 6 batteries. Even in this case count the considerations given for the Autumn results on the comparison between case a) and b). Table 12 and Figure 29 show the most significant results obtained for a typical Spring week.

Case a): charging/discharging constraints Case b): no charging/discharging constraints	**Case a)**	**Case b)**
Total energy demand by families	712,16 kWh	712,16 kWh
Total energy produced by PV system	679,2 kWh	679,2 kWh
Number of batteries needed	6	10
Average number of charge/discharge cycles	7	5,6
Total self-consumed PV energy	315,5 kWh	315,5 kWh
Total energy from batteries discharge	115,2 kWh	280,87 kWh
Total energy to batteries charge	100,8 kWh	240,87 kWh
Total energy imported from the grid	281,5 kWh	115,81 kWh
Total energy exported to the grid	262,95 kWh	122,87 kWh
Share of PV to self-consumption	46,44 %	46,44 %
Share of PV to batteries charge	14,84 %	35,46 %
Share of PV to the grid	38,71 %	18,09 %
Share of demand met by PV	44,29 %	44,29 %
Share of demand met by batteries	16,17 %	39,44 %
Share of demand met by the grid	39,52 %	16,26 %

Table 12 – Spring week main results.



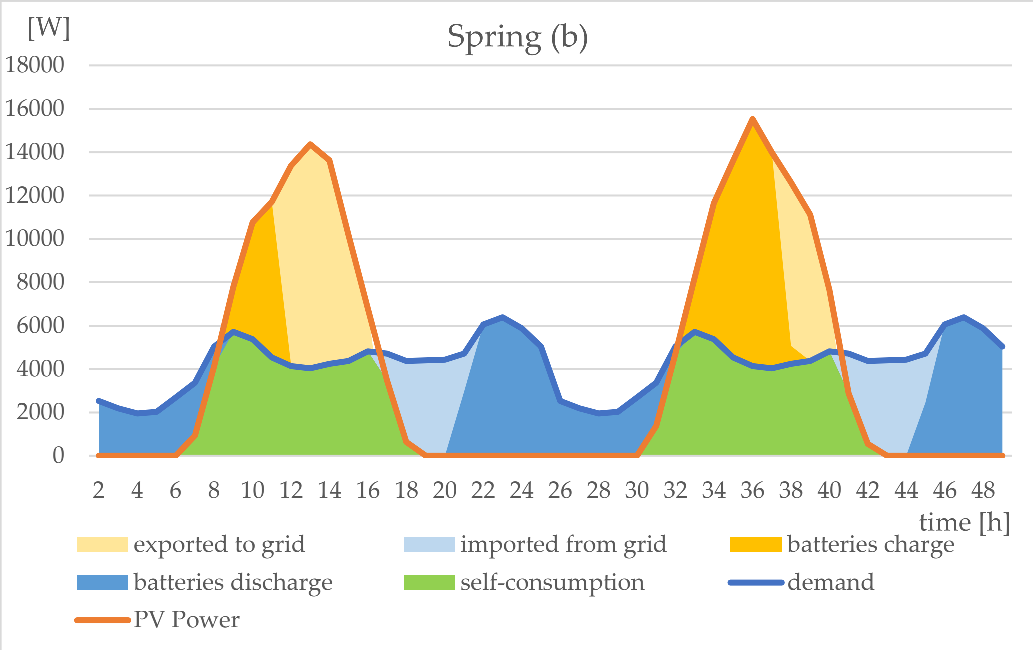


Figure 29 – Spring power profiles and battery charging/discharging scheduling results.

5.1.3 Summer

Summer is the period with the highest energy demand by families, but also with the greatest energy produced by PV system, ensuring a share of self-consumption of 62%. Because of the high energy need for the families, the model uses more batteries than the previous cases. In particular, in the case b) the model can significantly reduce the total energy imported from the grid and exported to the grid with only two more batteries respect to the case a). It is important to specify that the average number of charge/discharge cycles in the case b) has been calculated considering only the full cycles between SOC_{min} = 0% and SOC_{max} = 100%, but the batteries may also present lots of partial cycles in the case b). Table 13 and Figure 30 illustrate the main results for a typical Summer week.

Case a): charging/discharging constraints Case b): no charging/discharging constraints	**Case a)**	**Case b)**
Total energy demand by families	1060,6 kWh	1060,6 kWh
Total energy produced by PV system	770,6 kWh	770,6 kWh
Number of batteries needed	8	10
Average number of charge/discharge cycles	7	6,1

Total self-consumed PV energy	478,11 kWh	478,11 kWh
Total energy from batteries discharge	153,6 kWh	291,67 kWh
Total energy to batteries charge	134,4 kWh	251,67 kWh
Total energy imported from the grid	428,8 kWh	290,80 kWh
Total energy exported to the grid	158,10 kWh	40,83 kWh
Share of PV to self-consumption	62 %	62 %
Share of PV to batteries charge	17,44 %	32,66 %
Share of PV to the grid	20,51 %	5,30 %
Share of demand met by PV	45 %	45 %
Share of demand met by batteries	14,48 %	27,5 %
Share of demand met by the grid	40,44 %	27,42 %

Table 13 – Summer week main results.

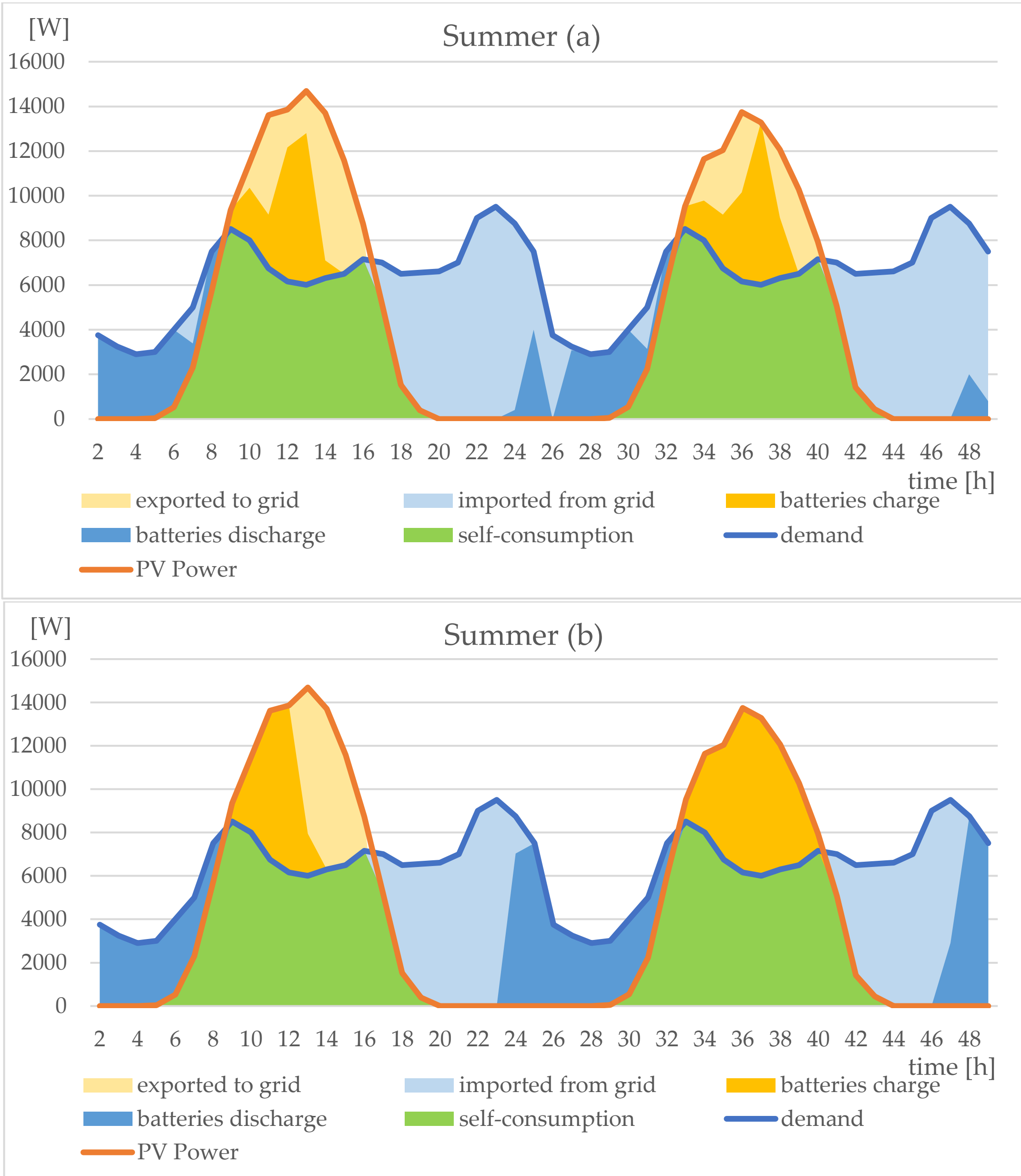


Figure 30 – Summer power profiles and battery charging/discharging scheduling results.

5.1.4 Winter

During a typical Winter week the highest gap between the energy demand and the energy produced by PV system is observed. Contrary to what one might expect, the model prefers to import energy from the grid rather than using the batteries. The most likely reason for this trend is that it could never find a way to charge the batteries since the PV power is always considerably lower than the families demand. Therefore, in this case the penalty coefficient minimizing the number of batteries prevails on the benefits provided from the installation of the storage system more than in all previous cases. The most important results are summarized in Table 14 and illustrated in Figure 31.

Case a): charging/discharging constraints Case b): no charging/discharging constraints	**Case a)**	**Case b)**
Total energy demand by families	958,9 kWh	958,9 kWh
Total energy produced by PV system	293,9 kWh	293,9 kWh
Number of batteries needed	0	1
Average number of charge/discharge cycles	0	4
Total self-consumed PV energy	253,8 kWh	253,8 kWh
Total energy from batteries discharge	0 kWh	23,51 kWh
Total energy to batteries charge	0 kWh	19,51 kWh
Total energy imported from the grid	705 kWh	681,5 kWh
Total energy exported to the grid	40,10 kWh	20,59 kWh
Share of PV to self-consumption	86,35 %	86,35 %
Share of PV to batteries charge	0 %	6,64 %
Share of PV to the grid	13,64 %	7 %
Share of demand met by PV	26,47 %	26,47 %
Share of demand met by batteries	0 %	2,45 %
Share of demand met by the grid	73,53 %	71 %

Table 14 – Winter week main results.

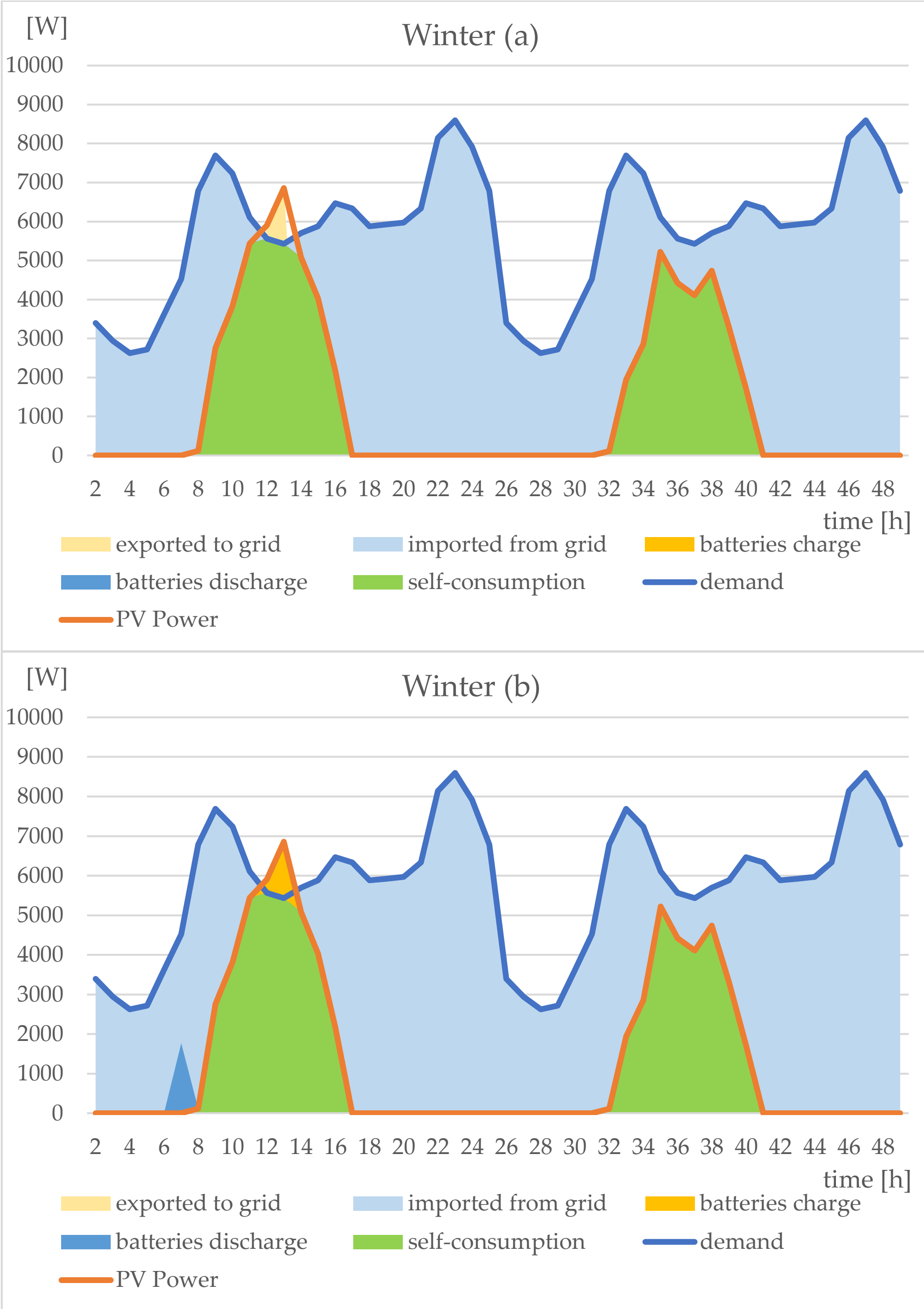
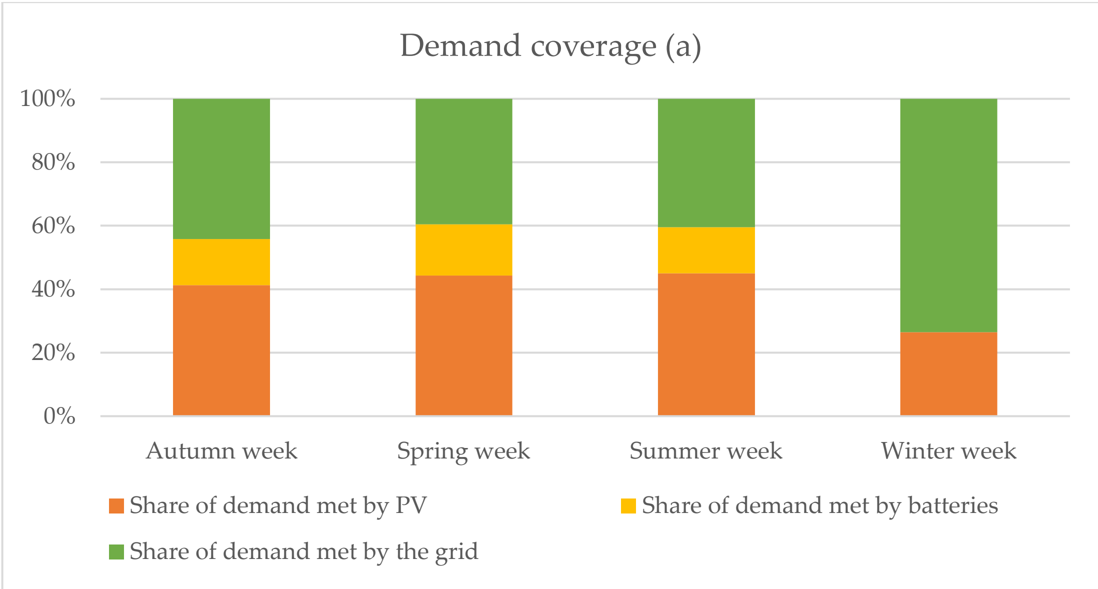


Figure 31 – Winter power profiles and battery charging/discharging scheduling results.

Finally, Figure 32 and Figure 33 summarize the overall results for the different typical weeks during the four seasons in both cases a) and b), in terms of demand coverage and exploitation of energy produced by PV, respectively. In particular, in the first case the percentage of energy from PV, batteries and grid covering the families demand has been calculated on total energy need, while in the second case the percentage of PV to self-consumption, to batteries charge and to the grid has been calculated on the total energy produced by the PV system.



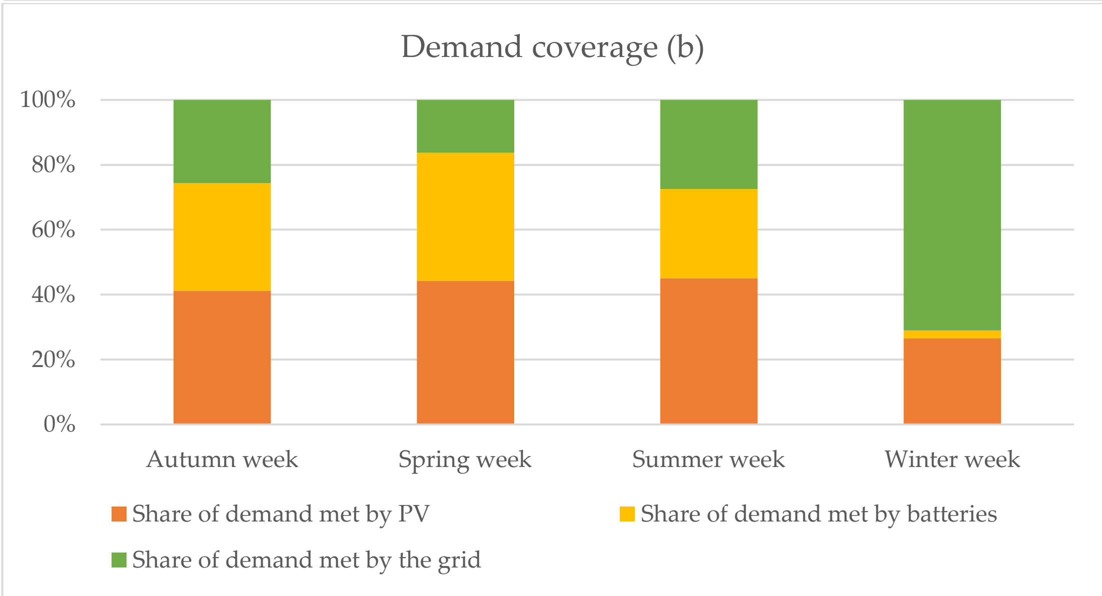


Figure 32 – Share of demand coverage by PV, batteries and grid.

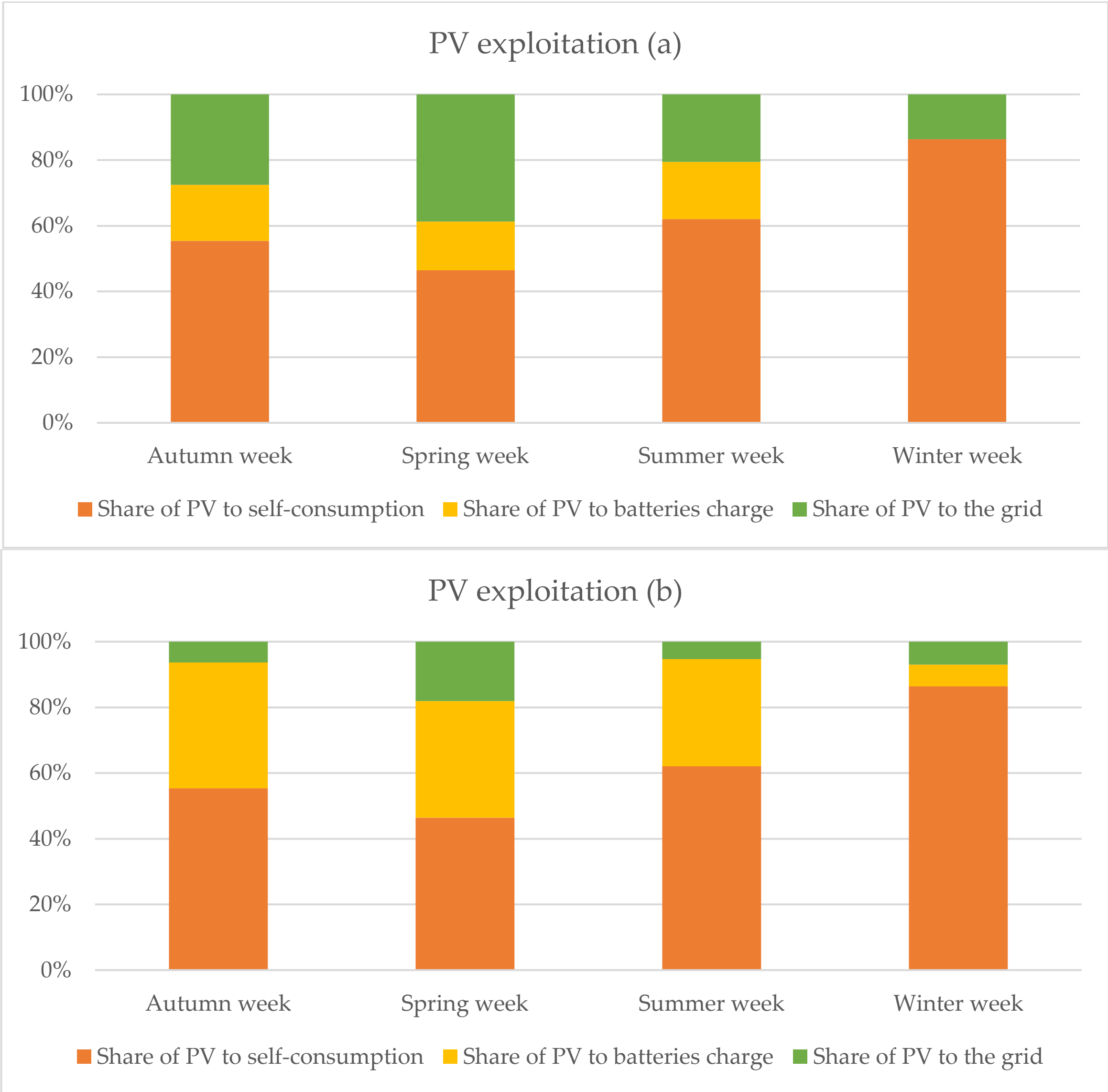


Figure 33 – Share of PV to self-consumption, to batteries charge and to the grid.

As evident in the figures, the removal of charging/discharging constraints obviously allows to reduce the total energy imported from and exported to the grid, although generally with a greater number of batteries needed and without taking the necessary precautions on charging/discharging strategy to prolong battery lifetime. Focusing on case a), the Summer week reveals the best results in terms of exploitation of batteries and minimization of purchase and sale of energy.

5.2 Model results performance

Despite very restrictive constraints imposed on the batteries charging/discharging strategy, however, a preliminary economic assessment underlines significant benefits in terms of energy and costs savings achieved through the batteries storage system exploitation. Table 15 compares the energy imported from and exported to the grid with and without the batteries energy storage system. Results relate to a typical week during the four different seasons. In particular, the comparison between the results obtained in the two different cases, with or without the storage system, also represents an indirect measure of the performance of the optimization model. The removal of the objective function, i.e. the minimization of energy imported from and exported to the grid, from the optimization model implies, in fact, that the model will not use the batteries. It represents the easiest feasible solution to find and it will be considered as the worst-case scenario.

	Autumn		**Spring**		**Summer**		**Winter**	
Case a): with BESS Case b): without BESS	a)	b)	a)	b)	a)	b)	a)	b)
Total energy imported from the grid [kWh]	350,5	465,71 +33%	281,5	396,7 +41%	428,8	582,5 +36%	705	705
Total energy exported to the grid [kWh]	162,7	263,53 +62%	262,95	363,7 +38%	158,10	292,5 +85%	40,10	40,10

Table 15 – Week results on energy imported from and exported to the grid with and without the batteries energy storage system.

The Winter week presents the same results in both cases because, as described above, the high gap between the energy demand and the energy produced by PV system stops the model from using batteries, also having them available, because there would never be a way to charge them.

Conclusions and future research

In this thesis the optimization of an energy storage system operation has been presented and a mixed-integer linear programming model has been implemented with the aim to define an appropriate energy management model and a resolution approach for the optimal control and scheduling operation of a solar PV plant coupled with a battery energy storage system in the context of residential collective self-consumption. In particular, a building with ten apartments owned by a social housing public entity is equipped with a 20 kW_P grid-connected PV, for the purpose of household demand reduction, thus allowing subsequently the reduction of the total electricity cost for the families. For this system layout an energy storage system with ten batteries has been thought to maximize the local use of PV generated power. Different types of constraints have been taken to prolong the life of the batteries since inappropriate operational patterns can result in increasing degradation processes. The mathematical representation based on MILP method has been run with hourly time resolution over a week period for different seasons. However, continuous time models could be investigated by performing longer simulations using a full year of data with the help of a higher computational power and a sensitivity analysis could be performed to identify the battery parameters most impacting on the global results of the system. Moreover, there is several potential directions to extend the future research in this field and alternative optimization models can be considered for future work. For instance, the individual batteries could be modeled as a virtual community storage system, or power can be transferred among the households in a neighborhood. Furthermore, the objective function could be modified taking into consideration the financial incentives for consumers and the variable electricity sale and purchase pricing schemes. In particular, from this point of view, a new control strategy distributing the charging and discharging processes basing on the variable purchasing and sale electricity costs could be investigated in order to maximize the total savings for each charge-discharge cycle. It represents the most interesting future development of the present work.

Appendix A: Il Progetto "Civitavecchia SMART-A.T.E.R."

AZIENDA TERRITORIALE PER L'EDILIZIA RESIDENZIALE PUBBLICA DEL COMPRENSORIO DI CIVITAVECCHIA

PROGETTO "SMART-*A.T.E.R.*"

RIQUALIFICAZIONE ENERGETICA DEGLI EDIFICI DEL PATRIMONIO DELL'A.T.E.R. DEL COMPRENSORIO DI CIVITAVECCHIA

Convenzione Prot. n. 1153 del 14 giugno 2017	Dipartimento di Ingegneria Meccanica e Aerospaziale Sapienza Università di Roma **Dipartimento di Ingegneria Meccanica e Aerospaziale** **Università degli Studi di Roma "Sapienza"** Via Eudossiana 18, 00184 Roma T (+39) 06 44585902 F (+39) 06 4881759 http://www.dma.uniroma1.it

Premessa

La legislazione adottata dall'UE stabilisce che la quota di energia da fonti rinnovabili deve rappresentare almeno il 32% del consumo finale lordo dell'UE entro il 2030. La Legge Regionale 18 Luglio 2017, n. 7 "Disposizioni per la rigenerazione urbana e per il recupero edilizio", gli obiettivi fissati nel VII Programma Europeo d'azione per l'ambiente e nondimeno la Energy Roadmap 2050, fissano una vera e propria tabella di marcia che delinea le strategie per la rigenerazione urbana e la riqualificazione del tessuto edilizio esistente. Partendo da tali riferimenti, l'A.T.E.R. del Comprensorio di Civitavecchia intende perseguire sempre di più la realizzazione di progetti per il recupero e la rigenerazione urbana, promuovendo altissimi standard di edilizia in termini di ecosostenibilità e di sviluppo innovativo. Per trovare le risorse necessarie a garantire tale politica, l'A.T.E.R. sta sviluppando e svilupperà, sempre di più, la ricerca di finanziamenti terzi attraverso la partecipazione a specifici bandi europei, nazionali e regionali e ricorrendo alle fonti di incentivazione previste per l'efficientamento energetico e la produzione di energia da fonti rinnovabili.

Obiettivi del progetto "SMART-A.T.E.R."

L'A.T.E.R. del Comprensorio di Civitavecchia gestisce il patrimonio dell'edilizia residenziale pubblica; il progetto "SMART-A.T.E.R." ha come obiettivo sviluppare la prima *smart communitiy* nazionale nell'ambito dell'edilizia residenziale pubblica, rendendo energeticamente autosufficienti tutti gli immobili del proprio patrimonio, utilizzando energia da fonti rinnovabili. La realizzazione della smart community prevede che l'energia elettrica prodotta dagli impianti fotovoltaici che verranno realizzati venga condivisa fra tutte le utenze coinvolte. Questo meccanismo sarà attuabile perché tutta l'energia prodotta verrà immessa in rete e prelevata in base agli specifici fabbisogni energetici delle singole unità abitative. Lo scopo è quello di garantire vantaggi ambientali ed economici alle famiglie, grazie ad un accordo con una società di dispacciamento che gestirà tutti i contratti e offrirà l'energia ad un prezzo calmierato (coerente con i canoni di locazione) rispetto alle tariffe applicate dagli enti fornitori di energia elettrica. Allo stato attuale, infatti, da un'attenta analisi effettuata dall'A.T.E.R. del Comprensorio di Civitavecchia sulle spese di locazione e le spese per l'energia elettrica, sostenute dai propri inquilini dell'edilizia sovvenzionata, è emerso che la spesa energetica pesa fortemente sul bilancio delle famiglie interessate. Un inquilino A.T.E.R., infatti, a fronte di una spesa annua di € 93,00 per il canone di locazione, può arrivare a pagare, per l'energia elettrica, una spesa annua compresa tra € 630,00 e € 900,00, a seconda del fabbisogno famigliare. Oltre ai notevoli vantaggi economici per le famiglie, il progetto descritto genererà altresì un aumento della redditività aziendale per effetto della vendita di energia, ammortizzando il costo dell'investimento, il tutto attraverso un'attività sicura e compatibile con gli obiettivi europei.

Architettura del sistema proposto

In un contesto dove fenomeni come la decarbonizzazione, la decentralizzazione, la digitalizzazione e la democratizzazione dell'energia sono immersi in un mondo sempre più denso di tecnologie all'avanguardia per la micro-generazione distribuita e per l'accumulo di energia, si inquadrano ed emergono i maggiori fabbisogni e le migliori opportunità di digitalizzazione delle reti energetiche. In particolare, il progetto intende sviluppare una vera e propria rete intelligente, composta da tanti piccoli nodi (smart building), che consente, non solo, il trasporto di energia dal produttore al consumatore, ma la realizzazione di nuovi modelli di routing allo scopo di ottimizzare la distribuzione delle informazioni energetiche determinando, quindi, in anticipo le richieste di energia, convogliando i flussi laddove servono ed imparando dalle abitudini di consumo di ogni singola unità abitativa. Ogni smart building sarà, pertanto, un nodo della rete e sarà costituito dalla sperimentazione di sistemi evoluti ed ecosostenibili per la produzione da fonti rinnovabili e per l'accumulo di energia elettrica. Gli archi che collegano i singoli nodi della rete non saranno costituiti dai semplici collegamenti energetici ma da nuove forme di cablaggio che portano con sé nuovi flussi di comunicazione (energy information data) che viaggeranno tra produttori, consumatori e viceversa (prosumer); essi trasporteranno nuove informazioni in grado di far interoperare sistemi informatici diversi ma con gli stessi obiettivi: gestire con migliore efficienza i picchi di richiesta, evitare interruzioni di elettricità (resilienza), ridurre il carico dove necessario e arbitrare l'energia verso l'autoconsumo o verso il mercato. Nell'architettura della nuova rete energetica, assimilabile al concetto di internet delle cose, si parla, infatti, di internet dell'energia o Energy Cloud, tutte le unità abitative di uno smart building saranno dotate di dispositivi intelligenti per la raccolta dei consumi periodici e delle abitudini di consumo, grazie ai quali tutti i building interconnessi tra loro, ricevono e inviano informazioni sulla gestione dell'energia e traggono vantaggio da questo scambio di informazioni. Ogni building costituirà quindi una micro energy community dove sarà garantita la fornitura di energia elettrica e sarà possibile accedere alla produzione di energia elettrica da fonti rinnovabili e lo stoccaggio intelligente della stessa, il tutto con minori costi e, ovviamente, minore emissione di gas ad effetto serra. Inoltre, ci sarà notevole flessibilità per ogni consumatore nella gestione del proprio fabbisogno energetico, soprattutto, relativamente al consumo di energia che potrà variare in base al periodo dell'anno o, addirittura, in base all'orario della giornata. In particolare, dal punto di vista delle soluzioni tecnologiche e dei sistemi impiegati si avrà che:

1) verrà attrezzato il locale tecnico del building con un cabinet contenente un sistema di accumulo modulare;

2) verrà integrato o realizzato un sistema fotovoltaico;

3) ogni unità abitativa sarà dotata di sistemi di contabilizzazione e disaggregazione dei carichi energetici (home energy device) capaci di raccogliere le informazioni di consumo in modalità near real time, identificare le tipologie di elettrodomestici collegati e rilevare e correlare le abitudini di consumo;

4) verrà realizzata una piattaforma per la gestione ed il controllo dei flussi di energia e di tutte le interazioni elettroniche ed informatiche con le risorse energetiche della rete e di tutti i nodi costituenti la stessa.

La piattaforma sarà costituita da un sistema locale per il controllo dell'energia e da un sistema di supervisione centrale, entrambi basati sui più moderni paradigmi di progettazione e su architetture aperte ed interoperabili. In particolare, la piattaforma consentirà:

a) tramite un modello cloud-based, di controllare, monitorare tutti gli energy device afferenti al building allo scopo di assicurare efficienza, automazione, security, comfort ed health;

b) di ottimizzare l'utilizzo di sistemi degli storage distribuiti (sia residenziali che mobili forniti da eventuali veicoli elettrici in ricarica nel building), integrandoli con i profili e le previsioni di consumo dell'utente specifico, i prezzi di mercato dell'energia elettrica e la gestione delle tecnologie «demand-side»;

c) di raccogliere i profili di consumo di ogni singola unità abitativa e di garantire il routing intelligente dell’energia consentendo, in tempo reale ed in modo dinamico, la democratizzazione della stessa e gli obiettivi di ogni singolo utente o building.

d) di arbitrare, tramite un sistema intelligente, i consumi, la produzione e l’accumulo di energia, ottimizzandone l’autoconsumo e l’immissione nella rete secondo le politiche costo efficacia e secondo funzioni obiettivo configurabili;

e) l’uso <<smart> dei building energy device utilizzando un pattern architetturale <<if this then do that» cioè ottimizzando l’interazione tra i device e la piattaforma cloud in modo tale da gestire i bisogni dell’utente in maniera facile ed intuitiva;

f) di suggerire gli interventi di manutenzione in modo reattivo e predittivo da effettuare sugli apparati controllati;

g) di rendere <<pluggable>> qualsiasi device implementando tutte logiche open di interoperabilità dei DER;

h) di costruire una Building Energy Network in grado di interoperare con altre eventuali Energy Community allo scopo di poter gestire isole off-grid;

i) di gestire la digital experience grazie una graphical user interface basata sul modello «mobile first» spingendo l’utilizzo di mobile native apps;

j) di garantire l'affidabilità ai black-out e la resilienza del building grazie ad algoritmi e modelli di interazione tra sistemi di produzione e di accumulo dell'energia;

k) di creare modelli di gamification atti a responsabilizzare gli utenti nell'uso delle risorse energetiche tramite giochi di competizione in cui ogni utente dell'unità abitativa partecipa condividendo le informazioni sui propri consumi;

l) di applicare e sperimentare i nuovi paradigmi della cyber security applicate sia alle reti energetiche che alle reti informatiche.

La convenzione con il DIMA

L'A.T.E.R. del Comprensorio di Civitavecchia si avvale della preziosa collaborazione con il DIMA, Dipartimento di Ingegneria Meccanica ed Aerospaziale dell'Università degli Studi di Roma "La Sapienza" attraverso un accordo di ricerca finalizzato allo svolgimento di attività inerenti l'efficientamento energetico del patrimonio immobiliare dell'Ente e lo studio di tecnologie innovative ad elevata sostenibilità energetica ed ambientale. Nella fattispecie, il DIMA si occupa dell'assistenza ante-operam alla progettazione degli interventi di efficientamento energetico, della definizione del mix ottimale di tecnologie e del supporto nella verifica dei requisiti per la predisposizione delle richieste al GSE, andando di volta in volta ad identificare le migliori opportunità di incremento dell'efficienza energetica e soprattutto di risparmio dei costi di gestione degli inquilini A.T.E.R.

Fattibilità tecnico-economica dell'intervento

All'interno del patrimonio di proprietà dell'A.T.E.R. del Comprensorio di Civitavecchia, sono stati individuati circa 40 fabbricati con 493 unità abitative. Le analisi effettuate hanno portato a definire il seguente scenario:

- Utenze coinvolte: n°493;

- Consumo annuo stimato delle utenze: 2.500 kWh * 493= 1.232.500 kWh/anno;

- Costo di acquisto totale dell'energia elettrica stimato delle famiglie: 1.232.500 kWh * 0,25 €/kWh = € 308.125,00;

- Costo per unità abitativa stimato per la spesa di energia elettrica = € 625,00/Anno (costo che può variare in virtù dei diversi fabbisogni energetici).

Scenario previsto per la produzione di energia elettrica da fonti rinnovabili:

- Irraggiamento medio del territorio di 1.250 kWh/kW_P;

- Potenza totale impianti fotovoltaici stimati sui fabbricati: 934,82 kW_P;

- Produzione annua totale impianti fotovoltaici installati: 1.168.525 kWh/anno.

- Costo di acquisto totale dell'energia elettrica dalla società di dispacciamento: 1.232.500 kWh * 0,18 €/kWh = € 221.850,00;

- Costo per unità abitativa stimato per la spesa di energia elettrica da fonti di energia rinnovabile = € 450,00/Anno;

- Risparmio annuo per ogni unità abitativa: € 175,00/Anno (circa il 33% per ogni famiglia);

- Ricavi A.T.E.R. per vendita a società di dispacciamento: 1.168.525 kWh * €/kWh 0,10= € 116.852,5.

I dati sono riassunti nella tabella di seguito.

indirizzo	**abitazioni**	**FV Ip 1**	**FV Ip 2**	**indirizzo**	**abitazioni**	**FV Ip 1**	**FV Ip 2**
	N°	kW_P	kW_P		N°	kW_P	kW_P
		terrazzo	tettoie			terrazzo	tettoie
Via Buonarroti 5	11	15,5	24	Via Navone 10	11	26,5	45
Via Buonarroti 11	12	15,5	24	Via Navone 12	8	26,5	45
Viale G. Baccelli 69	9	17,25	25,9	Via Navone 14	11	26,5	45
Viale G. Baccelli 73	9	17,25	25,9	Via Navone 16	7	26,5	45
Viale G. Baccelli 75	10	17,25	25,9	Via Navone 18	9	26,5	45
Viale G. Baccelli 77	10	17,25	25,9	Via Navone 20	9	26,5	45
Viale G. Baccelli 79	9	17,25	25,9	Via Navone 22	7	26,5	45

Viale G. Baccelli 83	10	17,25	25,9	Via Navone 19	9	26,5	45
Viale G. Baccelli 85	18		20	Via Navone 21	9	26,5	45
Viale G. Baccelli 87	18		20	Via Navone 23	10	20	28
Via XVI Settembre 13	15	25,5	37,95	Via Navone 25	12	20	28
Via XVI Settembre 19	13	28,98	41,4	Via Navone 27	12	20	28
Via XVI Settembre 20	17	41,4	57,96	Via Navone 29	12	20	28
Via XVI Settembre 23	16	18,28	27,9	Via Navone/Cerruti			79,7
Via Navone 9	6	26,5	45	Via Labat 4	39	47,2	47,2
Via Navone 13	10	26,5	45	Via Labat 6	40	51,75	63,8
Via Navone 15	10	26,5	45	Via Frezza 3	38	51,75	63,8
Via Navone 17	8	26,5	45	Via Falda 10	21		40
Via Navone 6	8	26,5	45	Centrale idrica		57,96	
Via Navone 8	8	26,5	45				
TOTALE	**493**	**934,82**	**1490,11**				

Copertura finanziaria del progetto

Per la copertura finanziaria dell'intero progetto l'A.T.E.R. chiederà un contributo europeo sulle risorse disponibili per la Regione Lazio e di un finanziamento bancario a tasso agevolato. L'utilizzo del contributo permetterà di non gravare sul Bilancio dell'Ente e al contempo di generare un beneficio economico e finanziario. Qui di seguito vengono riportati i costi dell'investimento. Ai valori attuali, tali costi vengono stimati, arrotondati, come previsti al momento della elaborazione del progetto esecutivo e che, da parte dell'Ente, si ritiene saranno mantenuti senza lievitazione fino al termine dei lavori: € 2.500.000,00, così suddivisi:

Quadro Generale Spese (cifre arrotondate)	**Importo**
Acquisto materiali	€ 1.500.00,00
Installazione e messa in opera	€ 750.000,00
Lavori e pratiche amministrative	€ 250.000,00
COSTO TOTALE INTERVENTO	**€ 2.500.000,00**

Il piano di copertura finanziaria prevede:

- un contributo a fondo perduto da reperire nei fondi europei (piano Juncker) pari al 50% dei costi: € 1.250.000;

- un finanziamento a tasso agevolato garantito dalla BEI: 50%, pari ad € 1.250.000.

Il periodo per il completamento del progetto è previsto entro la fine dell'anno 2019.

Conclusioni

La Regione Lazio è parte sostanziale del "Piano Verde" per rilanciare l'Italia, che vede come protagonisti proprio le Regioni e gli Enti locali, puntando sulla valorizzazione del territorio e sull'uso efficiente delle risorse. Nondimeno la Regione Lazio da anni opera, tra l'altro, intensamente sul tema dell'efficienza e sul risparmio energetico delle strutture pubbliche residenziali, mentre gli Enti preposti ad operare su tali strutture, come la A.T.E.R. del comprensorio di Civitavecchia, da tempo hanno recepito i modelli di sostenibilità ed attivano anche politiche ambientali ed energetiche nella loro gestione. La realizzazione di questo progetto rappresenterebbe, oltre ad una best practice nazionale, il consolidamento e la prosecuzione di una politica regionale finalizzata alla realizzazione di un modello di edilizia sostenibile, basata sulla sostenibilità ambientale. Con tale progetto si mira a diminuire i consumi di energia, migliorare la qualità della vita degli inquilini e soprattutto a promuovere e applicare modelli di finanziamento innovativi finalizzati al rilancio dell'economia locale e dell'Ente.

Appendix B: Overview of IBM ILOG CPLEX Optimization Studio solver

The proposed model is mathematically formulated and solved using Optimization Programming Language (OPL) syntax provided by IBM ILOG CPLEX Optimization Studio [90]. IBM ILOG CPLEX Optimization Studio is an analytical decision support toolkit for rapid development and deployment of optimization models using mathematical and constraint programming. It combines an integrated development environment (IDE) built on the Optimization Programming Language, through programmatic APIs, or alternatively through third-party modeling environments with the powerful Optimization Programming Language and high performance ILOG CPLEX optimizer solvers. The CPLEX solver is used to mathematically program and solve the engineering problems like inventory, capacity planning, scheduling and facility location, providing optimal solution to the problem in a reasonable computational time. The CPLEX CP Optimizer component is a second-generation constraint programming (CP) engine for automatically solving detailed scheduling problems, as well as certain combinatorial optimization problems that cannot be easily linearized and solved using traditional mathematical programming methods; it has been used for job-shop scheduling and shown as a proven tool for small and medium size problems [91].

Detailed Scheduling Problems in OPL

Detailed scheduling can be seen as the process of assigning start and end times to intervals, and deciding which alternative will be used if an activity can be performed in different modes. Scheduling problems also require the management of minimal or maximal capacity constraints for resources over time. CPLEX CP Optimizer features are specially adapted to solving detailed scheduling problems over fine-grained time [92].

A scheduling model has the following format in OPL:

- Data structure declarations

- Decision variable declarations
- Objective function
- Constraint declarations

OPL provides specialized variables, constraints and keywords designed for modeling scheduling problems.

In particular, a typical scheduling problem is defined by:

- A set of time intervals—definitions of activities, operations, or tasks to be completed, that might be optional or mandatory;
- A set of temporal constraints—definitions of possible relationships between the start and end times of the intervals;
- A set of specialized constraints—definitions of the complex relationships on a set of intervals due to the state and finite capacity of resources;
- A cost function—for instance, the time required to perform a set of tasks, cost for some optional tasks of non execution, or the penalty costs of delivering some tasks past a due date.

<u>Scheduling constraints</u>

CP Optimizer in OPL provides a number of specialized constraints for scheduling [92], such as:

- **Precedence constraints -** Common scheduling constraints used to restrict the relative position of interval variables in a solution. These constraints are used to specify when one interval variable must start or end with respect to the start or end time of another interval. A delay, fixed or variable, can be included. For example, a precedence constraint can model the fact that an activity a must end before activity b starts (optionally with some minimum delay z).
- **Cumulative constraints -** In some cases, there may be a restriction on the number of intervals that can be processed at a given time, perhaps because there are limited resources available. Additionally, there may be some types of reservoirs in the problem

description (cash flow or a tank that gets filled and emptied). These types of constraints on resource usage over time can be modeled with constraints on cumulative function expressions. A cumulative function expression is a step function that can be incremented or decremented in relation to a fixed time or an interval.

- **Sequence decision variable and no overlap constraints -** A scheduling model can contain tasks that must not overlap, for example, tasks that are to be performed by a given worker cannot occur simultaneously. To model this, two constructs are used: the sequence decision variable and the noOverlap scheduling constraint. Unlike precedence constraints, there is no restriction on relative position of the tasks. In addition, there may be transition times between tasks.
- **Alternative and span constraints -** Provide important ways to control the execution and synchronization of different tasks**.** An alternative constraint between an interval decision variable a and a set of interval decision variables B states that interval a is executed if and only if exactly one of the members of B is executed. In that case, the two tasks are synchronized. A span constraint between an interval decision variable a and a set of interval decision variables B states that interval a spans over all intervals present in the set. Some examples are shown in Figure 34 for alternative and span constraints, respectively.

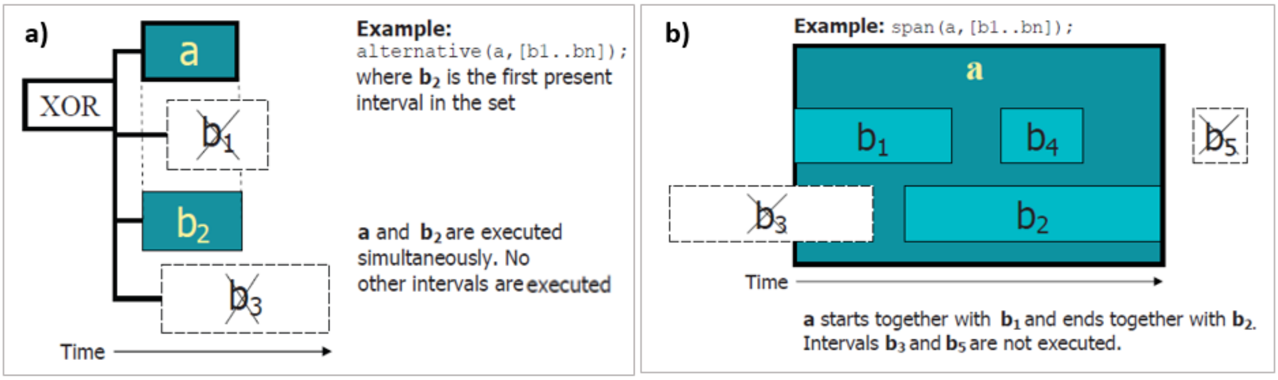


Figure 34 - Example of alternative **(a)** and span **(b)** constraints [92].

- **Synchronize constraints –** A synchronization constraint between an interval decision variable a and a set of interval decision variables B makes all present intervals in the set B start and end at the same times as interval a, if it is present.

Appendix C: IBM ILOG CPLEX Code

In this section the most significant parts of the code are reported by way of example.

```
/*objective function*/

minimize
  (sum(t in Time: Demand[t] >= PVPower[t]) Buy[t]  /* bought quantity
*/
   +
  sum(t in Time: Demand[t] < PVPower[t]) Sell[t]   /* Sold quantity
*/
   +
  sum(i in Batteries) Flag[i]*200*card(Time) /*penalty for used
batteries */


/* constraints forcing the satisfaction of the demand at every time
*/

forall(t in Time: Demand[t] >= PVPower[t]){
         Demand[t] == PVPower[t]+Buy[t]+sum(i in Batteries) x[i][t];
          Sell[t] == 0;
     }
     forall(t in Time: Demand[t] < PVPower [t]){
          PVPower[t]   ==   Demand[t]+Sell[t]+sum(i   in   Batteries)
y[i][t];
         Buy[t] == 0;
     }


/* constraints for the batteries charging and discharging */

    forall(i in Batteries, t in Time: (t > 0) && (Demand[t] < PVPower
[t]))
      ct: Charge[i][t] == Charge[i][t-1] + y[i][t];
```

```
    forall(i in Batteries, t in Time: (t > 0) && (Demand[t] >
PVPower[t]))
     ct2: Charge[i][t] == Charge[i][t-1] -  x[i][t];
    forall(i in Batteries, t in Time: (t > 0) && (Demand[t] ==
PVPower[t]))
      Charge[i][t] == Charge[i][t-1];


/* constraints defining if the battery is charging or discharging
*/

    forall(i in Batteries, t in Time: t > 0){

        c[i][t] <= c[i][t-1] + (2-MinFlag[i][t]-MaxFlag[i][t]);
        c[i][t] >= c[i][t-1] - (2-MinFlag[i][t]-MaxFlag[i][t]);

        c[i][t] >= 1 - MinFlag[i][t];
        c[i][t] <= 1 + MinFlag[i][t];

        c[i][t] >=  -MaxFlag[i][t];
        c[i][t] <=  MaxFlag[i][t];
      }

    /* constraints required to make the problem linear */

    forall(i in Batteries, t in Time: t>0) {
           y[i][t] <= M*c[i][t-1];
           y[i][t] <= DiffChargeP[i][t];
           y[i][t] >= DiffChargeP[i][t] - (1-c[i][t-1])*M;
           x[i][t] <= M*(1-c[i][t-1]);
           x[i][t] <= DiffChargeN[i][t];
           x[i][t] >= DiffChargeN[i][t] - (c[i][t-1])*M;
    }
```

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