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EXPLOITATION OF DEMAND SIDE FLEXIBILITY WITHIN RENEWABLE ENERGY COMMUNITIES

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Chapter 1
Introduction

1.1 The objective

The objective of the research activity is the development of innovative strategies for the integration of Distributed Generation from Non-Dispatchable Renewable Energy Sources (V-RES) into the Electricity Grid.

Solutions providing decentralized and demand-side flexibility are analyzed, with a focus on the implementation of enabling technologies and devices, such as Battery Energy Storage Systems (BESS) and IoT devices for loads and generators monitoring and control.

The research activity focuses on residential and commercial situations, spanning from single behind-the-meter applications to more articulated microgrids, aiming at modular solutions. In both cases the main focus is on Renewable Energy self-consumption, being it within single prosumer premises or within enlarged microgrids through Peer-to-Peer energy exchanges. The main theoretical framework is the Virtual Power Plant concept, specifically declined as a Renewable Energy Community (REC), as defined by EU and then Italian legislation.

The main field of application presented in this work regards the optimal scheduling of flexibility assets such as Battery Energy Storage Systems (BESS), through different algorithmic approaches. Furthermore, given the recent development of REC Italian legislation and related user-base wide enlargement, optimal clustering methods for consumers and prosumers into REC have been evaluated. Finally, controllable loads databases for demand-response simulations are explored.

1.2 Contributions

This PhD thesis aim to new methods for the optimal management of Renewable Energy Community type of Virtual Power Plants, especially through the use of Mixed Integer Linear Programming.
In the field of optimal scheduling of flexibility assets such as BESS, the first approach proposed regards a simplified self-consumption optimization model for prosumers, which operates in real-time and pairs with a peer-to-peer model for sharing excess solar energy. The model is tested within a small Energy Community where the prosumer also possesses a Battery Energy Storage System (BESS).

Scope of the activity is to develop a simplified BESS management methodology that operates without any forecast on near-future electricity generation and consumption. This sets a baseline for the evaluation of more complex scheduling methods for the operation of BESS and the management of RECs.

The results, in terms of technical, environmental, and financial benefits, demonstrate that peer-to-peer energy trading enhances the balance of energy production and usage in the local area.

Once having set this simple reference as baseline, the REC Energy Management System model has been upgraded into a three-phases model:

- a Machine Learning-based forecast algorithm for prosumers' and consumers' loads, as well as for FV generation, with a 1-hour resolution over the next 24 hours;
- a Mixed Integer Linear Programming (MILP) algorithm, based on ML forecast outputs, that optimizes the BESS scheduling for minimal REC operating costs for the following 24 hours;
- a decision tree algorithm that works at intra-hour level, with 1-minute timestep and using the real load and generation curves. It aims to reach the energy exchanges as defined by the MILP; anyway, using real loads and generation curves it has to take into account the forecast errors.

The ML forecast algorithm provided Mean Absolute Percentage Errors (MAPE) of around 8% for the PV generating power, and of around 19-35% for the prosumers and consumers loads.

Moreover, a more comprehensive techno-economical evaluation model has been developed and added to pursue additional financial evaluations.

In order to be able to add demand-response simulation potential to the MILP-based model, and considering that one of the main hindrances to the development of demand-response simulators, at least at residential levels, is the lack of free-access databases, comprising large enough dataset, activity related to the creation of a database of potentially controllable household loads, mainly of the appliance type has been carried out.

The work leveraged on the existence of the Pecan Street database, one of the few available free-access dataset. Pecan Street Dataport [1] is a database of detailed, time-resolved energy consumption data collected from residential and commercial customers in the Pecan Street neighborhood form Texas, New York and California.

Scope of the activity was then to prepare a suitable tool for the simulation of demand-response activity at the residential level, for the integration into the MILP-based scheduling optimization model. The database has been structured to provide several possible uses within this framework:

- The average load profiles could be used as dummy for in-advance load scheduling (i.e. for day-ahead scheduling, under forecast assumptions)
- The raw load strips can be used in real-time management phase
- The database of single events, provided with actual timestamps, can be used randomly as an alternative in both the other previously described situations

Finally, the REC optimization topic is addressed from an external, combinatorial approach, that is being used to determine the optimal assignment to one or more RECs of the consumers and prosumers from a given set; the complementarity of their load and generation profiles is considered, to achieve maximum economic revenue. This approach gains even more importance under the light of the upcoming REC definition modifications provided by the Italian law 199/2022, that extends the topological limitations of the REC. The chosen approach uses numerical optimization algorithms, with a multi-objective approach; the problem is formulated as a two-objective Pareto optimization problem. The first objective aims at maximizing the economic revenue derived from the RECs, while the second aims at maximizing the uniformity of the revenues among the different RECs created.

In conclusion, an experimental work has been carried out in the last part of the PhD, regarding the realization of a feasibility study for several RECs located in Tuscany countryside, all participated by the municipality governance that will act as a prosumer.

Chapter 2 Theoretical Aspects: Legislative Framework and Literature Review

2.1 Legislative Framework

Energy Communities are one of the several legislative and policy tools that could enable the EU citizens to be an active part in the so-called clean energy transition, as fostered by the Clean Energy Package (CEP) [2]. The CEP is a set of eight Regulations and Directives that aims at shaping the EU energy policies, with an overall target for a 40% greenhouse gas reduction by 2030 and specific targets for a 32.5% of improvement in energy efficiency and for a 32% of the remaining electricity consumption coming from renewable energy sources (RES), both by the same timeframe. The recent "Fit for 55" package of legislative proposals [3], together with the EU Green Deal package [4], aim to push further these targets, i.e. increasing the RED II [5] 2030 target for renewables from 32% to 40% of the EU energy mix, roughly doubling the 2019 level of 19.7%; For what it concerns buildings energy needs, the European Commission is proposing an indicative goal of getting at least 49% of them from RES by 2030; to reach this target there would be the need to steeply increase the use of renewable electricity, heat pumps, solar thermal and district heating.

More specifically, the 2019/944 Directive on common rules for the internal electricity market [6] includes new rules to make it easier for citizens to interact with the electricity system as active participants and to improve the uptake of energy communities. Such market participation could be related to the generation, consumption, share or sale of electricity, as well as to the provision of flexibility services through demand-response and storage; all these activities could be done individually or through citizen energy communities. Moreover, the 2018/2001 revised Renewable Energy Directive (RED II) aims to strengthen the role of renewables self-consumers and Renewable Energy Communities, as defined in Art. 22, with a specific attention to household consumers [5].

EU Member States (MS) are called to ensure that they can participate in available support schemes, on equal footing with large participants. Italy transposed the general legislative framework for REC as set in Directive 2018/2001, with the Law n.8 28/02/2020, M.D. 16/09/2020 and regulation 318/2020/R/EEL [7]–[9]. The two laws are currently in force as a transient regime, since they will be updated by the transposition law for Directive 2018/2001. Specific rules and limits for the operation of Italian REC, as well as incentive schemes, are described in detail in the following section. The Italian REC could be operated in a very simple way, potentially with no additional efforts; anyway, high level of energy sharing could only be reached by deploying assets that could ensure additional level of flexibility, such as Battery Energy Storage Systems (BESS) or controllable loads.

Italy-based RECs are operated under the framework set by Italian Law n.8 28/02/2020, M.D. 16/09/2020 and regulation 318/2020/R/EEL[7]–[9]that transposed the EU Directive 2018/2001 [5]. Visually summarizes the legislative evolution of the sector at Italian and European level, up to 2021.

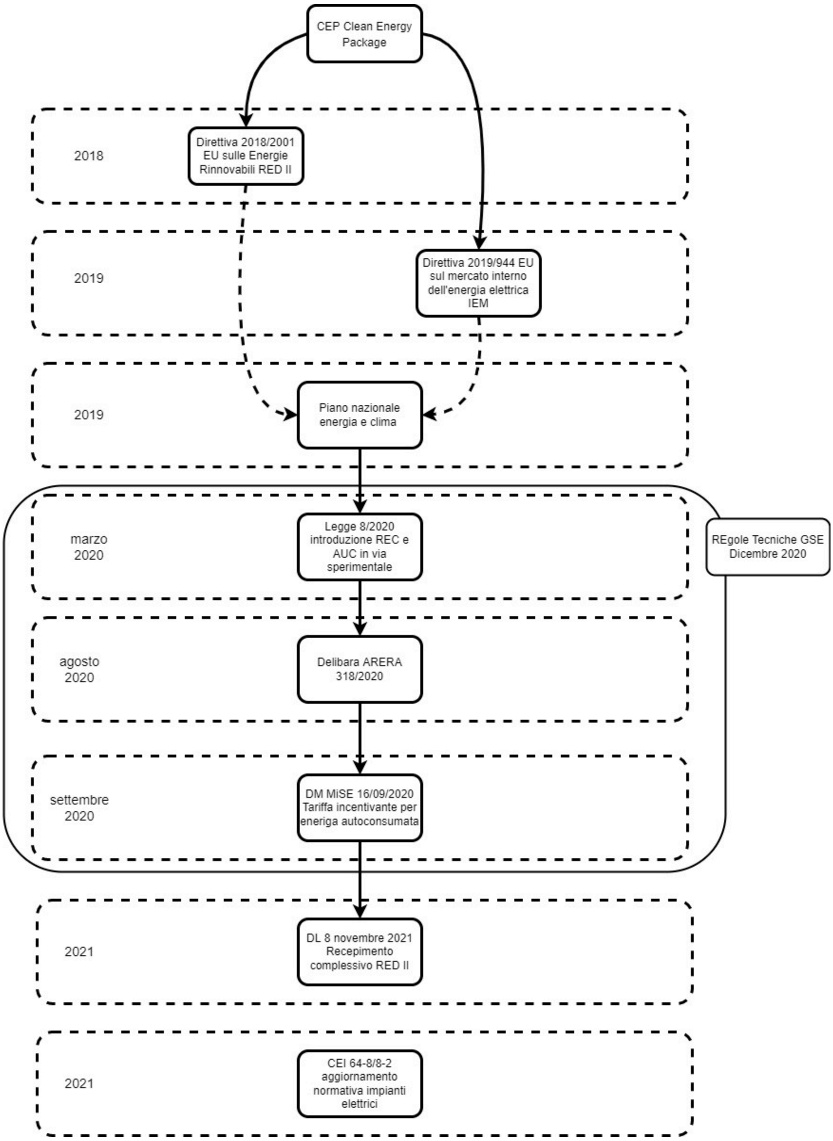

Figure 2-1: Visual summary of the main legislative packages involving REC regulation at EU and Italian level

Within this framework, a REC is considered as a virtual community, composed by a set of consumers M and a set of RES-powered generators G. The number of consumers is not explicitly limited, while there must be at least one generator for each REC, with a constraint on REC maximum generating power set at 200 kW (to be shared among total set of generators G). It is important to highlight that all the users have to be connected to the public Low Voltage (LV) distribution grid, that is used to virtually share the energy among them and have to be under the same LV/MV transformer. Each user load is defined by its Point Of Delivery (POD), while a generator could either be defined as stand-alone entity, with its own POD, or could share the POD with a user load, thus under a prosumer framework. In this latter case, the POD energy profile would be seen at time as either a net load or a net generation profile, depending on current load and generation profiles. The BESS, whenever available, has to be deployed behind a POD connected to a generator, as already mentioned above. Figure 2-2 presents the general architecture of an Italian REC.

The energy shared within this type of REC is defined as the minimum, on an hourly basis (i.e., between 11:00 and 12:00), between the total energy injected in the grid by all REC's generators and the total energy withdrawn from the grid by all REC's loads. Because of this virtual approach, generators continue to sell the energy to the grid at day-ahead market prices and users continue to pay the bills for their loads as before. On top of that, a premium of 110 €/MWh is paid to the REC [7]–[9] for the shared energy and has to be divided among the community; no specific rules are defined by the authority on how to share the premium among the REC members, thus this has to be decided by the members itself when the REC is created.

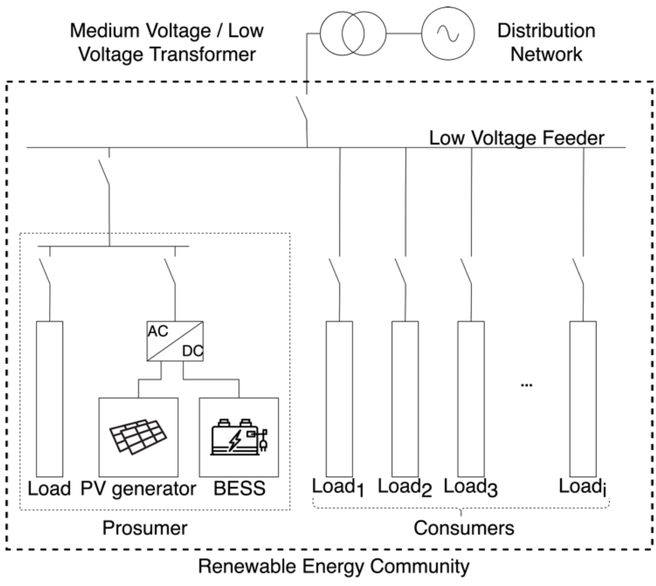

Figure 2-2: General architecture of a Renewable Energy Community

2.1.1 EU Directives

At the European level, specific targets for reducing greenhouse gas emissions, increasing the share of renewable energy and improving energy efficiency were defined by the 2030 climate and energy framework [10]. The Clean Energy Package[11] provided the policy and regulatory instruments to support the achievement of the targets. Within this framework, the European Green Deal [4] represented the EU's ambition to reduce greenhouse gas emissions by 55% by 2030 and laid the foundation for achieving net zero emissions by 2050. To implement the -55% target, in July 2021 the European Commission presented the 'Fit for 55' package [4], which introduces legislative proposals to revise the entire EU climate and energy framework for 2030.

(i) EU Directive 2018/2001 on the promotion and use of energy from renewable sources (RED II)

Key Points:

> Defines targets for RES-based energy in the European Union's gross final energy consumption by 2030, and defines functional rules, principles and criteria for Member States internal regulations.

> Introduces the concept of Self-consumer of energy from renewable sources (Art. 21)

> Introduces and defines the Renewable Energy Community (Art. 22) and related activities.

> The concept of Renewable Energy Community is transposed into Italian national legislation by Legislative Decree 199/2021

Within the overall policy framework, Directive 2018/2001 - usually referred to as REDII - was adopted in December 2018 and stipulates that Member States shall collectively ensure that, by 2030, the share of energy from renewable sources in the Union's gross final energy consumption is at least 32 per cent and the share of energy from renewable sources in transport is at least 14 per cent of final energy consumption in that sector. Functional to the achievement of the 2030 targets are the rules - contained in the Directive itself - that provide member states with the principles and criteria to regulate:

- the financial support for electricity from renewable sources (Articles 4-6 and 13);

- the self-consumption of electricity produced from these sources (Articles 21 and 22);
- the use of energy from RES in the heating and cooling sector and in the transport sector (Articles 23-24 and 25-28);
- cooperation between Member States and between Member States and third countries on projects for electricity production from renewable energy sources (9-12 and 14);
- guarantees of origin of energy from RES (Article 19), administrative procedures to ensure an appropriate regime for production from RES, and information and training on RES (Articles 15-18).
- sustainability and greenhouse gas emission reduction criteria for biofuels, bioliquids and biomass fuels (Articles 29-31).

In this chapter, Articles 21 and 22, which are relevant to the topic of Renewable Energy Communities, will be analysed in detail.

Article 21: Renewable Energy Self-consumers

Paragraph 1 of the article provides for Member States to authorise consumers to become self-consumers of renewable energy[1].

Paragraph 2 states that, individually or through aggregators, self-consumers shall be allowed to:

a) produce renewable energy, including for their own consumption; store and sell surplus renewable electricity generation, including through renewable electricity purchase

[1] "self-consumer of renewable energy" means a final customer who, operating at its own sites within defined boundaries or, if permitted by a Member State, at other sites, produces renewable electricity for its own consumption and may store or sell self-produced renewable electricity provided that, for a self-consumer of renewable energy other than a household, such activities do not constitute its principal commercial or professional activity;

and sale agreements[2], electricity suppliers and peer-to-peer trading agreements[3];

b) install and operate electricity storage systems coupled with renewable electricity generation facilities for self-consumption purposes without being subject to any dual charges, including grid tariffs for the stored electricity that remains in their possession;
c) maintain their rights and obligations as final consumers;
d) receive remuneration, including where appropriate through support schemes, for the self-produced renewable electricity they feed into the grid, which corresponds to the market value of that electricity.

Paragraph 3 provides that Member States may apply non-discriminatory and proportionate charges and tariffs to self-consumers of renewable energy, in relation to their self-produced renewable electricity that remains in their possession, in one or more of the following cases

a) if the self-produced renewable electricity is actually benefiting from support schemes, only to the extent that the economic viability of the project and the incentive effect of such support are not affected;
b) from 1/12/2026, if the total share of installations for self-consumption exceeds 8 % of the total installed electrical capacity of a Member State, and if it is demonstrated, through a cost-benefit analysis, that the production, storage and/or sale of renewable energy has led to a significant disproportionate burden on the long-term financial

[2] "Renewable electricity purchase agreement" means a contract whereby a natural or legal person undertakes to purchase electricity from renewable sources directly from an electricity producer

[3] "Peer-to-peer trading" of renewable energy means the sale of renewable energy between market participants under a contract with pre-determined terms and conditions governing the automated execution and settlement of the transaction, either directly between market participants or indirectly through a certified third party market participant, such as an aggregator. The right to conduct peer-to-peer trading is without prejudice to the rights or obligations of the parties involved as end consumers, producers, suppliers or aggregators;

sustainability of the electricity system or creates an incentive that exceeds what is objectively necessary to achieve the economically efficient deployment of renewable energy

c) if the self-generated renewable electricity is produced in installations with a total installed electrical capacity exceeding 30 kW.

Paragraph 4 provides that Member States shall ensure that self-consumers of renewable energy located in the same building, including blocks of flats, are allowed to collectively engage in the activities referred to in paragraph 2 and to organise amongst themselves the exchange of renewable energy produced at their site or sites, subject to the grid charges and other relevant charges, fees, levies and taxes applicable to each self-consumer of renewable energy. Member States may distinguish between individual self-consumers of renewable energy and self-consumers of renewable energy acting collectively [4]. Any different treatment shall be proportionate and duly justified.

Paragraph 5 provides that the installation of the self-consumer of renewable energy may be owned or operated by a third party, provided that the third party remains subject to the instructions of the self-consumer of renewable energy. The third party is not considered a self-consumer of renewable energy per se.

Paragraph 6 requires Member States to establish a favourable framework for promoting and facilitating the development of self-consumption of renewable energy, with the following specific objectives

a) accessibility of self-consumption of renewable energy to all final consumers, including those from low-income or vulnerable households;
b) removal of unjustified market and other unjustified regulatory barriers to financing projects for self-consumption of renewable energy, including for tenants; implementation of measures facilitating access to financing;
c) incentives for building owners to create possibilities for self-consumption of renewable energy, including for tenants;

[4] "Self-consumers of renewable energy acting collectively": a group of at least two self-consumers of renewable energy acting collectively within the meaning of point 14) and located in the same building or apartment block;

d) non-discriminatory access to relevant existing support schemes, as well as to all segments of the electricity market for self-consumers of renewable energy, against self-produced renewable electricity fed into the grid
e) an obligation for self-consumers of renewable energy to make an appropriate and balanced contribution to the overall system cost allocation when electricity is fed into the grid.

Article 22: Renewable Energy Communities
Paragraph 1 requires Member States to ensure that final customers, in particular household customers, have the right to participate in renewable energy communities[5], while maintaining their rights or obligations as final customers. They must not be subject to unjustified or discriminatory conditions or procedures that prevent them from participating; with regard to private companies, a condition is included that their participation does not constitute their principal commercial or professional activity.

Paragraph 2 requires Member States to ensure that renewable energy communities have the following rights

a) produce, consume, store and sell renewable energy, including through sale and purchase agreements;
b) trade, within the same community, the renewable energy produced by the production units held by that renewable energy producer/consumer community, subject to the other requirements set out in this Article and the maintenance of the rights and obligations of the members of the renewable energy producer/consumer community as customers

[5] "Renewable energy community" means a legal entity: (a) which, in accordance with applicable national law, is based on open and voluntary participation, is autonomous and is effectively controlled by shareholders or members who are located in the vicinity of the renewable energy production facilities owned and developed by the legal entity in question; (b) whose shareholders or members are natural persons, SMEs or local authorities, including municipal authorities; (c) whose main objective is to provide environmental, economic or social benefits at community level to its shareholders or members or to the local areas in which it operates, rather than financial profits;

c) access all appropriate electricity markets, either directly or through aggregation, in a non-discriminatory manner.

Paragraph 4 obliges Member States to provide a supportive framework to promote and facilitate the development of renewable energy communities. This framework shall, inter alia, ensure:

a) the removal of unjustified regulatory and administrative barriers;
b) that Renewable Energy Communities providing energy or aggregation services, or other commercial energy services are subject to the provisions applicable to such activities;
c) that the relevant distribution system operator cooperates with renewable energy communities to facilitate energy transfers within renewable energy communities
d) that renewable energy communities are subject to fair, proportionate and transparent procedures, in particular those relating to registration and licensing activities, grid charges and overall system cost allocation
e) that Renewable Energy Communities are not subject to discriminatory treatment with respect to their activities, rights and obligations as final consumers, generators, suppliers, distribution system operators, or other market participants
f) that participation in renewable energy communities is open to all consumers, including those from low-income or vulnerable households;
g) that tools are available to facilitate access to finance and information;
h) that public authorities are provided with regulatory and capacity-building support to foster the creation of renewable energy communities and help authorities to participate in them directly;
i) that rules are available to ensure fair and non-discriminatory treatment of consumers participating in a renewable energy community.

Paragraph 6 states that Member States may provide that renewable energy communities are open to cross-border participation.

(ii) EU Directive 2019/944 on common rules on the internal energy market, amending directive 2012/27

Key Points:

- Introduces the concept of **direct line** between production plant and user (Art. 7)
- Defines **active customer** as a final customer or group of final customers who consume or store self-produced electricity, or sell self-produced electricity, or participate in flexibility or energy efficiency mechanisms (Art. 15)
- Defines **citizens' energy communities** as a legal entity that may participate in generation, **including from renewable sources**, distribution, supply, consumption, aggregation, energy storage, energy efficiency services, or electric vehicle charging services, or provide other energy services to its members or associates (Art. 16).

Directive 2019/944 lays down common rules for the generation, transmission, distribution, storage and supply of electricity and provides consumer protection provisions in order to create truly integrated, competitive, consumer-centric, flexible, fair and transparent electricity markets in the European Union.

It also sets out how Member States, regulators and transmission system operators shall cooperate with a view to creating a fully interconnected internal electricity market that enhances the integration of electricity from renewable energy sources, free competition and security of supply.

Article 7: Direct lines

Paragraph 1 requires Member States to take the necessary measures to enable:

a) all producers and electricity supply undertakings established within their territory to be able to supply their own installations, subsidiaries and customers through a direct line[6],

[6] 'Direct line' means an electricity line connecting an isolated generation site with an isolated customer, i.e. an electricity line connecting a producer and

without being subject to administrative procedures or disproportionate costs;
b) all customers in their territory are supplied, individually or collectively, through a direct line by producers and supply undertakings.

Paragraph 2 requires that the criteria for granting authorisations for the construction of direct lines in their territory must be established by the member states in an objective and non-discriminatory manner.

The possibilitỳ of concluding contracts for the supply of electricity remains unaffected by the possibilitỳ of supply through a direct line (paragraph 3); the authorisation of the latter may be subject to the denial of system access pursuant to Article 6 (paragraph 4).

Article 15: Active customers

Paragraph 1 requires Member States to ensure that final customers have the right to act as active customers without being subject to discriminatory or disproportionate technical or administrative requirements, procedures and network charges that are not cost-reflective.

Paragraph 2 requires Member States to ensure that active customers

a) have the right to trade directly or in aggregate;
b) have the right to sell self-generated electricity, including through power purchase agreements;
c) have the right to participate in flexibility mechanisms and energy efficiency mechanisms
d) have the right to delegate to a third party the operation of facilities necessary for their activities, without the third party being considered an active customer
e) are subject to network charges that are cost-reflective, transparent and non-discriminatory, and account separately for electricity injected into the network and electricity absorbed from the network, so as to ensure that they contribute in an appropriate and balanced way to the overall allocation of system costs

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an electricity supply company to supply their own plants, subsidiaries and customers directly;

f) are financially responsible for the imbalances they bring to the electricity system; to this extent, they are responsible for balancing or delegate their balancing responsibility.

Paragraph 3 provides that the national legislation of Member States may contain different provisions applying to individual and pooled active customers, provided that all rights and obligations under this Article apply to all active customers.

Paragraph 5 requires Member States to ensure that active customers owning an energy storage facility

a) have the right to be connected to the grid within a reasonable time after the relevant request, provided that all necessary conditions, such as balancing responsibility and adequate metering, are met;
b) are not subject to any double charges, including grid charges, for the stored electricity that remains in their possession or for the provision of flexibility services to system operators
c) are not subject to disproportionate licensing requirements or charges;
d) are allowed to provide several services simultaneously, if technically possible.

Article 16: Citizens' Energy Communities

Paragraph 1 requires Member States to provide a regulatory framework for citizens' energy communities[7] that ensures:

a) the open and voluntary participation of citizens;

[7] "citizens' energy community" means a legal entity that: (a) is based on voluntary and open participation and is effectively controlled by members or partners who are natural persons, local authorities, including municipal authorities, or small enterprises; (b) has the primary purpose of providing environmental, economic or social benefits to its members or partners or to the territory in which it operates at community level, rather than generating financial gain and (c) may participate in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services, or electric vehicle charging services or provide other energy services to its members or associates;

b) the right of members or associates to leave the citizens' energy community, in which case Article 12 shall apply
c) the maintenance of the rights and obligations of household customers or active customers for members or associates of a citizens' energy community
d) the cooperation of the relevant distribution system operator - subject to the payment of equitable compensation as assessed by the regulatory authority - to facilitate transfers of electricity within them
e) non-discriminatory, fair, proportionate and transparent procedures and charges, including in relation to registration and licensing, and transparent, non-discriminatory and cost-reflective network charges[8].

Paragraph 2 considers that Member States may provide in the regulatory framework that citizens' energy communities

a) are open to cross-border participation;
b) have the right to own, establish, acquire or lease distribution networks and operate them independently under the conditions set out in this Article, paragraph 4;
c) are subject to the exemptions provided for in Article 38(2).

Paragraph 3 requires Member States to ensure that citizens' energy communities

(a) have access to all electricity markets directly or in aggregate in a non-discriminatory manner;
(b) are treated in a non-discriminatory and proportionate manner with respect to their activities and their rights and obligations as final customers, generators, suppliers, distribution system operators or market participants involved in aggregation
(c) are financially responsible for imbalances they bring to the electricity system; to this extent, they shall be responsible for balancing or delegate their responsibility for balancing
(d) are treated as active customers in respect of their own electricity consumption

[8] Electricity sharing is without prejudice to applicable network charges, tariffs and taxes, based on a transparent cost-benefit analysis of distributed energy resources developed by the competent national authority.

(e) have the right to organise within the citizens' energy community the sharing of electricity produced by community-owned generation units, subject to other requirements set out in this Article and provided that the community members retain their rights and obligations as final consumers.

Paragraph 4 provides that Member States may decide to grant citizens' energy communities the right to operate the distribution system in their area of operation and to establish the relevant procedures, subject to the provisions of Chapter IV and other rules and regulations applicable to distribution system operators. Where such a right is granted, Member States shall ensure that the citizens:

a) have the right to enter into an agreement for the operation of the community's network with the relevant distribution system operator or transmission system operator to which their network is connected
b) are subject to appropriate network charges at the points of connection between their network and the distribution network outside the citizens' energy community itself, and that those network charges take into account and account separately the electricity fed into the distribution network and the electricity consumed by the distribution network outside the citizens' energy community
c) do not discriminate against or harm customers who remain connected to the distribution system.

2.2 Technical norms and standards

2.2.1 CEI 64.8 8-2

Key Points:

> Provides additional requirements, measures and recommendations for the design, installation and testing of all types of low-voltage electrical systems, including local generation and energy storage to optimise the overall efficient use of electricity.

> Introduces the figure of the PEI (Prosumer's low-voltage Electrical Installations).

> Introduces the definition and functionality of the Electrical Energy Management System (EEMS).
>
> Introduces the possible criteria for PEI management by one or more EEMS in relation to the use or non-use of the DSO's network.

The standard provides additional prescriptions, measures and recommendations for the design, installation and verification of all types of low-voltage electrical systems, including local generation and energy storage to optimise the overall efficient use of electricity. These requirements and recommendations apply, within the IEC 64-8 standard, to new installations and the modification of existing installations. In line with the CENELEC harmonisation documents, part 8-2 of IEC 64.8 contains solutions applicable throughout Europe. Consequently, among the various technical solutions, those in line with the acts and measures issued by the State and the ARERA authority must be identified. In particular, it is necessary to comply with:

- Law 28/02/2020 no.8;
- Decree-Law 162/2019;
- Legislative Decree 199 2021;
- Legislative Decree 210 2021;
- Resolution 318/2020/R/eel;
- DMEA/EFR/6/2020.

The installations covered by the standard include those for local energy production and/or storage, with the aim of **ensuring compatibility with current and future ways of supplying electricity to equipment fed from public grids or by means of local energy sources**. These electrical installations are identified as Prosumer's low-voltage Electrical Installations (PEI).

Section 5 generically defines a PEI as a set of electrical equipment that performs the following functions:

- power supply (e.g. connection to the public power grid, local generator, photovoltaic systems, wind turbines, batteries);
- distribution (e.g. distribution boards, pipeline systems);
- consumption (e.g. motors, heating systems, lighting, lifts);
- energy management (e.g. load shedding equipment, monitoring devices).

The same paragraph specifies that a battery may be considered both as a generator and as a load, while a static uninterruptible power supply (UPS) is not to be considered an active user when its purpose is only to supply the critical loads located downstream and does not provide for the reverse mode of supply from the public grid and/or the upstream connected consumer equipment within the electrical system.

Section 6.1 stipulates that Prosumers, i.e. active-passive users, may feed in and withdraw energy from the grid and operate in island mode in the following modes:

- at individual level
- at collective level (several electricity consumption plants, connected to the same public distribution grid and sharing a group for production and local electricity storage equipment)
- at shared level (several electricity consumption and/or production facilities, similar to an individual EIP, connected to the same low-voltage public distribution network and sharing individual power supplies and energy storage equipment).

Section 6.2 indicates the modes of operation that can be applied to any type of EIP:

- direct supply where the public grid supplies the EIP;
- reverse feed in which the EIP feeds the public grid ;
- island operation in which the EIP is disconnected from the public distribution system, but remains powered.

Paragraph 7 introduces the concept and general characteristics of the electricity management system (EEMS). In particular, the EEMS must monitor and control the operation of all power supplies, the loading of storage units and the operation of loads. The concept and design structure of the EEMS depends mainly on the concept on which the EEMS is based. The specific purposes of the EEMS are as follows:

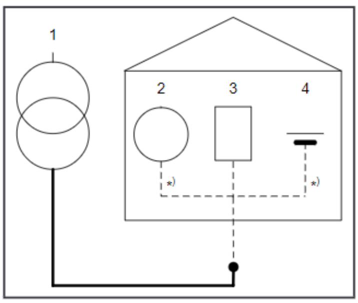
- to control the connection of the EIP to the smart grid;
- to locally manage electricity production;
- manage electricity consumption locally;
- to manage the supply of energy from the DSO.

Below are some examples of functions that can be under the control of the EEMS:

- managing power sources and loads;
- managing the connection of several sources;
- proposing load control mode (load disconnection and displacement);
- two-way exchange of information with the DSO;
- management of the back-up system by means of energy storage units and power sources;
- control of energy flow to and from the energy storage units;
- voltage quality control;
- providing the interface to the end-user.

EEMS can be installed as separate equipment or within different equipment, or integrated into existing equipment.

The management of different types of EIPs by one or more EEMS may be linked to their membership in a Renewable Energy Community. For example, in the case of individual EIPs, the plant operator can decide, through the EEMS and in accordance with the contract with the DSO, when it has to make energy production available for local storage, for local use or for transfer to the public grid.



Legenda

1	Rete pubblica
2	Alimentazioni elettriche
3	Carichi
4	Unità di accumulo
*)	Facoltativo (deve essere presente almeno uno di questi elementi)

Figure 2-3:Example of the electrical design of a single EIP

In the case of a collective EIP, the different power supplies may serve all active users concerned through the EIP's internal distribution system or that of the DSO, if so agreed with the latter. A group of active users may co-operate and co-ordinate their resources in order to realise a common power supply. In this case, all private electrical installations are considered consumers. For the consumer community, only one separate unit is operated that generates the electricity. In the case where the connection between all active consumers concerned uses the distribution system within the EIP, from the DSO's point of view the aggregation of all the installations of the active consumers corresponds to a single EIP. In other cases where the connection between all consumers concerned uses the public distribution network in combination with an internal distribution system within the EIP, the origin of the EIP for each consumer corresponds to the service entry point of each individual active consumer.

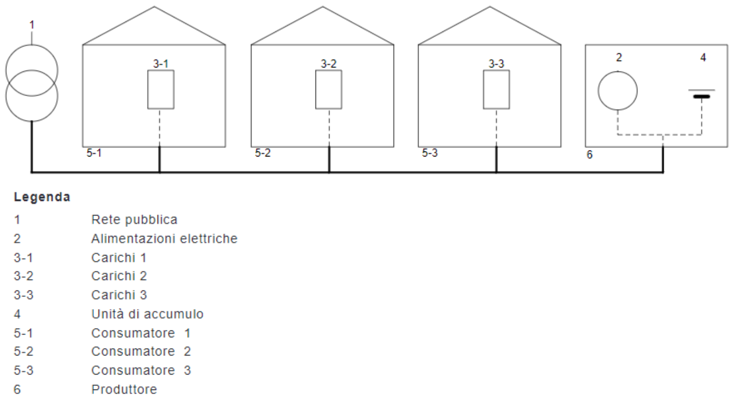


Figure 2-4: Electrical design example of a collective EIP that uses DSO network

In the case of a shared EIP, the different power supplies can feed all interested active users through the EIP's internal distribution system or through the DSO's, if so agreed with the DSO. Individual premises, such as a housing estate or shopping centre, may pool their interests by agreeing to share their locally produced power supply with their neighbors.

Each homeowner may have installed renewable energy sources that can power both their own and the group's electrical systems.

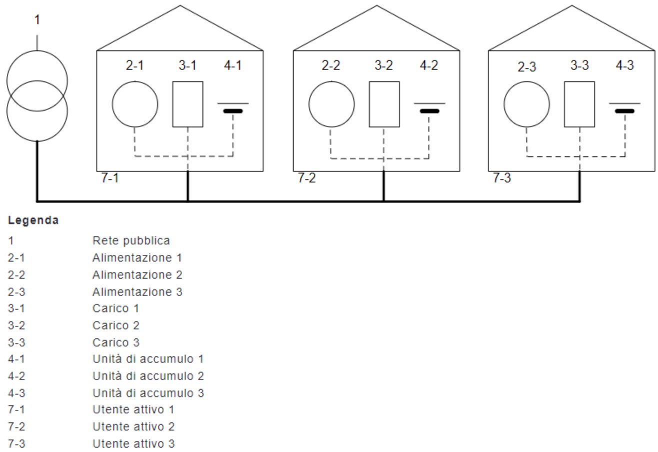


Figure 2-5: Electrical design example of a shared EIP that uses DSO network

2.2.2 Technical regulation from GSE

(iii) Technical regulation 4th April 2022.

Key Points:

- Introduces the concept of a group of self-consumers acting collectively and a renewable energy community.
- Defines the requirements for access to the incentive service.
- Introduces the modalities for submitting a request to activate the service.
- Defines the precise calculation criteria and measurement methods

The technical rule defines the criteria for access to the shared energy valorisation and incentive service in groups of self-consumers of renewable energy acting collectively and as a renewable energy community.

Paragraph 1.2 introduces the types of configuration admitted to the shared energy valorisation and incentive service. In particular, it is established that the renewable energy community is a legal entity that

- is based on open and voluntary participation (provided that, for private companies, participation in the renewable energy community is not the main commercial and/or industrial activity) and is autonomous
- whose shareholders or members exercising power of control are natural persons, small and medium-sized enterprises (SMEs), territorial authorities or local authorities including, pursuant to Art. 31(1)(b) of D.Lgs. 199/21, municipal administrations, research and training bodies, religious bodies, third sector and environmental protection bodies, as well as local administrations contained in the list of public administrations disseminated by the National Institute of Statistics (hereinafter also: ISTAT) in accordance with the provisions of Article 1, paragraph 3, of Law No. 196 of 31 December 2009, located in the territory of the same municipalities in which the production facilities held by the community of renewable energy are located;
- whose main objective is to provide environmental, economic or social benefits at community level to its shareholders or members or to the local areas in which it operates, rather than financial profits.

Paragraph 2.1 sets out the general requirements for access to the shared electricity valorisation and incentive service. In particular, the relations between the entities belonging to one of the two configurations described in paragraph 1.2 are governed by a private law contract that

- provides for the preservation of the rights of the end customer, including that of choosing one's own seller;
- univocally identifies a delegated party responsible for allocating the shared electricity, to whom the parties may also delegate the management of payment and collection items to the sales companies and the GSE;
- allows the entities to withdraw at any time and exit from the configuration, without prejudice to any fees agreed in the event of early withdrawal for the sharing of investments made, which must in any case be fair and proportionate.

Paragraph 3 clarifies the aspects relating to the identification of the contact person, the modalities for submitting the request for access to the contributions, the effective date of the valorisation and incentivisation service, and the effective date of the withdrawal service of the energy fed in. The technical rule also specifies the precise calculation criteria and measurement methods through which the GSE will provide for the payment of the fees.

(iv) Technical regulation 22nd January 2021.

Key Points:

> Defines the conditions for the installation of storage systems in production plants belonging to collective self-consumption configurations or energy communities.

> Establishes the modalities for submitting an application for the installation of storage systems within renewable energy communities.

The technical rule deals with the implementation of the provisions relating to the integration of electricity storage systems into the national electricity system pursuant to resolution 574/2014/R/eel and subsequent amendments.

Paragraph 5.1.7 deals with production plants belonging to configurations of collective self-consumption or energy communities referred to in the Ministerial Decree of 16 September 2020 and establishes that in these cases the measurement of the electricity absorbed and released by the storage systems, in addition to the measurement of the electricity produced referred to in TIME, is always necessary.

Paragraph 6.2.3 establishes the modalities for submitting the request regarding the installation of storage systems for plants that are part of configurations of groups of self-consumers acting collectively and of renewable energy communities. In particular, it is established that the Responsible Party of an electricity production plant fuelled by renewable sources admitted to the shared energy valorisation and incentive service, is required to submit a request aimed at defining the possible effects of the installation of the storage system on the contract for the regulation of the economic items, by sending a specific request through the application

"Production and Consumption Systems - SPC" available in the customer area of the institutional Portal of the GSE.

Section 7.1 shows the algorithms for the quantification of electricity entitled to incentives or special trading schemes managed by the GSE. For energy communities and collective self-consumption, the detailed formula for calculating hourly shared electricity (EAC) and the calculation of shared electricity (EAC) are given. The latter is carried out starting from the 'net' energy input, with the application of a coefficient α, which allows the energy fed into the grid to be roughly divided between the energy produced by the plant and the energy previously withdrawn and then released by the storage system.

2.3 Review of management and optimization methods for REC and flexibility assets management and optimization

2.3.1 Machine Learning for Battery Energy Storage Systems

BESS often require algorithmic approaches for both accurate modelling and optimal management of the operation modes. Concerning modelling, although several equivalent circuit models are available in literature [12], practical applications often face the problem of accurate state-of-charge and health level estimation [13]–[16] for the accumulator. Indeed the full system is strongly non-linear and affected by losses, that should be taken into account in all phases of energy conversion; this includes switching devices [17] and magnetic components [18], [19].

Concerning management, several figures of merit should be considered, such as reduced degradation of the battery, optimal power flow, and maximum economic revenue. Machine learning play an important role in this, and several techniques can be used to manage the system behaviour in an optimal way. In [20] authors proposes a comparison of different techniques (neural network, support vector machine, logistic regression, and random forest algorithms) for optimal scheduling of the real-time operations of the BESS, which is in general coupled with a higher level grid optimization [21]–[24].

At the base of the management systems is the knowledge of several electrical, environmental, and economic quantities. Knowledge of these quantities is often limited to historic values, and for this reason, ML based forecasting techniques are often proposed in literature. In [25] authors propose a proactive prediction of the energy demand of an entire city to be included in an intelligent management system for energy storage and flexible loads. Forecasting through deep learning techniques are also promising with good results for Long-Short-Term-Memory (LSTM) networks [26]–[28] and recurrent LSTM [26].

Load forecasting can be performed with convolutional neural networks as well, exploiting the different timescales of the features inherent in the time profile of the phenomenon as an advantage [29], [30]. Power Quality disturbances could sometime hider the load forecasting capabilities; for this reason, specific classification techniques are often employed [31]. Due to the complexity of the forecasting problem, deep convolutional networks can often benefit from an automated definition of the hyperparameters by means of metaheuristic or evolutionary optimization algorithms [32], [33], or networks trained through derivative-free optimization algorithms [34].

Forecasting of energy prices can be important to estimate future trends and optimize the economic aspects of a BESS [35]–[37]. As for any machine-learning approach, the size and quality of the dataset is of fundamental importance to achieve meaningful results and validate the generalization capability towards practical cases of study. Data concerning BESS and renewable energy communities on large scales can be difficult to obtain. For this reason, generative machine learning techniques [38]–[40] can be used to simulate an arbitrarily large REC featuring a variable number of prosumers, also including electric vehicles utilities [41] whose massive deployment is expected in the following years [42].

BESS CAPEX evaluation

Considering the cost of BESS is of fundamental importance when evaluating its optimal scheduling. In fact, through the evaluation of CAPEX (capital expenditure) and maximum number of cycles that the BESS could endure, it is possible to obtain a Levelized Cost of Storage (LCOS), that can be defined as the cost of use of the storage for each charged and discharged unit of energy. Several formulations of LCOS exists in literature [43], and several papers have been evaluated [44] in order to gather information on the expected lifetime of BESS [45] and on the calculation of the average costs related to BESS installation [44], [46], [47].

2.3.2 Renewable Energy Communities management using MILP techniques

Renewable Energy Communities (REC) [48], [49] are a growing and multifaceted phenomenon which involves one or more activities among production, supply, distribution, sharing and consumption of renewable energy. From a technical point of view, REC can be seen as proper or virtual microgrids, connected to the main grid and composed of controllable and non-controllable loads, renewable energy sources and, possibly, energy storages, among which Battery Energy Storage Systems (BESS) [50], [44]. In order to optimize REC assets usage a proper power and energy management system is of fundamental importance and thus is subject of significant ongoing research. Linear programming is often used for both offline and online scheduling and optimization of microgrid assets operation since the underlying economic functions can be expressed in many cases as linear functions of the decision variables [51].

Malysz et al. [52] proposed an optimal control method, based on a mixed-integer-linear-program (MILP) optimization, for the operation of a BESS in a grid-connected electrical microgrid, with the objective of minimizing operating costs and shape demand profile. BESS scheduling optimization using MILP techniques with the objective of increasing RES self-consumption is explored in [53], while the multi-objective optimization carried out by [54] had cost and emissions reductions as main goals. Collaborative approaches are also investigated, involving Demand Response management of residential loads and optimal scheduling of BESS [55], [56] with the objective of establishing P2P energy trading [57], [58].

Multi-time-scale models such as in [59] and [60] try to deal with load and generation forecast errors, adjusting in real time the day-ahead scheduling previously prepared.

Chapter 3 Application: Simplified Peer energy exchanges model to optimize the integration of Renewable Energy Sources

3.1 Introduction

This chapter proposes a simplified self-consumption optimization model for prosumers, which operates in real-time and pairs with a peer-to-peer model for sharing excess solar energy. The models are tested within a small Energy Community where the prosumer also possesses a Battery Energy Storage System (BESS). The results, in terms of technical, environmental, and financial benefits, demonstrate that peer-to-peer energy trading enhances the balance of energy production and usage in the local area. Scope of the activity is to develop a simplified BESS management methodology that operates without any forecast on near-future electricity generation and consumption. This sets a baseline for the evaluation of more complex scheduling methods for the operation of BESS and the management of RECs.
The model has been developed having in mind locally based RECs, where both prosumers and consumers are geographically close to each other and possibly connected to the same Low Voltage feeder and served by the same transformer. As an example, prosumers and consumers could be households located in the same neighborhood or even in the same building. The simultaneity of PV power generation and load requests, which is mandatory for the energy transaction to be completed, was granted in the project by the combined use of local smart-meters and centralized, blockchain-secured, database.

The work has been carried out as part of the activities of the Italian R&D project “E-Cube”. Scope of the project was to develop an innovative energy exchange system, which high-level system structure is reported in Figure 3-1, operating within a number of selected provider’s customers. Some of the main features of the prototypal system, are: 1) to increase customers observability and flexibility by providing them with Smart Meters and IoT devices for the remote and automated load control; 2) to develop optimal scheduling models for household appliances use, with

Demand Response purposes; 3) to promote the use of Electrical Vehicles as means of energy exchange within the customers and as distributed Battery Energy Storage Systems (BESS); 4) to develop and put into operation a blockchain-based "Energy Bank", used to securely track peer-to-peer energy exchange data within E-Cube participants.

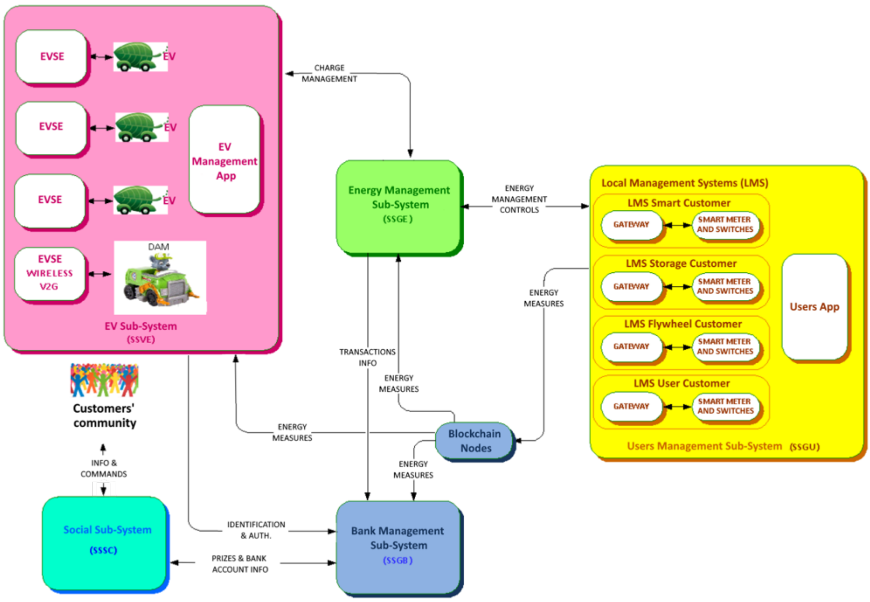


Figure 3-1: E-Cube System high-level structure (EVSE: Electric Vehicle Supply Equipment; V2G: Vehicle-to-Grid)

The first part of the paper describes the models and the algorithms regulating prosumer self-consumption optimization and the transaction strategies defined to appropriately share prosumer PV surplus energy, within the involved Energy Community, both directly and through the use of the BESS. The second part defines the specific set-up used for the simulation and evaluates the results, through a set of techno-economic and environmental indicators.

3.2 Model Description

The global structure of model processes and underlying algorithm is shown in Figure 3-2, where its six main parts are highlighted; in the following sub-sections, all of the main parts of the algorithm are explained in-depth. The model, for sake of simplicity, is applied to a single prosumer and to a plurality of consumers, but it can be easily extended to a REC with also a plurality of prosumers, simply stacking together the single contributions and creating a "Prosumer Aggregator". Beside that, the total energy transaction involving the Aggregator would then be proportionally shared between the prosumers.

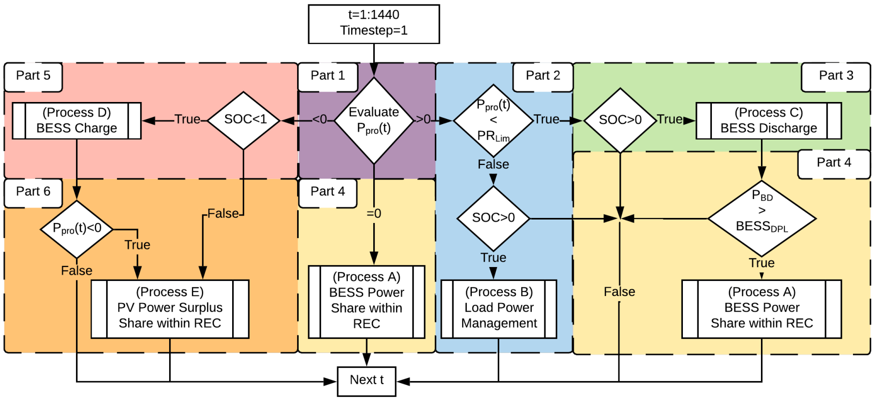


Figure 3-2:Model processes algorithm high-level structure

As a convention, within this model load power is considered positive and generation power negative. Following the same convention, BESS charging power $P_{BC}(t)$ is considered positive and discharging power $P_{BD}(t)$ negative; Charging (CPL) and Discharging Power Limits (DPL) are imposed by $BESS_{CPL}$ and $BESS_{DPL}$, respectively. BESS is considered a lossless storage system, with a unit round-trip yield, for the purpose of this simulation; moreover, its capacity $BESS_{size}$ is considered as net and fully usable. No explicit constraints are set on power exchanges of prosumer and consumers with the grid, both load- and PV-related. This choice is related to the existence of implicit constraints related to the contractual agreements already in place between consumers and grid operator or service providers, that shape and limit load and generation power curves.

All the power-related variables, such as loads power consumption, PV power generation, BESS charge and discharge power and power exchanges through the REC are related to a specific timestep. Energy related variables, such as BESS capacity and SOC are inherited from previous timestep at the beginning of each timestep and then updated accordingly to the power exchanges occurred.

Part 1: Prosumer characterization

The first part of the algorithm defines – for each timestep t – if the Prosumer is either a net power producer, a net load or is idle with respect to the grid. To do so, it solves (3.1), where $L(t)$ is the total load and $P_{PV}(t)$ is the total solar PV generation, both expressed in kW.

$$P_{pro}(t) = P_{PV}(t) + L(t) \quad (3.1)$$

Part 2: Prosumer Load Power Management

If $P_{pro}(t) > 0$, the prosumer is a net load for the grid; the Energy Management System (EMS) then checks if the contractual power limits Pr_{lim} are respected, by evaluating if $P_{pro}(t) < Pr_{lim}$.

If the Pr_{lim} threshold is surpassed and the BESS State of Charge (SOC) is higher than zero, the Prosumer Load Power Management process is activated, aiming at reducing prosumer's consumption under the threshold. Process B, as described in

Table 3.1, at first checks if $SOC(t) > 0.5$; if it's not, it allows only a limited discharge of BESS on the load with power $P_{BD}(t)$ – as described in (3.2) – just to reduce prosumer's power consumption and bring it back to below contractual power limit. Limiting BESS discharge power requests allows to preserve enough BESS capacity to cope with longer periods of threshold surpassing.

$$|P_{BD}(t)| = min\left((P_{pro}(t) - Pr_{lim}), |BESS_{DPL}|, |BESS_{DEL}(t)|\right) \quad (3.2)$$

where $BESS_{DEL}(t)$ represents BESS Discharge Energy Limit (DEL), which is the discharge power that brings BESS SOC to zero within the timestep, starting from the conditions in t-1:

$$BESS_{DEL}(t) = -(BESS_{size} * SOC(t-1) * 60) \quad (3.3)$$

If $SOC(t) > 0.5$, Process B enables at first Process C, which allows an unrestricted BESS discharge on prosumer's load $P_{pro}(t)$, as described in (3.4), with the purpose to bring consumption to zero. Then, if BESS has not yet reached its discharge power limit $BESS_{DPL}$ or its discharge energy limit $BESS_{DEL}(t)$, it enables Process A which defines BESS Power Share within REC.

$$|P_{BD}(t)| = min\left(P_{pro}(t), |BESS_{DPL}|, |BESS_{DEL}(t)|\right) \quad (3.4)$$

Once the Processes are completed, net Prosumer consumption is updated as described in (3.5) and BESS *SOC* is updated as described in (3.6):

$$P'_{pro}(t) = P_{pro}(t) + P_{BD}(t) \quad (3.5)$$

$$SOC(t) = SOC(t-1) + \frac{P_{BD}(t)}{60'} * \frac{1}{BESS_{size}} \quad (3.6)$$

Table 3.1: Prosumer Load Power Management Process

	Process B
	Prosumer Load Power Management
1	**If** $SOC(t) < 0.5$
	Then→BESS is used to reduce $P_{pro}(t)$ to below contractual power limit Pr_{lim} (2)
2	**else**
	Process C (BESS Discharge)
3	**If** $P_{BD}(t) > BESS_{DPL}$ AND $P_{BD}(t) > BESS_{DEL}$
	Then→Process A (BESS Power Share within REC)
4	**end If**
5	**end If**
6	Update all the involved variables

Part 3: BESS Discharge Management

In order for Process C to be activated, the prosumer must act as a net load for the grid; the EMS then evaluates the power to be exchanged by BESS with prosumer load, $P_{BD}(t)$, as described in (3.4). Then the discharge process is enabled, and Process C is completed as described in Table 3.2.

Table 3.2: BESS Discharge Process

	Process C
	BESS Discharge
1	Evaluate max exchangeable power and energy from BESS
	As described in (3) and (4)
2	**If** $P_{BD}(t) = P_{pro}(t)$
	Then→Set $P'_{pro}(t) = 0$
3	**else**
	Then→Set $\mathrm{P}'_{\mathrm{pro}}(\mathrm{t}) = P_{pro}(t) + \mathrm{P}_{\mathrm{BD}}(\mathrm{t})$
4	**end If**
5	Update all the involved variables

Part 4: BESS Power share within REC

Part 4 of the algorithm is enabled by two specific conditions:

1) when the prosumer is idle with respect to power exchanges with the grid and $SOC(t) > 0$

2) after Process C completion, if $P_{BD}(t) > BESS_{DPL}$.

As the first step, Process A (Table 3.3) evaluates the amount of Available Energy (AVE) and Power (AVP) to be shared within the consumers of the REC, respectively $BESS_{AVE}(t)$ and $BESS_{AVP}(t)$, as defined in (3.7).

$$\begin{cases} BESS_{AVE}(t) = -(BESS_{size} * SOC(t) * BESS_{Share}) \\ BESS_{AVP}(t) = BESS_{DPL} - P_{BD}(t) \end{cases} \tag{3.7}$$

$BESS_{Share}$ represents the percentage of BESS capacity made available at every timestep to be shared with REC. Taking into account all of the simulation parameters, $BESS_{Share}$ has been set to a 1% value. Successively, if energy and power from BESS are effectively available to share, power $P_{BS}(t)$, as defined in (3.8), is shared between the REC consumers, proportionally with the power absorbed from the grid by the loads of each one during timestep t.

$$P_{BS}(t) = \min\big(P_{AC}(t), BESS_{AVE}(t), BESS_{AVP}(t)\big) \tag{3.8}$$

$P_{AC}(t)$ represents the total load power of all REC consumers at timestep t. Once the Process is completed, BESS SOC is updated as described in (3.9).

$$SOC(t) = SOC(t-1) + \frac{P_{BS}(t)}{60\prime} * \frac{1}{BESS_{size}} \tag{3.9}$$

Table 3.3:BESS Power Share within REC Proces

Process A	
BESS Power Share within REC	
1	Define BESS available energy and Power for REC share
	As defined in (7)
2	**If** $BESS_{AVE}(t) > 0$ AND $BESS_{AVP}(t) > 0$
	Then→ Share $P_{BS}(t)$, as defined in (8), proportionally within REC Consumers
3	**end If**
4	Update all the involved variables

Part 5: BESS Charge Management

As reported in Fig.2, Process D is enabled when the prosumer acts as a net power producer, thus when $P_{pro}(t) < 0$, and when $SOC(t) < 1$. If both conditions are true, BESS is charged with power $P_{BC}(t)$, which is defined in (3.6) as:

$$P_{BC}(t) = \min\left(P_{pro}(t), BESS_{CPL}, BESS_{CEL}(t)\right) \tag{3.10}$$

Where $BESS_{CPL}$ is the power limit for BESS charging and $BESS_{CEL}(t)$ represents BESS Charge Energy Limit (CEL), which is the charge power that completely charge the BESS within the timestep starting from the conditions in t-1:

$$BESS_{CEL}(t) = \left(BESS_{size} * \left(1 - SOC(t-1)\right)\right) * 60 \tag{3.11}$$

Once the Process is completed, net Prosumer generation is updated as described in (3.12) and BESS SOC is updated as described in (3.13):

$$P'_{pro}(t) = P_{pro}(t) + P_{BC}(t) \tag{3.12}$$

$$SOC(t) = SOC(t-1) + \frac{P_{BC}(t)}{60'} * \frac{1}{BESS_{size}} \tag{3.13}$$

Table 3.4:BESS Charge Process

Process D	
BESS Charge	
1	Evaluate max BESS charging power and energy from PV
	As described in (8) and (9)
2	Charge BESS
3	Update all the involved variables

Part 6: PV Surplus Power share within REC

Part 6 of the algorithm, thus Process E, is enabled by two specific conditions:

1) when the prosumer is a net generator with respect to power exchanges and $SOC(t) = 1$, so BESS is not available to store PV surplus energy
2) after Process D completion, if $P'_{pro}(t) < 0$, thus PV surplus power is still available.

As with Process A, the first step of Process E evaluates the maximum amount of PV Surplus power $P_{PVS}(t)$ that can be shared within REC consumers, as defined in (3.14).

$$|P_{PVS}(t)| = \min\,(P_{AC}(t), |P'_{pro}(t)|\,) \tag{3.14}$$

Once $P_{PVS}(t)$ is defined, power is shared between the REC consumers, proportionally with the consumptions of each one during timestep *t*.

Finally, if according to (3.15) there is any PV power surplus left $P''_{pro}(t)$, that is considered as sold to the grid operator.

$$P''_{pro}(t) = P'_{pro}(t) - P_{PVS}(t) \tag{3.15}$$

Table 3.5: PV Power Surplus Share within REC Process

Process E	
PV Power Surplus Share within REC	
1	Evaluate $P_{PVS}(t)$, the maximum PV surplus power shareable within REC.
	As defined in (14)
2	Share $P_{PVS}(t)$ proportionally within REC Consumers.
3	If $P''_{pro}(t) < 0$
	Then→Sell to grid operator
4	end If

3.3 Case Study Definition and Simulation Results

The above-defined model has been used to simulate energy exchanges occurring within a small REC, composed by 1 prosumer and 3 consumers, which are all typical residential users, over a single day. For this case study, the prosumer is equipped with a PV generation unit rated for 3kW peak power, a BESS with 6 kWh of net capacity, capable of charging and discharging with a power of up to 3kW and with non-controllable loads. The consumers are only equipped with non-controllable loads; both consumers and prosumer are entitled of electricity contracts with service operator for a continuous maximum power of 3 kW.

Both the load profiles and the PV generation profiles used for the simulation are real datasets, acquired as an E-cube project activity; the simulation is run on both Matlab and Simulink environment and uses 12 days of consumption data for both consumers and prosumer and 6 days of PV generation data. The latter have been chosen among different periods of the year and different weather situation, in order to evaluate a comprehensive array of situation within the simulation. This leads to a total of 72 different days of data, among which the simulation runs recursively, over a 1-day period. In order to grant test repeatability, the BESS is set to be at $SOC = 0$ at the beginning of every period. BESS SOC could be higher than zero at the end of some simulation days; this is an effect of the combination of load requests, PV generation availability and, lastly, BESS size.

Within this simulation, two scenarios have been analysed: a “Baseline” scenario, where the optimization algorithm is applied only to the prosumer and a “REC” scenario, where the optimization algorithm is applied to the whole Energy Community. More precisely, in the Baseline scenario only Part 1,2,3 and 5 of the algorithm are implemented (see Figure 3-2 for reference); the BESS charges to recover PV surplus and discharges to supply load and eventual power contractual limits surpassing. Consumers power their loads using only grid electricity.

In REC scenario the algorithm is fully implemented, and both prosumer’s PV power surplus and BESS energy surplus are shared with the other consumers. Prices and actor of the various possible energy transactions are defined in Table 3.6:

Table 3.6: Description of Energy Transaction types

Transaction Type	***Price***	***Seller***	***Buyer***
Electricity Purchase from Grid	0.24 €/kWh	Service Provider	Prosumer Consumers
PV Net Metering Sale	0.08 €/kWh	Prosumer	Service Provider
PV Share within REC	0.16 €/kWh	Prosumer	Consumers
BESS Share within REC	0.16 €/kWh	Prosumer	Consumers

The prices of both PV Share and BESS Share within REC are defined as the average of purchase price of electricity from the Service Provider and PV Net Metering Sale Price to the Service Provider. Capital costs of PV and BESS installation are not considered in this simulation for sake of simplicity.

Key Performance Indicators Definition

In order to evaluate simulation results, a series of indicators has been defined. Some of them are defined as the variation ratio between Baseline and REC scenario and are identified by subscript “Var”; others are defined by the simple difference between the two scenarios, identified by the subscript “Diff”. Finally, some are defined by the value assumed in the REC scenario and are identified by the subscript “REC”.

Prosumer savings or earnings increase ratio between the scenarios is described by PS_{Var} in (3.9), while their net amount is described by PS_{Diff} in (3.10):

$$PS_{Var} = \frac{PS_{REC} - PS_{Base}}{PS_{Base}} \quad (3.16)$$

$$PS_{Diff} = PS_{REC} - PS_{Base} \quad (3..17)$$

The same way, consumers savings are defined byCS_{Var} and CS_{Diff}. Grid Dependency reduction ratio between scenarios is instead defined by GD_{Var}, while its value in the REC scenario is defined by GD_{REC}.

Self-Consumption efficiency is defined as the ratio between the reduction of energy purchase from the grid and the PV total energy generation. For the Baseline scenario the reduction of energy purchase from the grid is related only to the prosumer and it is defined as SCE_{Pro}, while for the REC scenario it is related to the whole REC and is defined as SCE_{REC}. Following these definitions, SCE_{Var} is described by (3.11) :

$$SCE_{Var} = \frac{SCE_{REC} - SCE_{Pro}}{SCE_{Pro}} \quad (3.18)$$

CO_2 savings related to the reduction of energy purchase from the grid are directly proportional to it; the 2013 CO_2 intensity of Italian Fuel Mix [61] for electricity production has been used for calculation, for a value of 343 gCO_{2eq}/kWh. The kWh of PV surplus energy non-allocated within the REC at the end of the day of simulation are reported by PVL_{REC}; finally, the kWh amount of PV-related energy shared within the REC is defined by SE_{REC}.

3.4 Results and Conclusions

The typical values assumed in Baseline scenario over a simulation day by the main prosumer variables, such as $SOC(t)$, Net PV power $P_{pro}(t)$, BESS charge and discharge power $P_{BC}(t)$ and $P_{BD}(t)$ and prosumer Net Load power $P_{pro}(t)$ are shown in the upper graph of Figure 3-3; in the lower graph the same variables are reported for the same simulation day but in the REC scenario. SOC reduction at the end of the day is evident, as well as the overall reduction of PV surplus power. This is one of the main results of the energy exchanges taking place within the REC and it directly leads to a raise in prosumer's earnings.

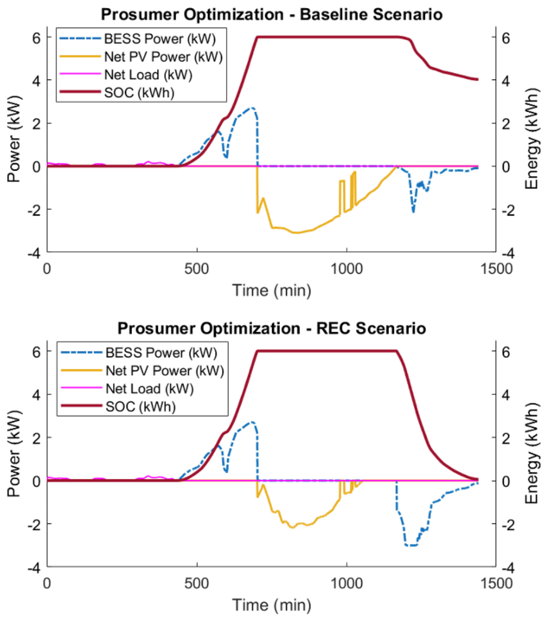


Figure 3-3:Prosumer main Power and Energy flows in the two considered scenarios over one single day

One side-effect related to the use of a part of BESS capacity for energy exchanges within the REC is a possible small increase in prosumer's energy purchase from the grid; anyway, as further shown in Fig. 5, the economic balance of prosumer improves when passing from Baseline to REC scenario. Figure 3-4 shows $SOC(t)$ and $\left(P_{pro}(t) - P_{PVS}(t)\right)$ trends over the all the 72 analysed 1-day periods, for both scenarios. It stands out clearly from the graphs that BESS end-of-the-day SOC is constantly reduced in the REC scenario when compared with Baseline; this confirms that the algorithm performs correctly throughout all the analysed situations. Looking at the graphs on the right side, it can be noted how PV power surplus left after optimization is thoroughly reduced in the REC scenario throughout all the periods.

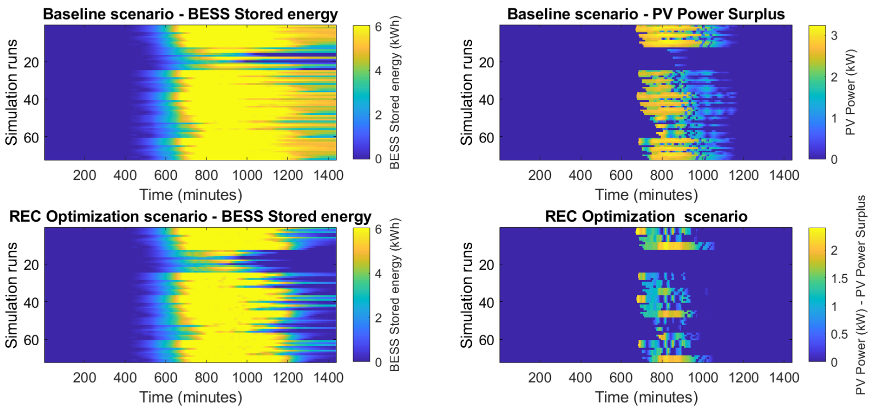


Figure 3-4: BESS SOC level and PV power surplus after REC share, over the various simulation days

Finally, an analysis of indicators' values, as shown in Figure 3-5, gives an overview on the improvements related to the implementation of the proposed REC model: first of all, the dependency on the grid for electricity is reduced, on average, by more than 40%, and CO_2 savings share is increased accordingly. In absolute terms this translates in an average of around 10 kWh/day of electricity that is shared within the Community. Moreover, self-consumption increases more than two-fold, on average, passing from the Baseline scenario in which only prosumer is involved in the optimization, to the REC scenario where also consumers are. This translates into more than 15 kWh/day self-consumed within the REC, of which around 10 kWh/day are shared – as already stated – and the rest is used by the prosumer.

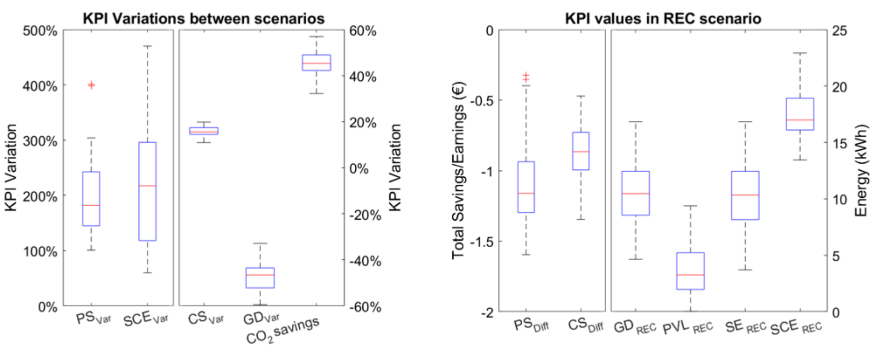


Figure 3-5: Boxplot showing median (red line), extremes data points (whiskers) and outliers (red crosses) of the main indicators analysed
(PS: Prosumer Savings; SCE: Self-Consumed Energy; CS: Consumers Savings; GD: Grid Dependancy; PVL: PV Lost; SE: Shared Energy)

The REC energy management and exchange optimization model presented in this chapter offers a simplified approach, that still allows to identify the main characteristics of typical REC energy flows. Even if the model functionality has been simulated, real load and PV production data has been used, spanning over a 72 days period. Simulation results show that the proposed model reduces grid dependency of the REC, thanks to the improved rates of PV self-consumption and local energy exchanges. Also, simulation shows that both prosumer and consumers improve their economic parameters: on average the first doubles its earnings while the latter save around 15-20%. As stated before, capital costs of prosumer's PV and BESS installation are not considered in this simulation, so the real prosumer's earnings have to be expected to be reduced by some extent.

Chapter 4 Application: MILP-based Optimal BESS Scheduling within Renewable Energy Communities

4.1 Introduction

This chapter proposes a methodology to optimize REC economic revenues and minimize the operation costs during the year; REC assets include PV generators, BESS and non-controllable loads, operating under the Italian legislative framework. The proposed BESS control strategy is composed by three different modules:

- a machine learning-based forecast algorithm that provides a 1-day-ahead projection for microgrid loads and PV generation, using historical dataset and weather forecasts;
- a Mixed Integer Linear Programming (MILP) algorithm that optimizes the BESS scheduling for minimal REC operating costs, taking into account electricity price, variable feed-in tariffs for PV generators, BESS costs and maximization of the self-consumption;
- a decision tree algorithm that works at the intra-hour level, with 1 min timestep and with real load and PV generation measurements adjusting the BESS scheduling in real time. Validation of the proposed strategy is performed on data acquired from a real small-scale REC set up within the E-CUBE project.

Case Study: Simulation of a 5-Households REC Based on Real Measurements

Here a small REC composed by five households is considered, modeled as a set of non-controllable loads, one rooftop PV system and a BESS; the BESS is considered to be a lithium-ion battery for stationary applications, used with a depth of discharge of 80%. The PV system and the BESS are modeled as a single, integrated system owned by one of the five households, that thus configures as a prosumer, while the other four are simple consumers. The BESS is constrained to be charged only by using energy produced by the PV system, while it can discharge on prosumer loads and on the grid. Discharging on the grid is allowed only when prosumer's loads are already covered, either by the PV system or by the BESS. Such constraints reflect the existing Italian regulatory framework, in force for the use of BESS in grid-connected applications [47], [62].

The data used to characterize the five residential loads and the PV system is derived from a proprietary dataset – inherited from E-CUBE project – composed by over 120 days of voltage, current, active and reactive power data, collected from several real loads and PV generators with a 1-min timestep. The revenues related to the sale of energy from PV generation are calculated using prices from the Italian day-ahead electrical market [63], corresponding to the same time period in which the load and generation dataset has been collected. Finally, BESS CAPEX costs have been calculated using data gathered from literature, using the model from [44] to obtain a total cost for BESS using both cell costs, proportional to BESS capacity (in kWh), and inverter costs, related to charging and discharging rated power (in kW). An additional constraint has been set on the inverter size, to match the maximum charge/discharge rates of the BESS. They have been set at $0.5 * SoC_{MAX}$, which is considered as a reasonable estimate for lithium-ion technology in stationary applications. A simplified value of the LCOS was calculated for each combination of BESS capacity and rated power used in the model, with the following equation:

$$LCOS = \frac{CAPEX_{BESS}}{2 * cycle * SoC_{MAX}} \tag{4.1}$$

The LCOS value is used in the mixed integer linear programming to optimize the BESS scheduling, by adding an estimation of the BESS usage cost to the energy arbitrage operations. Finally, a plausible sharing ratio between prosumer and consumers (as a whole) for the incentives related to PV energy exchanged within the REC was defined and set at 55% and 45%, respectively. Table 4.1 below summarizes all the previously described information.

Table 4.1:Main simulation parameters.

Property	Value of Function	Ref
REC load peak power	13.5 kW	
Single household load peak power	2.9 ÷ 4.5 kW	Database
PV gen. peak power	4.6 kW	
BESS net capacity	1 ÷ 10 kWh	Own assumption
BESS rated power	0.5 ÷ 5 kW	
BESS lifetime cycles	3000	[44]
BESS CAPEX	400 ÷ 3700 €	[44]
BESS LCOS	0.013 ÷ 0.025 €/kWh	Calculated
PV energy value (Day-ahead IT Market)	0.05 ÷ 0.11 €/kWh	[62]
Electricity cost for residential consumers	0.20 €/kWh	[63]
Subsidy on RES electricity shared in REC	0.06 €/kWh (prosumer)	[8], Own assumption
Subsidy on RES electricity shared in REC	0.05 €/kWh (all consumers)	

4.2 Methodology for the Optimal BESS Scheduling Process

The optimal BESS scheduling process described in this chapter focuses on maximizing the overall revenues of the REC, considering the hourly values of PV energy on the day-ahead market and the possibility to share energy within the community in order to take advantage of the existing incentives, also leveraging on the use of BESS. The methodology is composed by three successive steps, briefly listed below and then described in full detail in the remaining part of this section:

- Definition of 24-h ahead forecast of the hourly trends for PV produced power, prosumer load profile, and aggregated power demand from the rest of the REC. The forecast is obtained with a layer-recurrent neural network, using as inputs the 48 past hourly samples of the quantity to forecast, and the weather forecast for the coming 24 h.
- Optimization of the BESS scheduling within the previously defined REC. The optimization is carried out for the upcoming 24 h with a Mixed Integer Linear Programming (MILP)

approach, using as inputs the 24-h ahead forecasts as obtained in Step 1, together with information on PV energy sale price, cost of electricity, LCOS and specific values of BESS characteristics (capacity and rated power). The optimization is obtained by maximizing a revenue function, and the output is the BESS scheduling for the following 24 h in terms of power exchanges with both the PV system, the REC and the grid, with a 1-h timestep.

- Real-time BESS management across the 24 h forecasted in Step 1 and 2. The 24-h ahead BESS schedule obtained with the MILP-based, forecast-based optimization is used as a baseline for a real-time BESS management, using real PV production and load curves, with 1-min timestep resolution. A decision-tree algorithm is used to manage BESS charge and discharge phases, with the objective to reach the set points scheduled by the MILP optimization and coping with forecast errors. The final BESS SOC obtained as output from this step is then fed to Step 2 as the initial BESS SOC for the next 24-h ahead optimization process.

4.2.1 Dataset enrichment through implementation of 24-h Ahead Forecasts

Forecasting of the day-ahead quantities relevant for the BESS management is performed through a neural-network based forecasting model. The desired goal is to obtain a reasonably accurate prediction of the hourly trends for PV produced power, prosumer load profile, and aggregated power demand from the rest of the REC. Determination of these quantities can be seen as a classic time-series forecasting problem, for which several considerations must be done to lay out the individual instruments for predicting data.

First, a trend-seasonality-residual (TSR) test must be performed on data, to determine if it exhibit some type of periodic behavior. This analysis is, by itself, a very simple approach to create a forecast (if the assumption that the time series are stationary holds), but can fail for very complex phenomena, resulting in large residuals. However, determining the seasonality period is important to understand the length of the input sequence to be used in any machine-learning based approach.

Second, the exogenous data to be used in the time series must be determined. Very interesting results in the literature correlate energy production to several environmental quantities. Indeed, the most important one is instantaneous normal irradiance on the PV devices. However, considering this quantity would be unfair due to the difficulty of measurement/prediction and the almost unit correlation with power production. Instead, classic weather forecast quantities were used. These quantities exhibit a good correlation with power consumption as well, due to the heavy presence of HVAC loads which responds to environmental changes.

Third and last, the machine-learning architecture must be determined. This step involves the choice of the kind of algorithm/model to use, which, in this work, is a layer-recurrent neural network. This architecture features both a strongly non-linear and dynamic response capability with the inherent advantages related to the training algorithms used in neural networks which can be generalized easily in case of non-uniformly time-spaced data.

Once the forecasting model is determined and trained it is used to create forecasted time-series of the same length (through initial padding) of the original data. The resulting data frame features columns of the real, measured quantities aligned with the 24-h prior forecasts of the same quantities.

Trend-Seasonality-Residual Test

A test based on a TSR decomposition is at the base of any autoregressive integrated moving average (ARIMA) model. Time-series forecasting by the means of a neural network can be seen as a non-linear extension (with exogenous inputs) of an ARIMA forecasting. With TSR decomposition, data is split in three time-series with the same length of the original dataset. The only parameter used for the test is the seasonality window. The first component is the trend, which is obtained by using a moving-average filter on the data with window length equal to the seasonality window, and by applying suitable padding on the edges of the vectors to maintain the same length after convolution. The second is the seasonality itself, which is obtained by dividing the de-trended data in time-windows of length equal to the seasonality window and taking the sample-wise average of every window. The resulting average is then repeated to create a vector of the same length of the original data vector. The last is the residual, which is obtained by the difference between the original data and the product between the trend vector and the seasonality vector. An example of the TSR decomposition with a seasonality window size of 24 h is shown in Figure 4-1. The purpose of applying the TSR decomposition to each component of the dataset is to understand the best sequence-length to be used in the forecasting. Decomposing the series with a too-short seasonality window places the burden of reconstructing the time series on the trend (up to a point where the seasonality is, in general, a constant value). Decomposing the series with a too-long seasonality window raises the residual, leading to seasonality vectors with very little informative content.

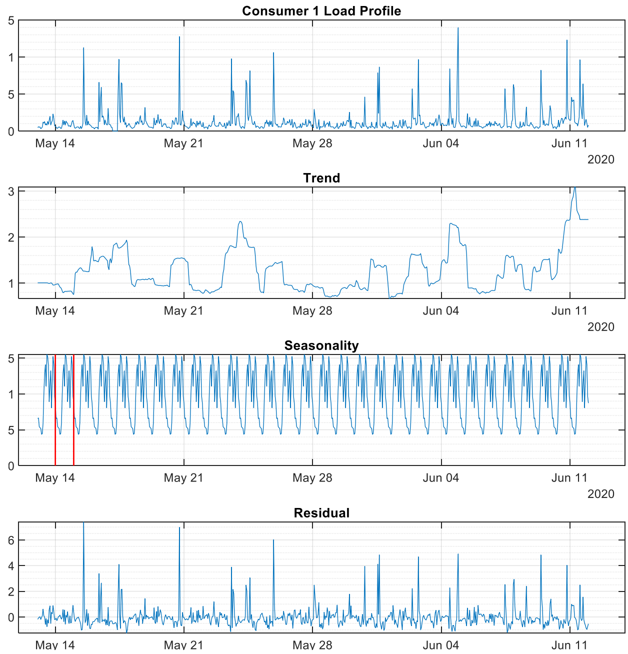


Figure 4-1: Example of the TSR decomposition on a section of the dataset, 30 days of the Consumer 1 Load Profile decomposed in Trend, Seasonality and Residual.

A sweet spot for the dataset is found at multiples of 24 and 48 h, as shown in Figure 4-2. This is expected both due to the natural periodicity of the produced power from the PV devices, and to the anthropic nature of the load profiles.

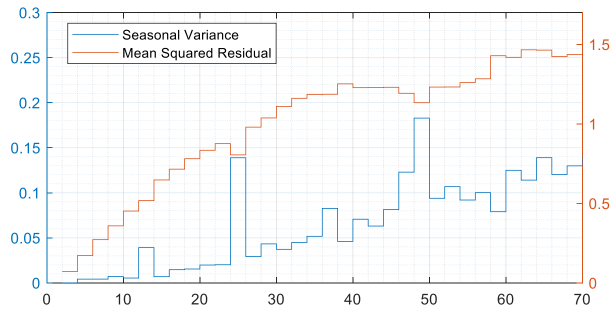


Figure 4-2: Seasonal Variance and Mean Squared Residual for different seasonality windows length. Two optimal values where both the variance is high, and the residual is low can be found for 24 h and 48 h.

Exogenous Data Selection

At the input of the forecasting model, alongside with the past values of the time series to be predicted, a set of exogenous independent data is added to help the forecasting procedure. This data is weather based and is a forecast directly acquired from the OpenWeather Map database. The full dataset includes the 1-day ahead forecast for temperature, pressure, absolute humidity, wind speed, wind direction and cloudiness percentage. In general, all the weather data could be added as exogenous input to the model, relying on the training algorithm to prune the non-useful data. A different approach consists in observing the correlation between the time series and the data to be forecasted. An example is shown in Figure 4-3 for the forecasting of the produced PV power. As can be seen, the produced PV power has a good linear correlation with both temperature and humidity, and unexpectedly, a very low correlation with the cloudiness index. This is probably due to the more local nature of the interaction between cloud shading and PV devices, making the effective correlation between a regional cloudiness forecast with the produced PV power low. Using as exogenous inputs weather data with low significance has the effect of inducing a noise source in the system that needs to be filtered by the training algorithm itself, leading to slower convergence and possibly local minima entrapment. For this reason, only the values of temperature and humidity are considered as exogenous inputs.

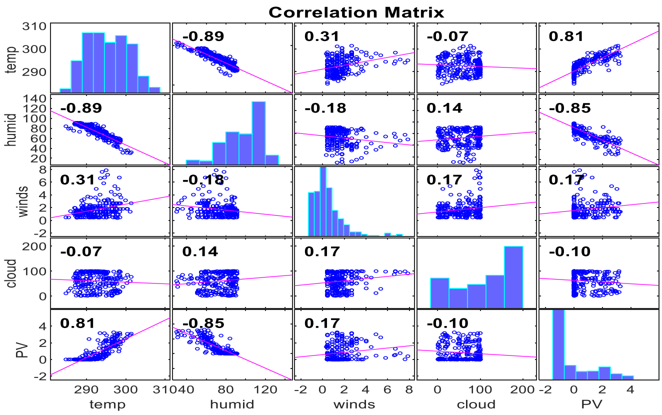


Figure 4-3: Example of the correlation matrix between the weather environmental variables and the produced PV power. Diagonal elements show the histogram of the variables, off-diagonal elements show the scatter plot between the variables.

Neural Architecture Determination

Considerations up to this point determined the optimal window length for past occurrences of the time series to be forecasted and the correlation of the future values with the exogenous weather data. This information can be used to create a very wide range of models for forecasting, including both static, dynamic, linear and non-linear. For the purpose of this work, a dynamic neural model is used. The neural architecture chosen is a layer-recurrent neural network. This architecture, shown in Figure 4-4, is derived from a feed-forward neural network by adding a delay-tapped feedback loop from the output of each hidden neuron to the input of the layer itself. This allows the network to exhibit a non-linear dynamic behavior, making it a prime candidate to represent systems with non-linear state-space equations. The full input of the neural network is composed by the 48 past hourly samples of the quantity to forecast, and the weather forecast for the next 24 h of temperature and humidity, for a total of 48 + 24 + 24 = 96 inputs. The outputs of the network are the 24 h prediction (thus a sequence-to-sequence forecasting paradigm) of the desired variable.

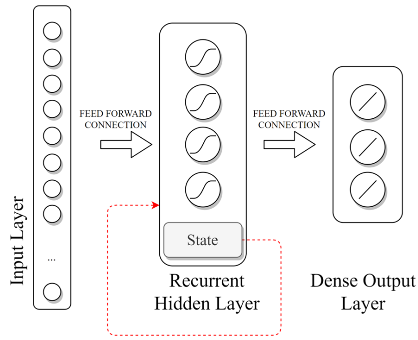


Figure 4-4: Layer diagram for a layer-recurrent neural network with a single hidden recurrent layer with neurons featuring non-linear activation function.

4.2.2 Mixed Integer Linear Programming-Based Economical Optimization of BESS Scheduling

MILP is used to solve constrained optimization problems which contains an objective function, a set of variables, of which some are not discrete and a set of constraints, that can be equations and inequalities. The scope of the optimization is to find the best solution for the objective function within the set of solutions that satisfy all the constraints. The mathematical formulation of a MILP problem is expressed as follows:

$$\begin{aligned} &\text{Objective: } maximize = Cx \\ &\text{Constraints: } A * x \leq b \\ &\qquad\qquad x_{min} \leq x \leq x_{max} \end{aligned} \tag{4.2}$$

where $x \in \mathbb{Z}^n$ C, b are vectors and A is a matrix.

Table 4.2 below summarizes the nomenclature used in this section:

Table 4.2: Nomenclature

$LCOS$	Levelized Cost of Storage (€/kWh)
$CAPEX_{BESS}$	Capital Expenditure for BESS (€)
$cycle$	Lifetime charge/discharge cycles
SoC_{MAX}	BESS Max capacity (kWh)
$P_{BESS}^{Ch,MAX}$	BESS max. charge power (kW)
$P_{BESS}^{Dis,MAX}$	BESS max. discharge power (kW)
P_{PR}^{LOAD}	Prosumer load (kW)
P_{PR}^{PV}	Photovoltaic generation (kW)
P^{NL}	Prosumer Net Load (kW)
P^{NG}	Prosumer Net Generation (kW)
P_{REC}^{LOAD}	Aggregate REC consumers load (kW)
P_{i}^{LOAD}	i-th REC consumers load (kW)
P_{GRID}	Total power virtually exchanged with grid (kW)
P_{REC}^{NG}	Net Generation power on REC load (kW)
P_{BESS}^{CH}	Total BESS charging power (kW)
$P_{BESS}^{Ch,GR}$	BESS charge from grid (kW)
$P_{BESS}^{Ch,REC}$	BESS charge when REC load is present (kW)
P_{BESS}^{DIS}	Total BESS discharging power (kW)
$P_{BESS}^{Dis,GR}$	BESS discharge on grid (kW)
$P_{BESS}^{Dis,REC}$	BESS discharge on REC load (kW)
$P_{BESS}^{Dis,NL}$	BESS discharge on prosumer net load (kW)
E_{BESS}	BESS State of Charge (kWh)
α_{GR}, α_{REC}	Multiplying coefficient for BESS charging
β_{GR}, β_{REC}, β_{NL}	Multiplying coefficient for BESS discharging
Pr_{INC}	Incentive value (€)
Pr_{ELEC}	Electricity price for residential customer (€/kWh)
Pr_{DAM}	Electricity price on DAM (€/kWh)
REV_{REC}	Total daily REC revenues (€)
$Incomes$	REC hourly incomes (€)
$Costs$	REC hourly costs (€)
NPV	Net Present Value (€)
DR	Discount Rate (%)

The objective function is formulated to maximize the REC revenues REV_{REC} within the considered 24-h ahead timeframe. These revenues are obtained as the difference between incomes and costs. Costs are related to the use of BESS and are defined by LCOS; incomes are related to the sale of PV net surplus to the grid, to the incentive related to the energy exchanges within the REC and finally to the avoided purchase of electricity from the grid by the prosumer. The daily revenue is formulated as follows:

$$REV_{REC}(day) = \sum_{h=1}^{24} Incomes(h) - Costs\,(h) \tag{4.3}$$

$$\begin{aligned} Incomes(h) = {} & (P_{GR}^{NG}(h) + P_{BESS}^{Dis,GR}(h)) * Pr_{DAM}(h) \\ & + (P_{REC}^{NG}(h) + P_{BESS}^{Dis,REC}(h)) * (Pr_{DAM}(h) \\ & + Pr_{INC}(h)) \; + P_{BESS}^{Dis,NL}(h) * Pr_{ELEC}(h) \end{aligned} \tag{4.4}$$

$$\begin{aligned} Costs(h) = {} & LCOS * (P_{BESS}^{Ch,GR}(h) + P_{BESS}^{Ch,REC}(h) \\ & + P_{BESS}^{Dis,NL}(h) + P_{BESS}^{Dis,GR}(h) \\ & + P_{BESS}^{Dis,REC}(h)) \end{aligned} \tag{4.5}$$

All the REC members are connected and exchange electrical energy with the main grid, thus the power balance is always obtained considering grid contribution, as described by (4.6).

$$(P_{PR}^{LOAD}(h) - P_{PR}^{PV}(h)) + (\alpha(h) * P_{BESS}^{CH}(h) - \beta(h) * P_{BESS}^{DIS}(h)) + P_{REC}^{LOAD}(h) = P_{GRID}(h) \tag{4.6}$$

The variable P_{REC}^{LOAD} represents the total load request from all the community members:

$$P_{REC}^{LOAD}(h) = \sum_{i=1}^{M} P_{i}^{LOAD}\,(h) \tag{4.7}$$

To model the fact that the BESS cannot be simultaneously charged and discharged, the variables $\alpha(t)$ and $\beta(t)$ describe for each time *h* the behavior. The variables are binary (1 or 0) and cannot be both 1 at the same time.

The prosumer is seen by the main grid as either a net load or a net generator, depending on the time, as described in (4.8). The BESS is enabled to charge only when the prosumer is a net generator; no constraints on the discharge are set, thus it can discharge both on the prosumer load and on the grid.

$$\begin{cases} P^{NL}(h) = P_{PR}^{LOAD}(h) - P_{PR}^{PV}(h)\ if\ P_{PR}^{LOAD}(h) > P_{PR}^{PV}(h) \\ P^{NG}(h) = P_{PR}^{PV}(h) - P_{PR}^{LOAD}(h)\ if\ P_{PR}^{PV}(h) > P_{PR}^{LOAD}(h) \end{cases} \quad (4.8)$$

The constraints related to BESS operation are formulated as follows:

$$0 \leq P_{BESS}^{Ch,GR}(h) \leq \alpha_{GR}(h) * \min\Big(\max\Big((P^{NG}(h) -$$

$$0 \leq P_{BESS}^{Ch,GR}(h) \leq \alpha_{GR}(h) * \min\Big(\max\Big((P^{NG}(h) - P_{REC}^{LOAD}(h)\Big), 0\Big), P_{BESS}^{Ch,MAX}) \quad (4.9)$$

$$0 \leq P_{BESS}^{Ch,REC}(h) \leq \alpha_{REC}(h) * \min\big(P^{NG}(h), P_{REC}^{LOAD}(h), P_{BESS}^{Ch,MAX}\big) \quad (4.10)$$

$$0 \leq P_{BESS}^{Dis,GR}(h) \leq \beta_{GR}(h) * P_{BESS}^{Dis,MAX} \quad (4.11)$$

$$0 \leq P_{BESS}^{Dis,REC}(h) \leq \beta_{REC}(h) * \min\Big(\max\Big((P_{REC}^{LOAD}(h) - P^{NG}(h)\Big), 0\Big), P_{BESS}^{Dis,MAX}) \quad (4.12)$$

$$0 \leq P_{BESS}^{Dis,NL}(h) \leq \beta_{NL}(h) * \min\big(P^{NL}(h), P_{BESS}^{Dis,MAX}\big) \quad (4.13)$$

where, respectively, ((4.10)) and ((4.9)) define the power limits to charge the BESS when either load from REC is present or not. From the optimization point of view, it is important to distinguish between these two situations, because the part of PV surplus energy $P^{NG}(t)$ that is used to charge the BESS cannot be exchanged with the REC or sold to the grid; thus, it is important to allow the MILP to correctly choose the optimal timing by differentiating the various possible situations in order to correctly address the corresponding revenue streams. Equations (4.12) and (4.13) instead define the power limits to discharge the BESS on the grid when either load from REC is available or not. In this case, the differentiation is needed to correctly address the revenue streams as well. All these equations are to be used in Equations (4.7)-(4.9) to define if the energy is shared among the REC or not, and thus if it is entitled for the payment of the incentive or not, in top of the day-ahead market price. Finally, Equation (4.14) defines the power limits for BESS discharge on prosumer's net load. All the non-zero constraints in (4.9)-(4.13) have a multiplying coefficient in the form of $\alpha_k(t)$ or $\beta_k(t)$. As previously stated, the value of these coefficients can be either 0 or 1 but not both 1 at the same time, and are used to avoid simultaneous charging and discharging of the BESS during the optimization process.

The other constraints set on BESS behavior concern its state of charge (SoC): the maximum and minimum SoC limits are defined in the following (4.14), while the variation of BESS SoC as a function of power exchanges is defined in (4.15).

$$0 \leq E_{BESS}(h) \leq SoC_{MAX}(h)$$
$$0 \leq E_{BESS}(h) \leq SoC_{MAX}(h) \quad (4.14)$$

$$E_{BESS}(h) = E_{BESS}(h-1) + (P_{BESS}^{Ch,GR}(h) + P_{BESS}^{Ch,REC}(h) - P_{BESS}^{Dis,NL}(h) - P_{BESS}^{Dis,GR}(h) - P_{BESS}^{Dis,REC}(h)) \quad (4.15)$$

The last two constraints set for MILP optimization are described by (4.16) and (4.17), regarding the PV net surplus from prosumer. They are represented by $P_{REC}^{NG}(t)$ and $P_{GR}^{NG}(t)$, that respectively describe the power virtually exchanged with the REC and the power simply sold to the grid.

$$P_{REC}^{NG}(h) = \max\left((P_{GR}^{NG}(h) - P_{REC}^{LOAD}(h)\right), 0) - P_{BESS}^{Ch,GR}(h) -$$
$$P_{REC}^{NG}(h) = \max\left((P_{GR}^{NG}(h) - P_{REC}^{LOAD}(h)\right), 0) - P_{BESS}^{Ch,GR}(h) - P_{BESS}^{Ch,REC}(h) \quad (4.16)$$

$$P_{GR}^{NG}(h) = P^{NG}(h) - P_{REC}^{NG}(h) \quad (4.17)$$

4.2.3 Real-Time BESS Management

The real-time BESS management algorithm is defined to reach the set-points defined by the MILP optimization for each of the following 24 h, while managing the forecast errors related to PV power generation and prosumer and REC aggregated load curves.

The set-points refer to the average power exchanges, during the hour *h,* between the BESS and the NL (discharge, $P'^{Dis,NL}_{BESS}(h)$), the BESS and the REC (discharge, $P_{BESS}^{Dis,REC}(h)$ and charge, $P_{BESS}^{Ch,REC}(h)$) and the BESS and the Grid (discharge, $P_{BESS}^{Dis,GR}(h)$ and charge, $P'^{Ch,GR}_{BESS}(h)$).

By following the charging and discharging set-points as suggested by the MILP, we ensure that the BESS scheduling takes into account parameters such as price of energy and forecast on the expected availability and need for energy. This task is performed by a decision tree algorithm, operated with a 1-m timestep *t*, the same of the dataset used.

This higher data resolution allows to get a view on the effect on BESS management system of much less smoothed load and power curves, when compared to 1-h averages of the same data. Using this approach, short and intense power peaks are present and the transition zones between prosumer net generation and net load are much less defined.

After each step *t* all the differences between real power exchanges and the expected ones, as defined by the set-points, are updated. The power exchanges continue until such differences are completely compensated, or the 1-h block *h* ends. In the latter case, the set-points are updated to the new values related to hour *(h+1)* and the process starts again.

As a consequence of using forecasted data for the MILP-based optimization and real data for the here described real-time BESS management, it is possible that the algorithm couldn't manage to reach the expected set point. The flowchart in Figure 4-5 below describes the main algorithm steps, while the sub-algorithms triggered by the various set points are described in the followings.

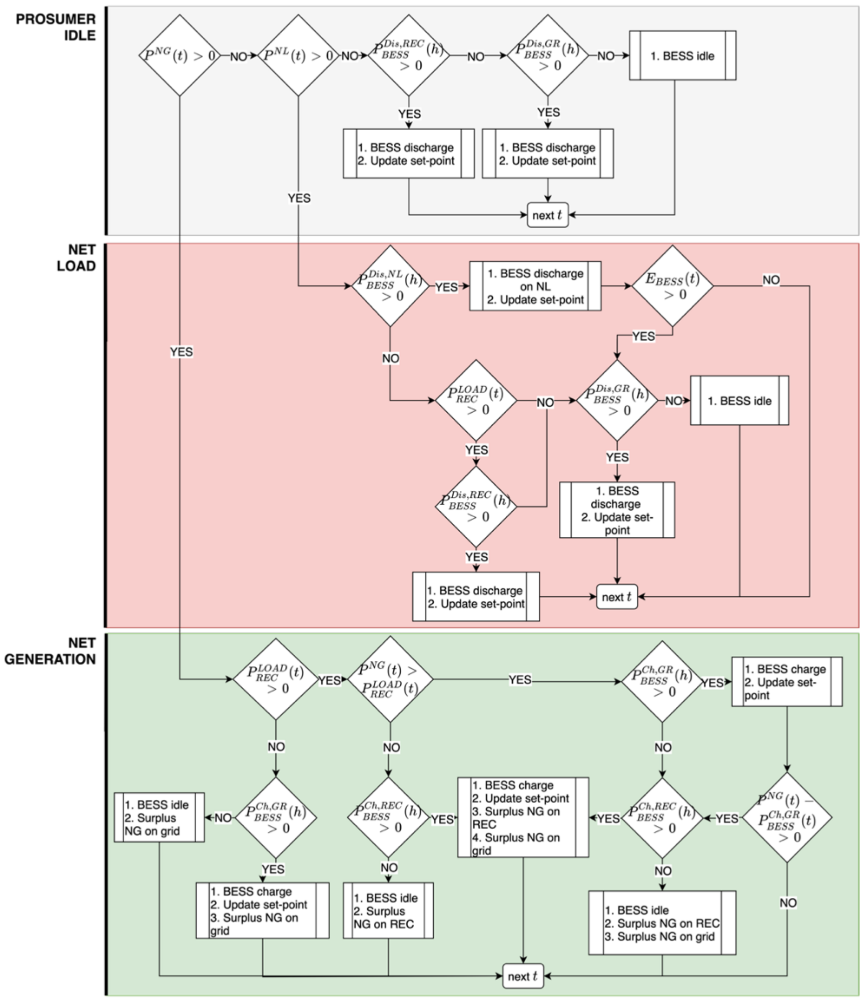


Figure 4-5: Decision tree algorithm flowchart.

BESS power exchanges are always limited by a set of parameters: some inherently technical such as the state of charge $E_{BESS}(t)$ and the rated power $P_{BESS}^{Dis,MAX}$ and $P_{BESS}^{Ch,MAX}$, others related to the availability of surplus energy from PV system $P^{NG}(t)$ or to the availability of loads on which to discharge such as $P^{NL}(t)$ and $P_{REC}^{LOAD}(t)$ and finally of course by the set points previously described. Once that the power exchange involving the BESS in the step *t* is defined, the SoC is updated. If the prosumer acts as a net generator, thus $P^{NG}(t) > 0$, the algorithm evaluates if there is still available power beside the part used to charge the BESS; if so, it is accounted as energy shared within the REC up to the limit defined by the underlying $P_{REC}^{LOAD}(t)$, and the exceeding part $P_{GRID}^{NG}(t)$ is considered as sold to the grid. The following equations explain in details the above-described procedure for the case in which $P^{NG}(t) > 0$, the set-point $P_{BESS}^{Ch,REC}(h) > 0$, and $P_{REC}^{LOAD}(t) > 0$: in this case the BESS is managed to charge, as described by (4.18), and the SoC is updated accordingly to (4.21). The power exchanges within the REC and with the grid are respectively described by (4.18) and (4.19).

$$P_{BESS}^{Ch,REC}(t) = \min\big((SoC_{MAX} - E_{BESS}(t-1)) * 60, (P^{NG}(t) - P_{REC}^{LOAD}(t)), P_{BESS}^{Ch,MAX}, P_{CER}^{TGT,Ch}(h)\big) \quad (4.18)$$

$$P_{REC}^{NG}(t) = \min\left(\left(P^{NG}(t) - P_{BESS}^{Ch,REC}(t)\right), P_{REC}^{LOAD}(t)\right) \quad (4.19)$$

$$P_{GRID}^{NG}(t) = \min\left(\left(P^{NG}(t) - P_{BESS}^{Ch,REC}(t) - P_{REC}^{NG}(t)\right), 0\right) \quad (4.20)$$

$$E_{BESS}(t) = E_{BESS}(t-1) + \frac{P_{BESS}^{Ch,REC}(t)}{60} \quad (4.21)$$

The other cases, described in Figure 4-5, are managed similarly, and not described here for sake of brevity.

4.2.4 Macro-Scenarios description

Two different scenarios have been evaluated in this work to better understand the impact of BESS use on REC revenues:

- Baseline: in this scenario, the REC is composed by only PV generator and loads, and no management is applied. This represents the minimal set-up for REC operation.
- BESS, MILP: all the previously explained three-steps methodology is applied in this scenario, the load and generation forecasts, the MILP optimization and the real-time BESS management.

In order to take into account the possible REC configuration that could be found in a real life set-up, five different REC have been evaluated, by the permutation of the prosumer within the set of residential loads available; all these permutations were applied to the 120-day loads and generation database as well as to the related forecasts. Ten values of BESS capacity and ten rated BESS power were evaluated in all the BESS-based scenarios, to get perspective on their impact on REC operations and revenues, as described in Table 4.1. Revenues were calculated using the following NPV formula, using a discount rate (DR) of 5% and a 20-year lifetime:

$$NPV = -CAPEX + \sum_{i=1}^{20} \frac{\left(revenues_i^{MILP,BESS} - revenues_i^{BASELINE}\right) - costs_i}{(1+DR)^i} \quad (4.22)$$

It can be noticed that the NPV calculation refers only to the part of the revenues enabled by the deployment of the BESS; such revenues are conventionally attributed to the prosumer since in this work it is considered as the BESS owner.

Whenever the cumulative use of BESS reached the maximum lifecycle capacity as defined by (4.23), it has been considered the deployment of a new one, and the costs related to BESS CAPEX were accounted to the specific year in the overall cash flow.

$$BESS_{capacity}^{MAX} = 2 * cycle * SoC_{MAX} \quad (4.23)$$

4.3 Results

4.3.1 Optimal Neural Network Hyperparameters Sizing and Forecasting Accuracy

The experimental dataset features three variables to be determined: the produced PV power, the self-consumed power from the prosumer, and the aggregated consumed power from the REC.

Although both seasonality and exogenous data considerations applies to either of these cases, the optimal sizing of the neural network hyperparameters is slightly different. For this reason, three different neural networks were created, sized and trained for the different purpose of predicting produced PV power, individual self-consumed power and aggregated consumed power. Through a heuristic approach, already used with success in different other works, the optimal sizing for hidden layer number of neurons and number of delay-taps is shown in Table 4.3.

	Hidden Layer Size	Delay-Taps
PV Production	3	1
Consumed Power	9	2
REC Consumed Power	5	1

Table 4.3: Optimal hyperparameters for the three Layer-Recurrent Neural Networks.

Since no prior constraint is given on the role of consumer or prosumer, the problem of forecasting can be formulated considering either of the five households as prosumer and the remaining four as the components of the REC. Thus, the number of time-series to be forecasted is a total of 11:

- 1 PV power production
- 5 Consumed Power from the individual households
- 5 REC Consumed Power from the remaining households

The performance of forecasting varies, especially considering that some households show profiles with a much less regular behavior if compared to the others. In scenarios where these irregular households are the prosumers, forecasting is difficult. However, when the irregular households belong to the REC, forecasting the cumulative power is easier and achieves better performance. An extract of about 8 days showing the comparison between real quantities (black) and forecast quantities (red) is shown in Figure 4-6.

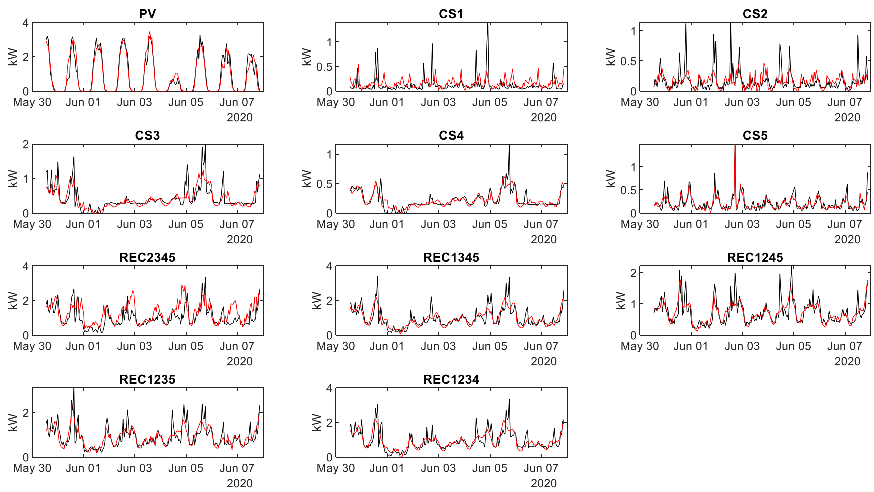


Figure 4-6: Extract of the enriched dataset showing forecasts for the PV produced power, the individual consumed power and the REC consumed power with different compositions.

The mean error related to the forecasted quantities has been calculated using the Mean Absolute Percentage Error (MAPE) formulation:

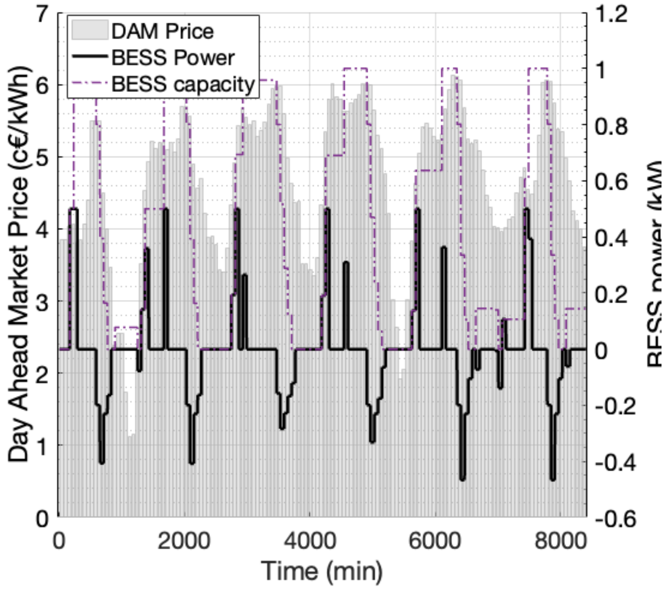
$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{P_{FORE}(t) - P_{REAL}(t)}{P_{REAL}(t)} \right|}{n} \quad (4.24)$$

On average, across the 120 days of dataset and for the various consumers and REC compositions, the obtained values are:

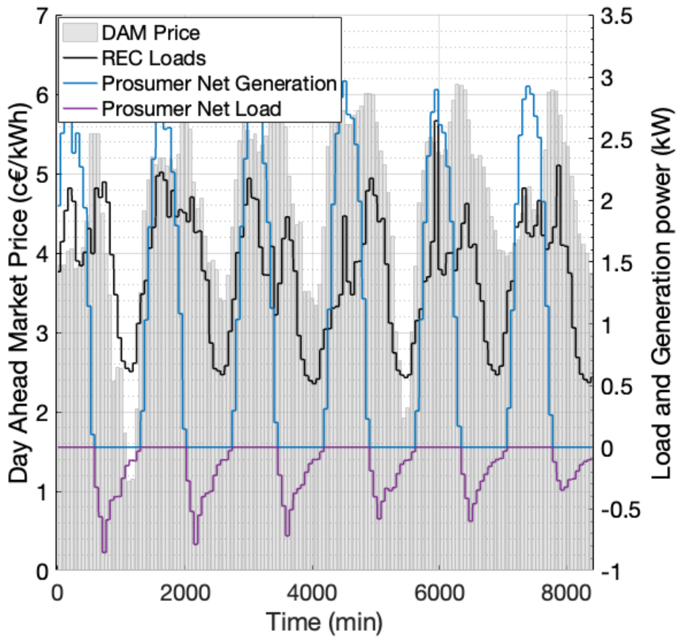
- Single household load MAPE: 19.9–34.3%
- REC composed by the remaining households MAPE: 26.1–29.7%
- PV power production MAPE: 8.2%

MILP Optimal Scheduling

Simulations are performed under a variety of conditions, using the forecasted data for loads and PV generation to test the optimal BESS scheduling capability. BESS is charged using PV surplus energy, that otherwise would have been discharged on the grid, possibly accounted as shared energy within REC if loads from other REC members are actives at the same time. In order to maximize REC revenue, BESS has to be charged when energy price is low on DAM and possibly when no loads from other REC members are active, in order not to lose the relative incentive; BESS has to be discharged in an opposite situation, when electricity price is high on DAM and other REC members' loads are present, in order to get the additional incentive. Moreover, BESS can be discharged on prosumer net load; in this case the revenue is the avoided cost for electricity purchase. In the specific situation investigated in this work, the revenue related to the avoided electricity purchase is the highest one, followed by the one related to the energy shared within the REC. The least remunerative solution sees the PV surplus energy sold to the grid without being accounted as shared energy within the REC. Figure 4-7 below shows 6 days of MILP output: on the left BESS total power exchanges are reported in black and the corresponding BESS SoC in purple, while the DAM price values are reported as gray bars. It is to be noticed that the algorithm most of the times schedules the BESS to charge in low-price periods and also schedules it to discharge either on prosumer net load or in high-price periods, as should be expected. On the right, instead, the REC loads curve is shown together with the prosumer's net load and net generation curves, across the same 6 days. These are the main inputs, together with the various electricity prices, incentives and LCOS, that are used by the MILP to optimize the BESS scheduling with the objective of REC revenues maximization.



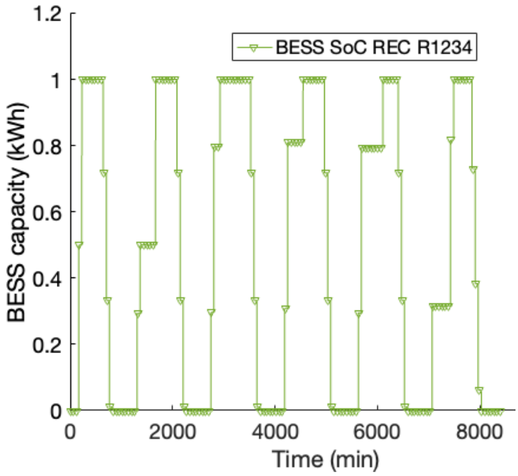
(a)



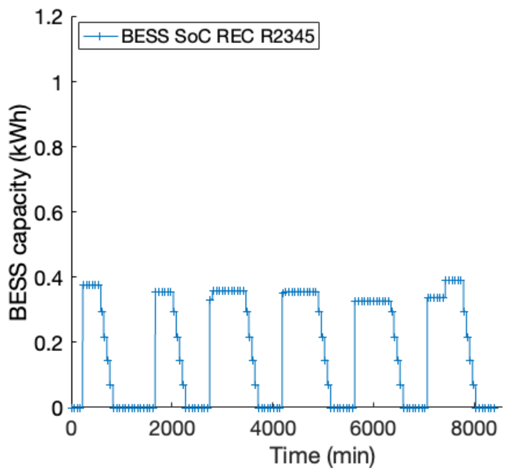
(b)

*Figure 4-7: Extract of the BESS charge (positive) and discharge (negative) power curve (black) and corresponding BESS SoC curve (purple) (**a**); extract of forecasted REC loads (black) and prosumer net load (light blue) and generation (purple) curves (**b**). On the* *background of (**a**) and (**b**) the DAM prices. Both (**a**) and (**b**) are related to the same REC configuration and to the same 6-days period.*

Figure 4-7 refers to one of the five analyzed REC compositions; each composition has different inputs for the MILP and this in turns affects optimization results; Figure 4-8 below shows the BESS SoC curve for two out of the five different REC compositions analyzed in this study, over the same 6 days.



(**a**)

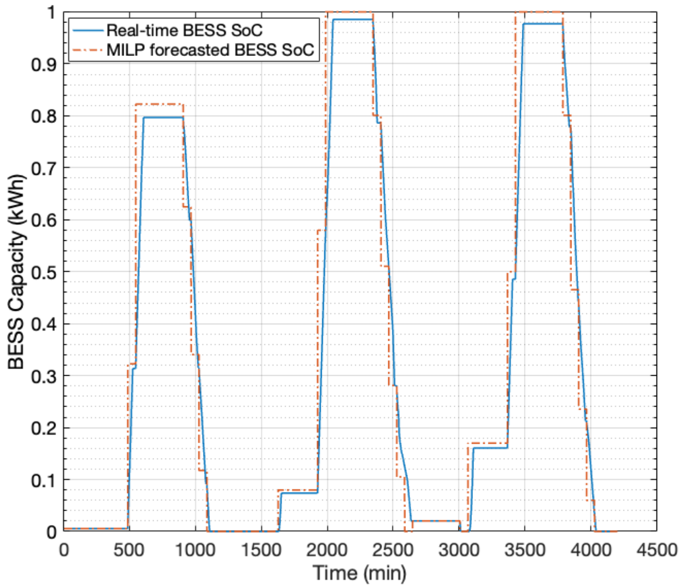


(**b**)

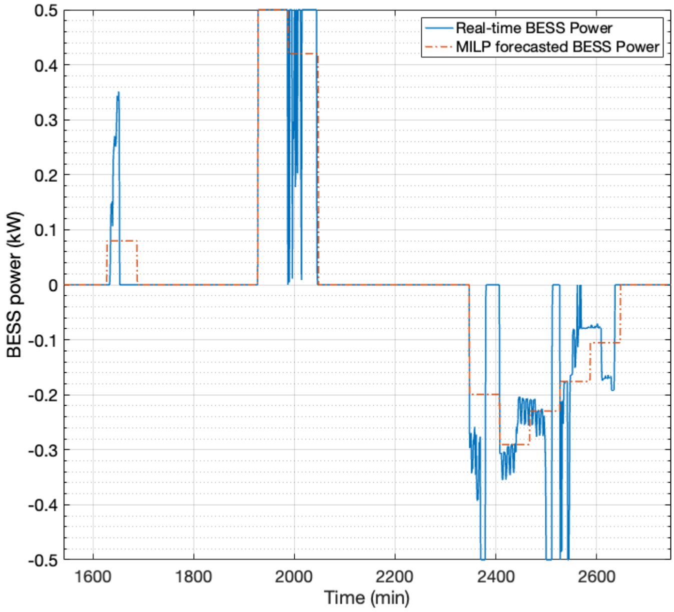
Figure 4-8: Extract of the BESS SoC curve (purple) over the same 6-days period for REC R1234(a) and R2345 (b) configurations.

4.3.2 Real-Time BESS Management Operation

The optimal scheduling calculated using MILP methodology with forecasted data has then been tested against real data with 1-min timestep. The decision tree algorithm used in this phase has the objective of reaching the set-points previously calculated by the MILP for the following 24 h, while coping with possible forecast errors. Figure 4-9 (a) below shows the real-time SoC curve, compared with the one proposed by the MILP, over 3 days. It can be seen that in some periods the real-time algorithm is not able to reach the proposed SoC set point, due to errors in the forecasts. At the end of the day, if the final real-time SoC is different than the forecasted one, the next MILP iteration updates its starting SoC level to the value of the final real-time one. Figure 4-9 (b) shows instead the total BESS real-time power exchange, compared to the forecasted one. It can be noticed the difference in smoothness between the two curves: this is due to the different timestep—1-h for the MILP and 1-min for the decision tree algorithm. It becomes evident how using only 1-h timestep-based simulations leads to underestimate the peak power exchanges between BESS and either REC or PV system.



(a)



(b)

*Figure 4-9: Three-days extract from real-time BESS management outcomes showing a comparison between real-time operation (light blue) and MILP scheduled setpoints (red) for BESS capacity and usage (**a**). Comparison between MILP scheduling for average BESS power exchange over hourly time periods (red) and corresponding real-time BESS power exchanges (light blue) (**b**).*

4.3.3 Techno-Economic Outcomes for the Analyzed Scenarios

To evaluate the performance of the proposed REC management algorithms, their outcomes were compared against the ones obtained in two other different scenarios: a “Baseline” depicting an unmanaged REC without BESS and a “BESS, no MILP” one, where the BESS is deployed in the REC, but no generation and loads forecast, nor BESS management are applied; just the basic opportunity charging is enabled. As already mentioned in the previous section, 55 different BESS configurations—related to capacity and rated power—have been considered, within the ranges defined in Table 4.1. Due to the small dimensions of the considered REC, only BESS with capacities and power rating in the lower range provided good economics, with the overall revenue maximum obtained by the 1 kWh—0.5 kW BESS in the “BESS, MILP” scenarios. Given that, unless otherwise stated, the following part of this section refers to the above-mentioned BESS configuration.

Table 4.4 reports the average values of the main outcomes, in terms of energy exchanges within the REC and with the grid, in terms of BESS overall use and finally in terms of revenues divided among the REC participants. Since the results were provided for the 5 different REC configurations analyzed, the variation range was provided within parentheses whenever possible.

Table 4.4: Main techno-economic outcomes of the scenario-based analysis.

	Baseline	**BESS—MILP**
Total REC demand (MWh)	13.03	
Prosumer demand (MWh)	2.606 (1.296–5.323)	
Other REC members demand (MWh)	10.424 (7.707–11.734)	
PV generation (MWh)	6.744	
Prosumer Self-consumption (MWh)	*1.157 (0.628–2.293)*	*1.405 (0.749–2.605)*
Shared energy within REC (MWh)	*3.211 (2.074–3.738)*	*3.29 (2.074–3.922)*
Exports to grid (MWh)	*2.376*	*2.37*
Imports from grid (MWh)	8.662	8.412
Total BESS use–capacity: 1 kWh, power 0.5 kW(kWh)	-	0.496 (0.242–0.625)
REC yearly revenues (€/year)	733 (595–819)	859 (671–947)

Prosumer revenues (€/year)	*574 (493–636)*	*627 (495–687)*
Other REC members tot. rev. (€/year)	*158 (102–184)*	*232 (176–260)*

On average, having a 1 kWh/0.5 kW BESS available as a REC asset allows to increase prosumer self-consumption by 21.4%. Overall, the average energy exchanges within the REC and with the grid aren't much affected by BESS deployment. Anyway, the optimal scheduling allows to better distribute across the day such exchanges, synchronizing them with the day ahead market electricity price trends. This in turn translates to a 45 to 47% revenues increase for the REC customers; regarding the prosumer, the revenue increase reaches 17.8% using the MILP-based optimization. Such different behaviors are related to the fact that, on customer side, the revenues are based only on the volume of shared energy and on the fixed incentive. Prosumer revenues, instead, also consider PV electricity sales to the market, inherently affected by the time of injection in the grid and avoided purchase costs related to self-consumption.

It should be noticed that in the scenario with BESS deployed the self-consumption share strongly increase, at the expenses of grid exports. The higher price for electricity purchase, together with the reduced spread between high and low DAM prices for the sale of PV surplus energy, makes self-consumption the preferred option for BESS usage: in fact, the price arbitrage activity finds a hindrance also in the still high LCOS, that is of course related to the high CAPEX costs for BESS deployment.

Figure 4-10 below, reports in more details the financial analysis outcomes, for the REC in the "BESS, MILP" scenario. The five solid lines describe the NPV values for different REC combinations, plotted against the 1-10 kWh range of BESS capacity considered in this work; here the rated power is considered to be equal to $0.5 * SoC_{MAX}$. The dashed line refers instead to the average NPV value, calculated over a 20-year time period, with a 5% discount rate and plotted against the various BESS capacities. The model takes into account the BESS expected lifetime, as calculated in (4.23); if the overall BESS energy exchanges reach $BESS_{capacity}^{MAX}$ value, a new BESS is deployed, and the corresponding CAPEX is accounted to that year cash flow. Such situation occurs in REC R1235 and REC R1245 configurations, respectively for BESS with capacity up to 5 kWh and 7 kWh. This can be note by the trend change for the two curves when the two capacities are reached; the NPV value grows due to the fact that only one BESS is needed across the 20-year period from that point onward, compared with the two BESS, although smaller in size, needed up to that point. Finally, the corresponding average pay back time (PBT) is evaluated for all the BESS capacities related to positive values of

NPV at the end of the analyzed period. The figure highlights that only BESS with capacities in the range of 1 to 4 kWh are to be considered. Anyway, only the 1 to 2 kWh range provides more interesting NPV for the investment, with a final average NPV maximum value of 1467€, and a variation range of 771€—1982€. This result has to be compared with a corresponding BESS CAPEX cost of 800 €, across the considered time period.

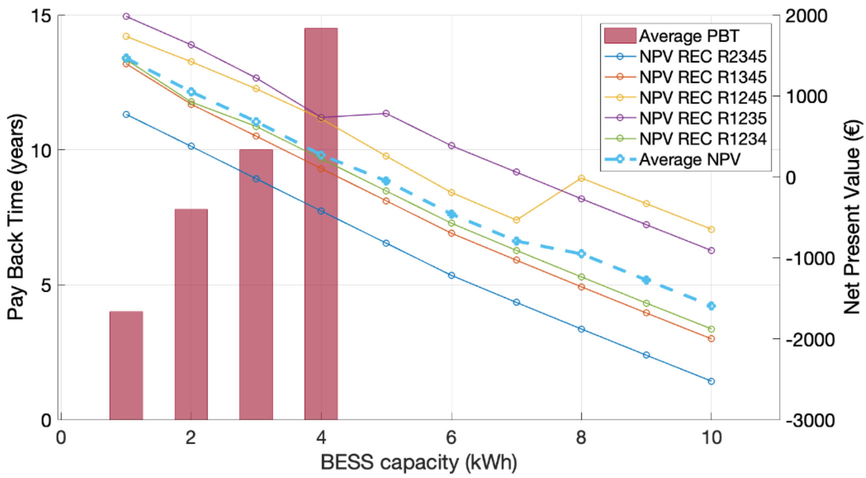


Figure 4-10: NPV (line chart) and PBT (bar chart) for BESS investment in the "BESS, MILP" scenario. The light blue, dashed line refers to the averaged NPV across all the REC configurations, while the solid lines refer to the NPV for one of the five specific REC configuration analyzed.

4.4 Conclusions

This chapter analysed the techno-economic impacts of the use of forecast-based, mixed integer linear programming (MILP)-based scheduling for a BESS deployed within a small residential REC. Several REC compositions were tested, together with different BESS parameters, in three different scenarios, to find the techno economic optimum for the analyzed REC. It emerged that:

- BESS implementation could help to improve both prosumer self-consumption and virtual energy exchanges within the REC. Anyway, only a careful charging and discharging scheduling allows to optimize its usage and the related revenues.
- By applying the MILP-based, forecast-based scheduling optimization presented in this work, a 10% average revenue

increase could be obtained for the prosumer alone when compared to the non-optimized BESS usage scenario.

- Such revenue increase is obtained by reducing the BESS usage by around 30%, thus guaranteeing longer lifetime and, in perspective, the possibility to use the remaining overall capacity for providing different, non-energy-related services to the grid (i.e., flexibility and distributed balancing services).
- The optimal BESS sizing analysis carried out for the considered REC, considering net present value over a 20-year investment lifetime as the main target, described as the optimal choice a 1 kWh / 0.5 kW BESS;
- Such finding could be mainly related to the small size of the considered REC on the one hand, and on the other hand to the combination of little price arbitrage possibility on the Italian day-ahead market and high BESS CAPEX.

Chapter 5 Application: Economic Optimization Strategies for Clustering of Prosumers and Consumers into a set of RECs

5.1 Introduction

In the previous chapters, REC optimization has been approached from the internal management point of view; the REC composition in terms of users, both prosumers and consumers, was provided from the start. The addressed means of flexibility regarded BESS scheduling, and sensitivity analyses on BESS techno-economical parameters has been carried out. In this chapter, the REC optimization topic is addressed from an external, combinatorial approach, that is being used to determine the optimal assignment to one or more RECs of the consumers and prosumers from a given set; the complementarity of their load and generation profiles is considered, to achieve maximum economic revenue. This approach gains even more importance under the light of the upcoming REC definition modifications provided by the Italian law 199/2022, as described in Chapter 2: the topological limitations of the REC are about to be extended to the MV/HV transformer, and the maximum RES power installed will grow from 200 kW to 1 MW. This is in general a numerical optimization problem that can exhibit local minima and a non-smooth functional in the solution space [64], [65]. In general, such problem must be solved through numerical optimization algorithms relying either on meta-heuristic strategies or evolutional algorithms [66]. Special care must be taken in the formulation of the optimization problem associated to the assignment. The problem can be simply formulated as a single-objective problem, for the purpose of maximizing the revenue for the incentives (in this case, the solved problem could be later solved through a neural network trained on the problem solutions [34]). In this case, the exploration and refinement capabilities of the optimization algorithm are paramount. However, if a multi-objective approach is proposed, the chosen algorithm must include in its capabilities the solution spread along the pareto front describing the problem solution. For the purpose of this work, the problem is formulated as a two-objective Pareto optimization problem. The first objective aims at maximizing the economic revenue derived from the RECs. The second aims at maximizing the uniformity of the revenues from different RECs. A penalty system to exclude solution where marginal revenue is too low for prosumers is also included, to favour smaller and more numerous RECs. The problem is solved by means of the Nondominated Sorting Genetic Algorithm II (NGAS-II) [67] which is a well-affirmed evolutionary strategy often used in literature for optimization problems in the energy sector [68]–[70]. The chapter is structured as follows: first, the dataset associated to the problem is described both in terms of sheer size and numerical management in the programming environment; then, the fitness functions and some penalty systems are defined to complete the Pareto optimization problem formulation. Following, the optimization evolutionary strategy is described, and the results obtained for different scenarios are presented.

5.2 Implemented Dataset and Methodology

Data for the whole power grid is composed by the hourly averaged production and load of N=73 households equipped with PV plants, obtained from the PecanStreet database [1]. Profiles of production and load are separated for each prosumer and cover a timespan of about 6 months (4416 hours – extract in Figure 5-1 below).

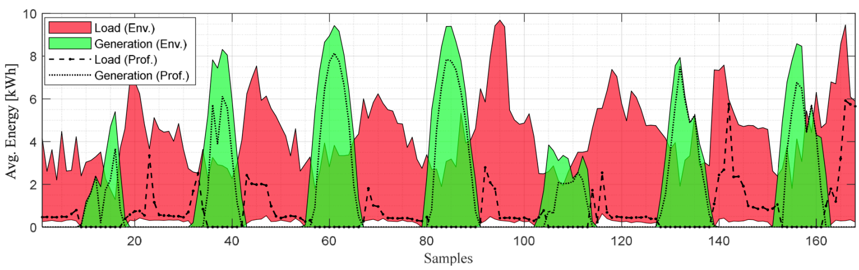


Figure 5-1: Extract from the Pecan Street dataset. In green and red the max-min envelopes of the load and generation profiles for the 73 prosumers are shown. Dashed and dotted lines represent an example extracted from the 73 profiles for generation and load.

5.2.1 Fitness Functions

Prosumer data is used in conjunction with an assignment vector γ to distribute the individual prosumers in the different renewable energy communities. Each element of the γ vector is representative of a specific prosumer (i.e. the vector size is 1x73). The value assumed by each element of the vector denotes in which REC the prosumer was assigned. Thus, the gamma vector describes a possible configuration of the 73 prosumers in the different RECs. Indeed, the domain of the gamma vector is discrete, positive, and theoretically unbounded towards infinity (however, the total number of RECs will always be below 10 for this number of prosumers). An example of this repartition can be seen in Figure 5-2, considering a gamma vector partitioning the prosumers in four different RECs. As can be seen, for this vector, the prosumers 1, 3 and 4, are all assigned to the REC 4.

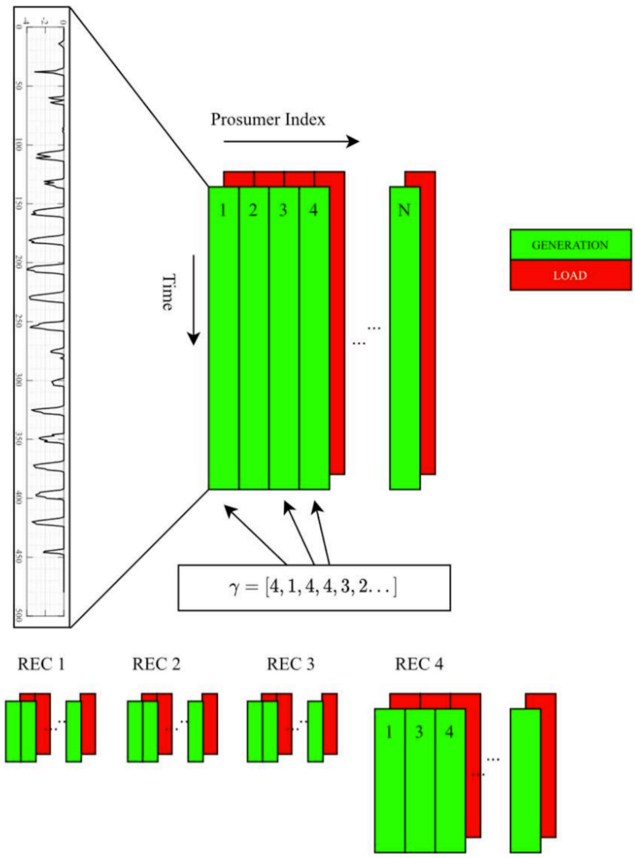


Figure 5-2: Partitioning of the prosumers in different RECs using the gamma vector. Green and red squares represents column vectors containing the time- series for PV generation and load (respectively).

The fitness function is associated to a specific partitioning of the prosumers. Since this partitioning is unique for each value of the $\boldsymbol{\gamma}$ vector, the fitness function can be specified as:

$$\boldsymbol{ff}(\boldsymbol{\gamma}) = [ff_1(\boldsymbol{\gamma}), ff_2(\boldsymbol{\gamma})] \quad (5.1)$$

Where the fitness function **ff** is a vector function of the $\boldsymbol{\gamma}$ vector. The two components of ff are the individual fitness functions that formalize the pareto optimization problem approached in this work.

The first fitness function ff_1 is related to the total economic revenue derived from the incentives obtained from energy self- consumption in the REC. The second fitness function ff_2 is related to the uniformity of the revenues among the RECs.

$$R_k = INC \cdot \sum_{t=1}^{t_{max}} \min(P_{GEN}^k[t], P_{LOAD}^k[t]) \quad (5.2)$$

$$ff_1 = \sum_{k=1}^{REC_{max}} R_k \quad (5.3)$$

$$ff_2 = \frac{1}{\sqrt{\frac{1}{REC_{max}} \sum_{k=1}^{REC_{max}} (R_k - \mu)}} \quad 5.4)$$

$$\mu = \frac{1}{REC_{max}} \sum_{k=1}^{REC_{max}} R_k \quad (5.5)$$

Where $P_{GEN}^k(t)$ is the total generated power at the discrete time t in the k-th REC, $P_{LOAD}^k(t)$ is the total load at the discrete time t in the k-th REC, *INC* is the economic incentive in €/kWh for energy self-consumption and REC_{MAX} is the total number of RECs considered (i.e. the number of unique elements in the $\boldsymbol{\gamma}$ vector). As can be seen (5.3) describes the total economic revenue obtained from the prosumers partitioning in the RECs, and 5.4)-(5.5) describes the fitness function proportional to the inverse of the standard deviation of the revenues among the RECs. Maximization of both fitness functions is the formulation of the pareto optimization problem.

The two fitness functions defined characterize the optimality of the solution from an aggregated point of view. From the individual prosumers point of view, joining a specific REC could be unbeneficial especially if the REC is already very large. Shared incentives are not equally distributed between prosumers and consumers. The pro-capita share of incentives for a consumer is

$$r^k = \frac{CR \cdot R^k}{N^k} \tag{5.6}$$

Where CR is the consumer ratio, a proportionality factor describing the reduced revenues form the consumers (e.g. if b is 0.4, consumers takes 40% of the revenue, and prosumers take 60% of the revenue) and N^k is the total number of consumers and prosumers present in the k-th REC. Consumed energy still needs to be paid to the electric service, thus, it is possible to define the average energy cost:

$$c^k = \frac{CC \cdot \sum_{t=1}^{t_{max}} P_{LOAD}^k[t]}{N^k} \tag{5.7}$$

Where CC is the consumer cost, describing the cost of energy in €/kWh. The ratio between (5.6) and (5.7) defines the consumer cost balance for the k-th REC:

$$cCB^k = \frac{r^k}{c^k} \tag{5.8}$$

This consumer cost balance can be used to mitigate the natural tendency of this problem in choosing few, larger RECs where the pro-capita savings can be very small for pure consumers. For the optimization process, the penalty is applied directly to ff_1. If the cCB for the k-th REC is below a definable threshold (e.g., 0.01, equivalent to a ratio of 1%), the contribution of the k-th REC to ff_1 is considered null.

5.2.2 Algorithm Choice for Pareto Optimization

The complexity of the proposed optimization problem is clear even by considering a single element of the vector fitness function described in (5.1). The fitness function is inherently nonlinear due to its combinatorial nature, and for this reason, is subject to local minima entrapment if approached by classic deterministic optimization algorithms. Even if the domain of the solution space is considerably narrow (as will be shown in the results, the REC_{MAX} will always be below 10), the number of dimensions is very high. Moreover, the discrete nature of the domain completely excludes gradient-based optimization algorithms. The optimal choice for this kind of problem is an optimization algorithm with highly explorative capabilities, not based on gradient or restrained to a continuous domain, such as a genetic algorithm that is search heuristic inspired by the theory of natural evolution. This algorithm reflects the process of natural selection where the best (fittest) individuals are selected for reproduction in order to produce better and better generations. The algorithm begins with a set of individuals (chromosomes) which is called a “population”. Each chromosome represents a solution of the problem to be solved (see Figure 5-3).

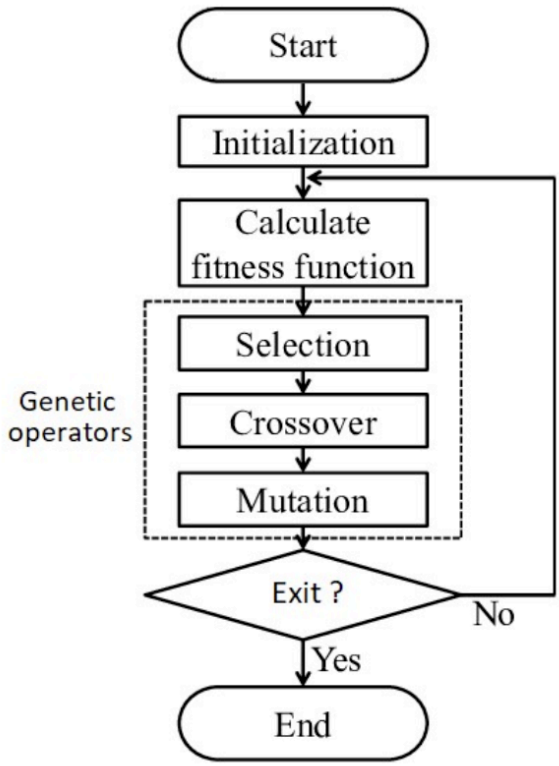


Figure 5-3:Flow-chart of a basic genetic algorithm.

For our specific case, the chosen algorithm was the Nondominated Sorting Genetic Algorithm II (NGAS-II). This algorithm is a multi-objective evolutionary algorithm based on a non-dominated sorting approach, it is widely used in literature due to its superior convergence and spread of solutions over the pareto front. The algorithm is natively implemented in MATLAB R2022b environment. For this work, the options reported in Table 5.1 were used for the algorithm configuration.

Table 5.1: NSGA-II configuration

Parameter	Value
Crossover Fraction	0.7
Function Tolerance	1 e-5
Population Type	'doubleVector'
Population Size	250
Integer Constrain	1:73
Solution Boundaries	1-10
Pareto Fraction	0.20

5.3 Results

To obtain a better distribution of case studies and tests, a range of RECs and chromosomes of the genetic algorithm have been set (parameters). In particular, each test has been performed by using a maximum value of RECs, $N_{max,REC}$ and a number of chromosomes equal to N_{chromo}. In view of the stochastic nature of genetic algorithm, each test consists of ten different launches of the MATLAB script with the same $N_{max,REC}$ and N_{chromo}. The best solution is selected among the ten performed launches and it is taken as outcome of the test. Figure 5-4 shows an example of Pareto front at the end of a single test.

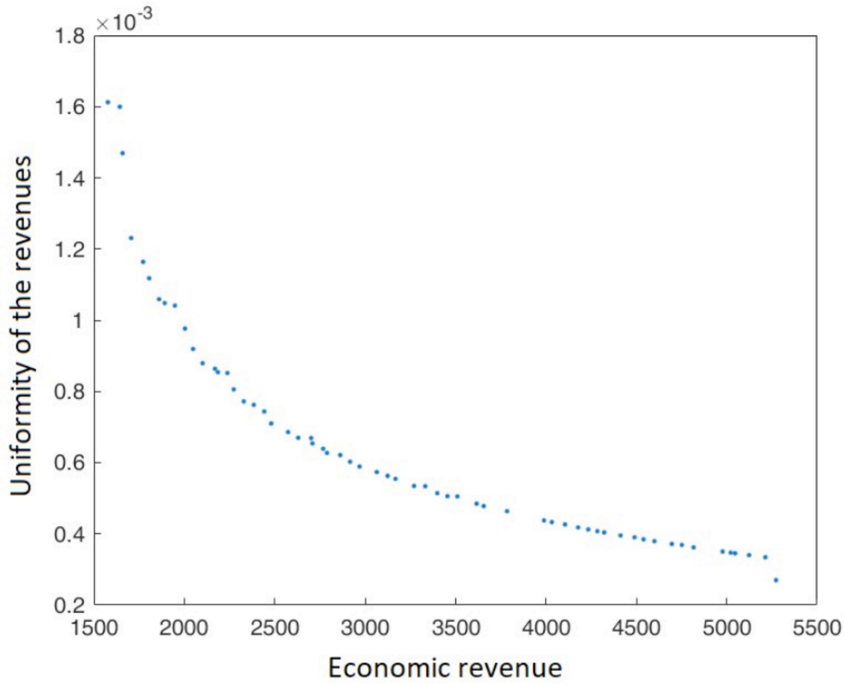


Figure 5-4: Example of Pareto front at the end of a single test.

Table 5.2 shows all the obtained results in terms of the inverse of the standard deviation of the revenues among the RECs (uniformity of the revenues from different RECs) and the total economic revenue obtained from the prosumers partitioning in the RECs. To select one of the 10 algorithm launches as result of each test, the maximum of the product between the two functionals, (5.3) and 5.4), was taken. That product is indicated into the last column of the Table 5.2. This is just a possible criterion to select one solution among those on Pareto front in which there is a balance between the values of the two functionals.

Table 5.2: Economic revenues and related number of RECs

Test	Parameters	Revenue [€]	n. RECs	$ff_1 \cdot ff_2$
1	$N_{max,REC} = 2$ $N_{chromo} = 100$	1829	2	2.10
2	$N_{max,REC} = 3$ $N_{chromo} = 100$	1631	3	34.53
3	$N_{max,REC} = 4$ $N_{chromo} = 100$	1754	4	5.10
4	$N_{max,REC} = 5$ $N_{chromo} = 100$	2292	5	10.23
5	$N_{max,REC} = 6$ $N_{chromo} = 100$	1659	6	4.88
6	$N_{max,REC} = 2$ $N_{chromo} = 170$	2057	2	1.97
7	$N_{max,REC} = 3$ $N_{chromo} = 170$	1666	3	4.13
8	$N_{max,REC} = 4$ $N_{chromo} = 170$	1609	4	5.07
9	$N_{max,REC} = 5$ $N_{chromo} = 170$	1835	4	3.42
10	$N_{max,REC} = 6$ $N_{chromo} = 170$	1834	5	4.71
11	$N_{max,REC} = 2$ $N_{chromo} = 250$	1885	2	1.69
12	$N_{max,REC} = 3$ $N_{chromo} = 250$	1982	3	7.95
13	$N_{max,REC} = 4$ $N_{chromo} = 250$	1710	4	2.56
14	$N_{max,REC} = 5$ $N_{chromo} = 250$	1870	4	3.18
15	$N_{max,REC} = 6$ $N_{chromo} = 250$	1630	4	3.10

Table 5.3 shows an additional information to the Table 5.2, that is the number of prosumers distributed among RECs for each test. From Table 5.2 and Table 5.3 it is possible to note that Test 4 seems to be the best the solution in terms of maximization of economic revenues and distribution prosumers among RECs.

Table 5.3: Number of prosumers distributed among RECs

	Number of prosumers					
Test	**REC 1**	**REC 2**	**REC 3**	**REC 4**	**REC 5**	**REC 6**
1	44	29				
2	46	12	15			
3	16	23	21	13		
4	20	12	8	10	23	
5	2	17	36	13	3	2
6	30	43				
7	20	21	32			
8	9	35	18	11		
9	3	14	45	11	0	
10	52	6	3	3	0	9
11	43	30				
12	15	47	11			
13	5	37	27	4		
14	1	16	41	15	0	
15	0	9	33	24	7	0

On the other hand, in Table 5.4 we see that the standard deviation of revenue prosumers for the Test 2 is better than Test 4 (i.e., better uniform economic revenue). Let us to emphasize the results of Test 6 and Test 11 that could seem to contradict. Indeed, the number of prosumers among REC 1 and REC 2 (Table 5.3) are simply inverted, but the related results on Table 5.2 are different.

Table 5.4: Economic revenues distribution among RECs

	Economic revenues [€]					
Test	**REC 1**	**REC 2**	**REC 3**	**REC 4**	**REC 5**	**REC 6**
2	482.43	561.76	587.13			
4	565.94	553.76	60.44	481.05	631.45	

The reason for this seeming ambiguity is shown in Table 5.5, in which it is noted that the groupings of prosumers, each one respectively numbered from 1 to 73, are different. Since each prosumer has his own load and generation profiles, it is evident that different groupings bring to different revenues (functionals values).

Table 5.5: Grouping of the prosumers among REC 1 and REC 2

Test	Prosumers belonging to REC 1	Prosumers belonging to REC 2
6	1,2,3,4,5,6,7,8,9,10,11, 14,16,22,26,27,28,30, 31,32,38,39,40,42,45, 46,47,49,68,73	12,13,15,17,18,19,20, 21,23,24,25,29,33,34, 35,36,37,41, 43,44,48, 50,51,52,53,54, 55,56,57,58,59,60,61, 62,63,64,65,66,67,69, 70,71,72
11	11,12,13,17,18,19,20, 21,22,25,29,33,34,35, 36,37,41,42,43,44,48,50, 51,52,53,54,55,56,57, 58,59,60,61,62,63,64, 65,66,67,68,69,70,71,72	1,2,3,4,5,6,7,8,9,10,14,15, 16,23,24,26,27,28,30,31, 32,38,39,40,45,46, 47,49,73

Finally, as for all the Pareto problems, there is not a unique solution to the optimization problem. Thus, in our case, based on of the total economic revenue and the distribution of the number of prosumers and revenues among RECs, Test 2 and Test 4 seem to give the most suitable solutions, that are two configurations with 3 and 5 number of RECs respectively. Moreover, Tests 9, 10 and 14 have in common the REC 5 with zero prosumers. This could depend by the fact that, within the pareto front, many solutions of this kind are present. It is important to emphasize that, in this paper, RECs are like simple clusters, and they have not personal characteristics that make them different form each other.

5.4 Conclusions

In this work, the problem of optimal allocation of the prosumers in the communities has been faced. A metaheuristic pareto optimization algorithm, in particular genetic algorithm, has been used to investigate the optimal number of RECs given a set of prosumers and consumers based on their allocation for both maximum and most uniform economic revenue. This is a typical multiobjective optimization problem where a Pareto front exists in which it is possible to select more than one suitable solution. In our case, based on of the total economic revenue (5.3) and the distribution of the number of prosumers and revenues among RECs 5.4), Test 2 and Test 4 seem to give the most suitable solutions, that are two configurations with 3 and 5 number of RECs respectively.

It is worth noticing that in this case no REC management optimization is carried out, for sake of simplicity; anyhow, the optimized RECs resulting from this activity are also the optimal starting point for further optimization processes, since generation and consumption are well "tuned". This would allow to reduce i.e. BESS scheduling in order to obtain the same results.

Chapter 6 Application: Set-Up of a Database of Appliance-Type Loads for Demand Response Simulation Activities

6.1 Introduction

One of the main hindrances to the development of demand-response simulators, at least at residential levels, thus considering controllable loads of the appliance type is the lack of free-access databases, comprising large enough dataset.

One of the few available dataset corresponding to these requirements is the Pecan Street database. Pecan Street Dataport [1] is a database of detailed, time-resolved energy consumption data collected from residential and commercial customers in the Pecan Street neighborhood form Texas, New York and California. The data provides information about energy consumption for individual devices and appliances, and it can be used for research and analysis related to energy consumption and management. The database has a 1-second data resolution, spanning over more than 6 months for more than 70 different users, each owning more than one different appliance.

Anyway, data is provided as a continuous strip of information, thus not highlighting single cycle activities for the various loads. This way it is not possible to gather directly statistical information about the various consumers' loads; moreover, it is not possible to use such data in the MILP-based model of a REC, described in previous chapters. In this chapter a procedure for extraction of single load cycles information is described; the structure of the new organized dataset is provided, together with the obtained results in terms of controllable loads statistical properties.

6.2 Database Implementation

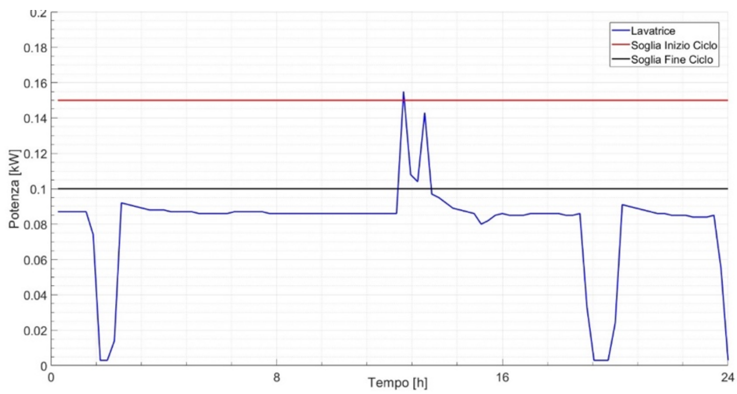
The Pecan Street Dataport comprises several different load types:

- Airwindowunit (Air Conditioning)
- Clotheswasher
- Dishwasher

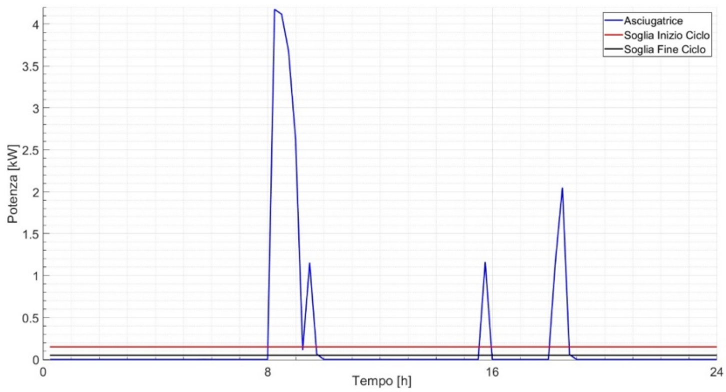
- Clothes Dryer
- Freezer
- Space Heater
- Microwave
- Oven
- Domestic water heater
- Electric Vehicle

Among them, only Clotheswasher, Dishwasher, Clothes Dryer, Domestic water heater and Electric Vehicle types of loads have been considered for this activity. Air Conditioning and Space Heating, even if of really high interest for the study, could not be used due to generalized lack of data; The other types of loads are of relatively low interest for demand-response research.

The raw data is provided as CSV files; first data elaboration consists in defining power threshold levels for start-of-cycle and end-of-cycle events. Usually start-of-cycle threshold is set at around 150 W and end-of-cycle threshold is set at 100 W; the rationale for the selection of such values can be found in the general idle consumption found in the dataset for the various appliances. Figure 6-1 (a) and (b) reports on typical data strips respectively for a Clotheswasher and a Clothes Dryer.



(a)



(b)

Figure 6-1: Typical 1-day data strip for clothes washer (a) and Clothes Dryer (b). In red the start-of-cycle threshold power level and in black the end-of-cycle cycle threshold power level

Four key parameters for the description of each extracted cycle has been defined:

- Cycle Duration (s)
- Peak cycle power (kW) P_{peak}
- Average cycle power (kW) P_{avg}
- Cycle total consumed energy (kWh) E_{tot}

All the gathered data is then collected into multi-dimensional databases (matrices), at user level; data is available with single-event granularity, with event timestamp, key parameters value and involved user information (red box in Figure 6-2). Average key parameters values for each type of load and for each involved user are also calculated and stored (blue box in Figure 6-2).

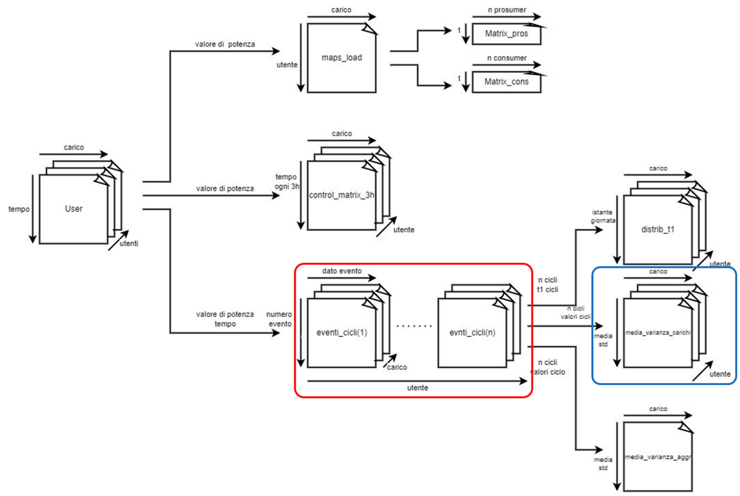


Figure 6-2: Database structure and internal correlations

6.3 Results

Figure 6-3 to Figure 6-7 report samples of the extracted cycles for different appliances and day of use. It can be noticed that time of use could differ on a day-by-day basis, as well as the load profiles, which are related to different appliances duty cycles.

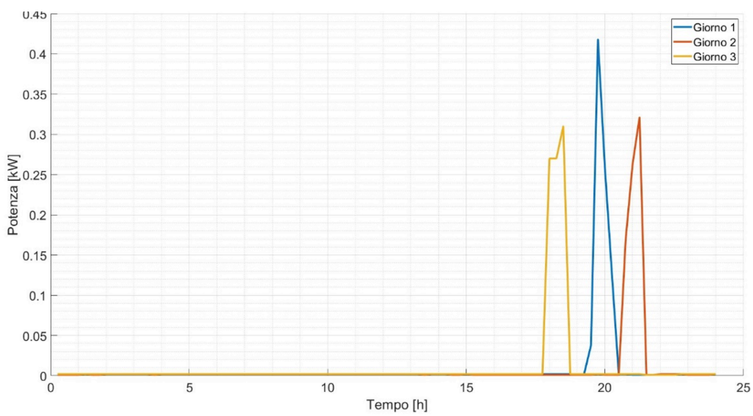


Figure 6-3Examples of extracted Clothes washer duty cycles

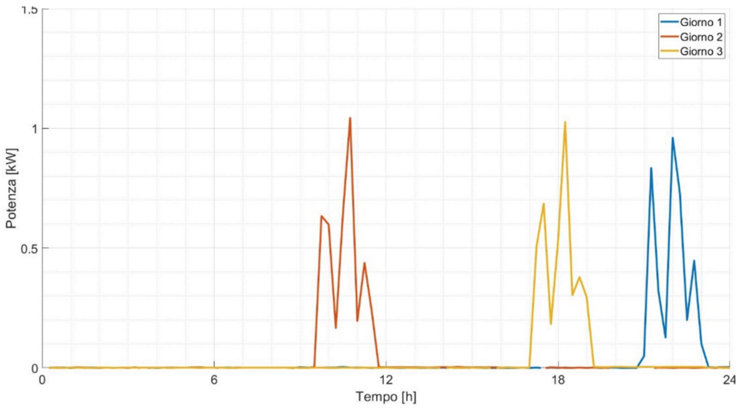


Figure 6-4: Examples of extracted Dish washer duty cycles

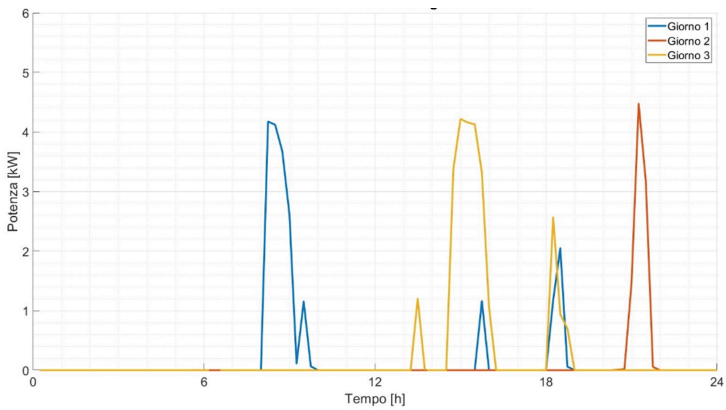


Figure 6-5: Examples of extracted Clothes dryer duty cycles

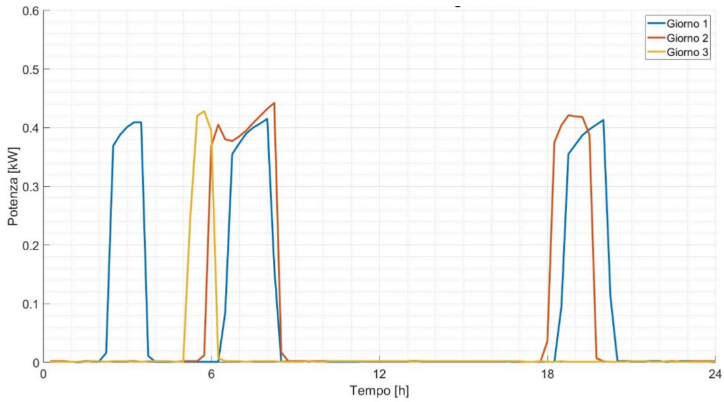


Figure 6-6: Examples of extracted Domestic Water Heater duty cycles

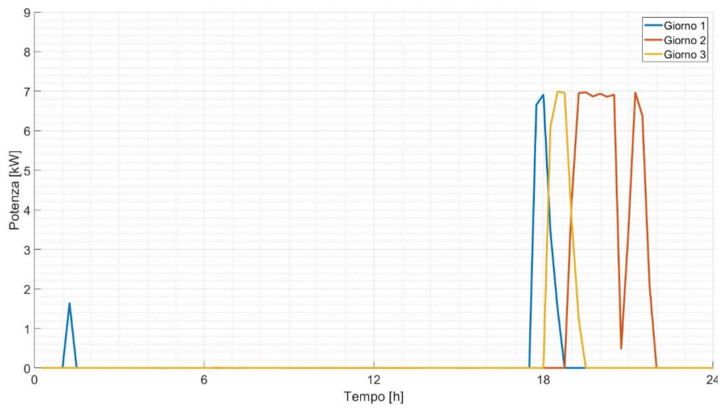
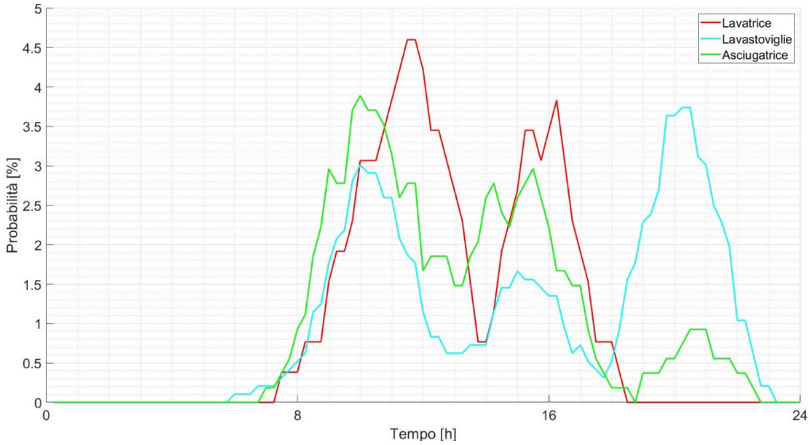
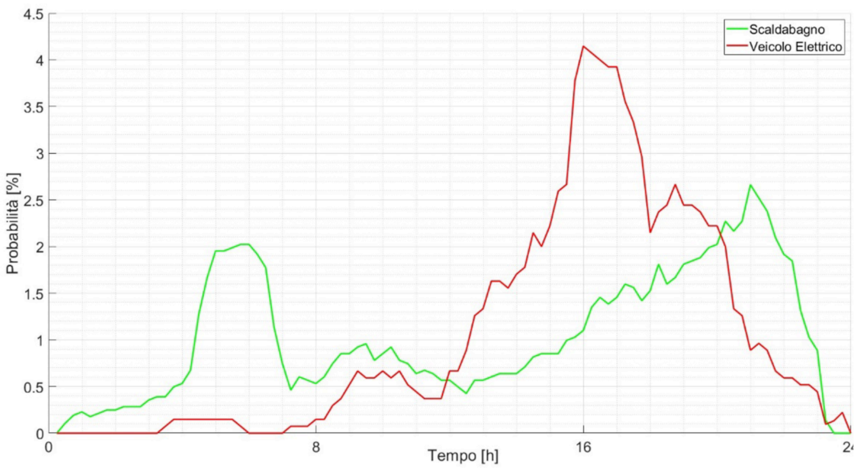


Figure 6-7: Examples of extracted Electric Vehicle charging duty cycles

(a) and (b) report the calculated probability distribution for the time of use of the various considered appliances.



(a)



(b)

Figure 6-8 to Figure 6-10 report instead on the calculated probability distribution for the key parameter values:

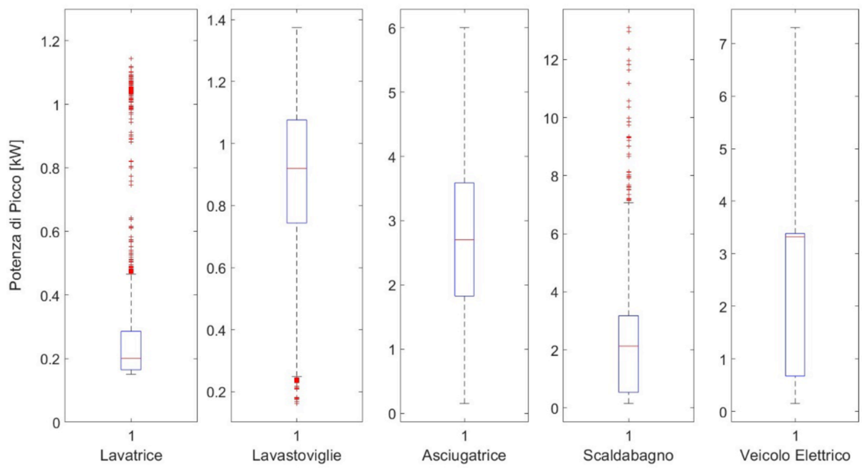


Figure 6-8Statistic values for Cycle peak power parameter for the considered appliances

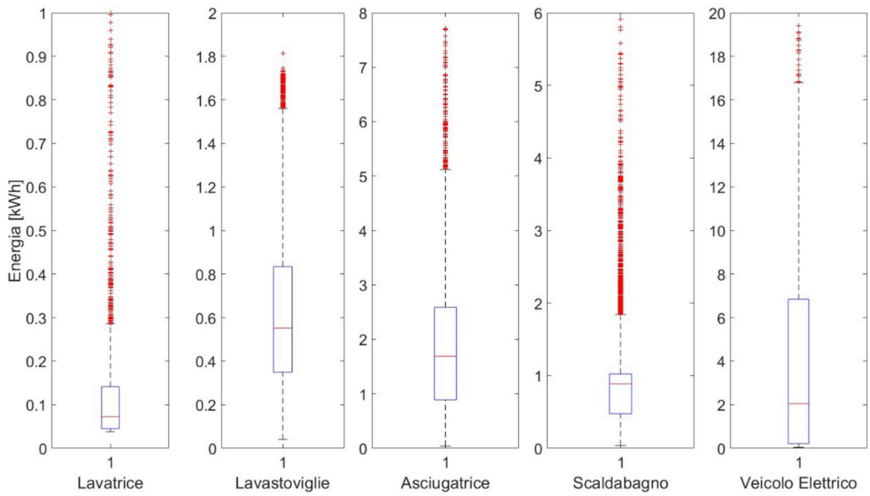


Figure 6-9: Statistic values for Total energy consumption per cycle parameter for the considered appliances

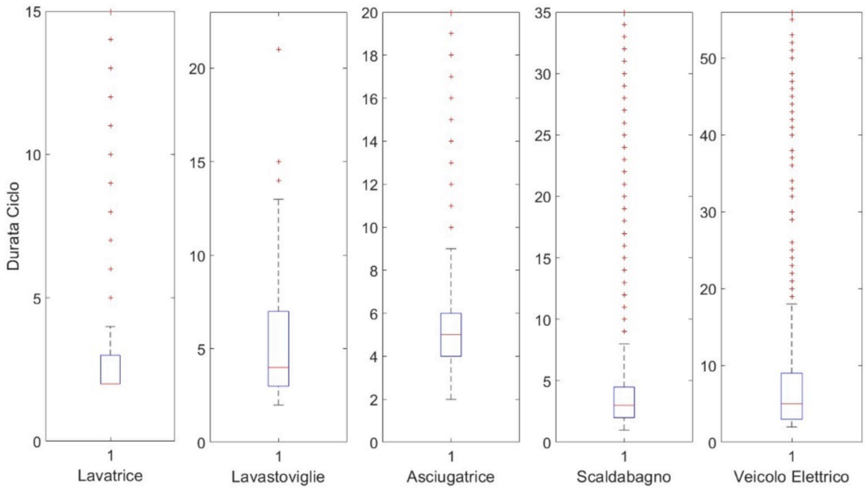


Figure 6-10: Statistic values for Cycle duration parameter for the considered appliances

Finally, Table 6.1 provides a summary of the average values for the considered key parameters:

Table 6.1: Summary of statistical values for the considered key parameters

		Clothes w.	*Dish w.*	*Dryer*	*DWH*	*EV*
T [h]	*avg*	*3.04*	*5.5*	*5.07*	*4.64*	*7.30*
	std	*1.65*	*3.02*	*2.33*	*4.35*	*8.51*
P_{peak} *[kW]*	*avg*	*0.25*	*0.89*	*2.70*	*2.06*	*2.64*
	std	*0.17*	*0.25*	*1.28*	*1.37*	*1.90*
Etot $[kWh]$	*avg*	*0.12*	*0.62*	*1.88*	*0.89*	*4.14*
	std	*0.15*	*0.39*	*1.35*	*0.63*	*5.39*
P_{avg} *[kW]*	*avg*	*0.13*	*0.44*	*1.4*	*1*	*1.7*
	std	*0.09*	*0.13*	*0.67*	*0.59*	*1.35*

6.4 Conclusions

This chapter reported on the activity related to the creation of a database of potentially controllable household loads, mainly of the appliance type. Scope of the activity is to prepare a suitable tool for the simulation of demand-response activity at the residential level, for the integration into the MILP-based scheduling optimization model already presented in the previous chapters. The database has been structured to provide several possible uses within this framework:

- The average load profiles could be used as dummy for in-advance load scheduling (i.e. for day-ahead scheduling, under forecast assumptions)
- The raw load strips can be used in real-time management phase
- The database of single events, provided with actual timestamps, can be used randomly as an alternative in both the other previously described situations.

Chapter 7
A Case Study: RECs evaluation for several Mugello municipalities

7.1 Introduction

This study developed from a cooperation between the Union of Mugello Municipalities (UCM) and the R&D Consortium RE-CORD. The UCM has been supported by RE-CORD in a National call for tender called "Green Communities", for the valorization and development of RES in rural environments. The work for the call consisted in the design of several small PV generation systems to be installed on the roofs of buildings owned by the municipalities, such as theaters, schools, sport centers and others (see Figure 7-1 below).

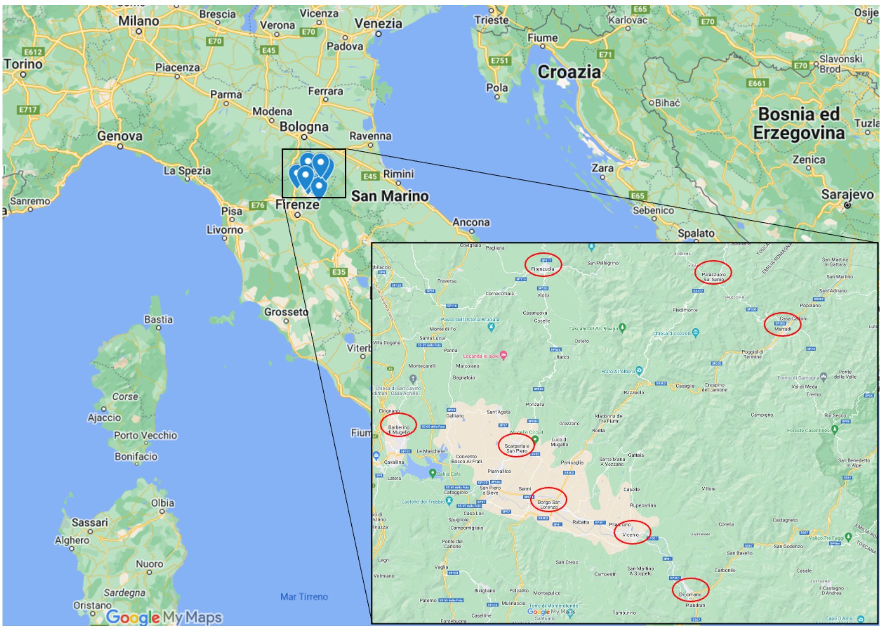


Figure 7-1: Location of the eight Municipalities part of the UCM and involved in the study

In a second moment it was decided, under the input of the UCM, to evaluate the possibility of starting up a REC for each municipality involved, by using the previously designed PV generators as the RES system. Objective of the work was to provide evidence of the possible benefits related to the REC, and to define a first-tentative optimal size for it. A Municipality-leaded (or at least participated) REC could provide several benefits: it would enhance citizens' trust and will to participate, overcoming the existing uncertainties related to the rues and structure of the REC itself; it will open up to many dissemination and scale-up possibility.

7.2 Methodology

For each site of interest, a technical report was developed, showing the main results obtained. The structure of the model report is shown below, and some methodological and source details are discussed in more detail.

7.2.1 Location and description of the PV plant and of the underlying potential REC

On the basis of the results of the work done for the call for tenders, the main data of the PV plant are reported: geographical location, estimated productivity, kWh of electricity expected to be fed into the grid downstream of direct self-consumption.

The area covered by the primary cabin to which the considered PV system would belong is then identified at a preliminary level. The reliability of this information is estimated to be sufficient for the level of detail in this document, but it will necessarily have to be further investigated with the grid operator should it be decided to proceed with the construction of the PV plant and the REC. It was decided to consider the primary cabin as the topological limit of the REC and not with the secondary cabin, even though the latter is identified as such by the regulations in force. This choice is based on two reasons: the new regulation that extends the perimeter of the REC to the primary cabin is in the approval phase; therefore it makes sense to carry out the analysis based on it, especially in view of subsequent expansions of the REC to new users. Furthermore, in order to carry out evaluations on RECs attributable to secondary substations, it becomes necessary to know the network topology precisely, to the point where any possible participation must be verified directly with the network operator.

Finally, an area with a radius of approximately 500 m is identified, within which the existence of commercial and industrial activities that could be part of the REC, as well as utilities traceable to the Public Administration (PA), is detected. The purpose of this activity is to provide qualitative information for the identification of possible participants, beyond residential users. The diversification of the type of utilities and their consumption profile certainly has a positive effect on the maximisation of shared energy within the ERC; since there are no sufficiently reliable data in the literature for profiling this type of utilities, it was preferred to use only residential utilities for the calculations, for which there is usable material available for the purposes of this paper.

7.2.2 REC residential users description

For the purpose of the techno-economic analysis of RECs, two types of residential users were defined:

- A so-called **standard user**, in which electricity consumption relates only to lighting, auxiliary and appliance-related components. In this case, the energy requirements for space heating, cooking and domestic hot water are considered satisfied through the use of natural gas.
- An **advanced user**, that uses electricity to also cover the consumptions related to space heating, through the use of a heat pump system.

The quantitative data on electric and thermal consumption for space heating were retrieved from the **Odyssee-Mure database**[9] and refer to an average Italian residential user and the year 2019. The **average electrical consumption** for an Italian residential household is quantified at approximately **2,200 kWh/year**, and the **thermal consumption for heating** at approximately **10,200 kWh/year**.

In order to use this information in the REC model used for the analysis, it is necessary to distribute the data on an hourly basis. From a literature search, average profiles of electricity and space heating consumption were identified. For the latter, constraints on the switching-on periods of the systems linked to the climatic class of the municipality to which the building belongs were also considered, both in terms of seasonality and the maximum number of switching-on hours per day. All the municipalities considered fall into climate classes D and E, therefore with a maximum of 12-14 hours of lighting per day and lighting periods 1 November - 15 April and 15 October - 15 April.

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[9] https://www.indicators.odyssee-mure.eu/online-indicators.html

Different mixes of users participating in the ERC were then considered in the analysis:

- 100% Standard - 0% Advanced (more conservative)
- 75% Standard - 25% Advanced
- 50% Standard - 50% Advanced
- 25% Standard - 75% Advanced

Advanced users have a significantly higher consumption and spread over more hours of the day, so they can support the ERC's energy exchanges to a greater extent. Scenarios with a higher penetration of Advanced users can be read as more "futuristic" or particularly optimised.

To complete the scenarios described above, a specific assessment was made of the volumes of energy not managed within the REC and therefore not incentivised; for at least part of these volumes, it is possible to hypothesise the activation of Demand-Response protocols in the future. The Demand-Response definition encompasses all activities and load management systems that allow usage curves to be modified according to specific objectives, including, for example, maximising self-consumption or energy sharing within a REC. On a practical level, managing a heat pump heating system to maximise self-consumption from PV is an example of Demand-Response, as is shifting the switch-on time of a household appliance such as a washing machine or dishwasher for the same purpose.

7.2.3 REC Techno-Economic Analysis

The main constraint imposed on the analysis is the presence of only one prosumer, identified in the PV plant proposed for the Green Communities call. This choice is linked to the need to identify a core around which to develop the REC; given the freedom of expansion and composition of the REC as defined by current legislation, there is nothing to prevent it from expanding to other renewable generation plants later on. Furthermore, the considerations made for one plant can easily be extended to others.

The results of the analysis are aimed at assessing:

- The value of the total incentive (i.e. aimed at the REC in its entirety) related to the shared energy, on an annual and 20-year basis
- The value of the incentive paid to individual prosumers and consumers, based on a hypothesis of its distribution, on an

annual and 20-year basis. To verify in more detail the impact of this choice on the economic results of the system, a sensitivity analysis was carried out on this parameter. The base value for the distribution used in this paper is 40% prosumer - 60% consumer (total). The range evaluated in the sensitivity analysis is 30-70%.

- The average bill savings on an annual basis for the typical consumer user, both in absolute terms and as a percentage of the cost paid pre-REC
- The impact of setting up a REC on the economic plan of the PV system already proposed in the Green Communities call for proposals. Specifically, the new NPV, the percentage change compared to the pre-ERC NPV and the change in payback time are evaluated.
- The optimal number of participants in the REC, depending on the results discussed above. In this case, one must balance the performance relative to the value of the total incentive, which always increases as the number of participants increases, against the performance relative to the value of the incentive received by the individual consumer. It is easy to imagine how the latter decreases as the number of participants increases, to a greater or lesser extent.
- The possibility of mobilising additional power volumes for sharing within the ERC through Demand-Response mechanisms, as explained above.
- A start-up and running cost of the ERC depending on the number of participants.

All the evaluations described above are always carried out by verifying the impacts as the number of users varies, i.e. by varying the number of consumers.

The cost of electricity considered in the study is approximately 0.4-0.45 €/kWh, including taxes and system charges. Although it is plausible that the price of energy will fall in the coming years, predictions of when and how it will do so are affected by a high degree of uncertainty and their evaluation is beyond the scope of this work.

7.3 Results

The evaluation has been carried out for seven of Municipalities part of the UCM, namely:

- Barberino di Mugello
- Borgo San Lorenzo
- Dicomano
- Firenzuola
- Marradi
- Scarperia – San Piero
- Vicchio

In the followings, two examples of the analyses are reported, together with the outcomes.

7.3.1 Barberino di Mugello – Municipality theater "Corsini"

(v) Geolocalization

The main information on the site in question is given below:

- Address: Via della Repubblica 3, 50031 Barberino di Mugello.
- GPS coordinates: 43.9999, 11.2381 (https://goo.gl/maps/FwutDqs2mUHms4V99)

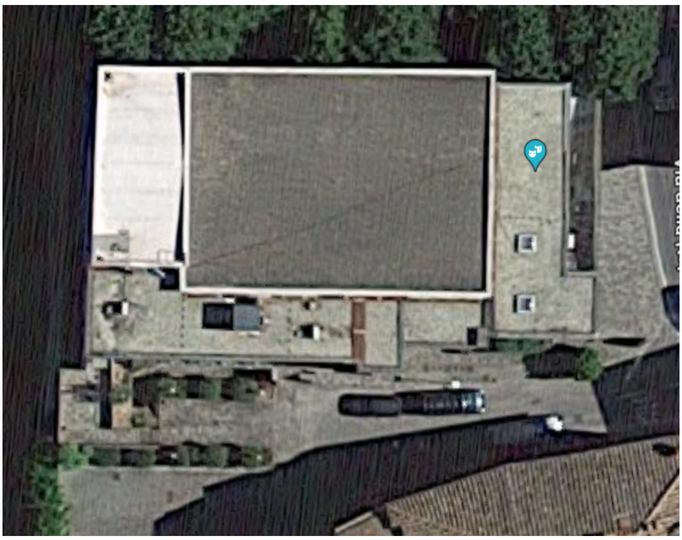


Figure 7-2: Satellite image of the coverage of the Teatro Comunale Corsini

The municipality of Barberino is served by a single primary cabin; within 500m from the Teatro Corsini (Figure 7-3) there are:

- At least 5 catering activities
- Two multi-sports/amateur sports associations

- A supermarket
- “Lorenzo De' Medici" Middle School Gymnasium, Via Monsignor Giuliano Agresti
- “G.Mazzini" Primary School, Viale della Repubblica
- “G.Mazzini" Primary School Gymnasium, Viale della Repubblica
- Municipal Palace, Viale della Repubblica n.24
- Technical Office, Via Trento n.1
- Kindergarten, Via F.Boccaccio
- Don Milani Kindergarten, Via F. Boccaccio
- Pretorio Palace - library, Piazza Cavour
- “Ex macelli" ERP housing, Via XX Settembre

Figure 7-3: Area considered for the assessment of commercial users and users belonging to the PA - Barberino di Mugello

(vi) PV plant design

Following the evaluation of the site and consumption characteristics, a system consisting of 77 modules (5 strings of 12 modules and one string of 17 modules) was chosen, positioned as described in Figure 7-4. The panels are oriented towards the south, with a tilt of 36° to the horizontal plane. A correct distance between module rows was considered to avoid self-shading.

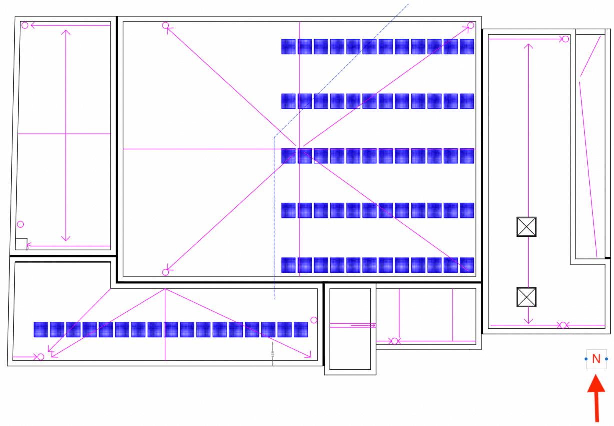


Figure 7-4: Plan of the roof of the Teatro Comunale Corsini, with the photovoltaic modules highlighted in blue

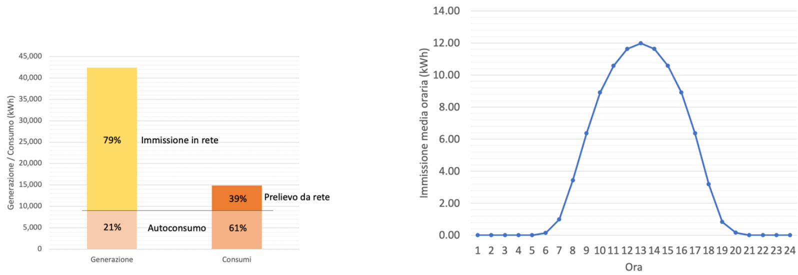
The planned peak power for the installation is therefore **31.6 kWp**, with an **annual output of 42,500 kWh/year**, estimated using irradiation tables in accordance with UNI 10349 standards. The evaluation of the building's electricity consumption bills revealed a **total annual consumption of about 15,000 kWh**, of which about two-thirds occurs in the F1 and F2 bands, which are more likely to overlap with the period of energy production by the photovoltaic system.

The estimated **CAPEX** for the PV plant is about **€81,000** with an **OPEX** of about **€2,200.**

The main resulting economic indicators are as follows:

- Net Present Value at 20 years: €43,600
- Payback Time: 9 years
- Internal Return Rate of Investment: 11.6%.

The PV system has an estimated annual productivity that is more than double the detected consumption of the underlying utility; this allows almost two thirds of the consumption to be covered with approximately 20% of the self-produced energy. The remaining 80% will be fed into the grid, as summarised in Figure 7-5 (a); Figure 7-5 (b) shows the average hourly energy feed-in profile, which is well centred within the day and suitable for the realisation of a Renewable Energy Community, given also the central location of the Theatre within the municipality.



(a) (b)

Figure 7-5: (a) Summary of the energy flows relating to the PV plant and the consumption user; (b) Grid injection profile downstream of self-consumption

Figure 7-6 shows the expected monthly trend of the plant's feed-in to the grid.

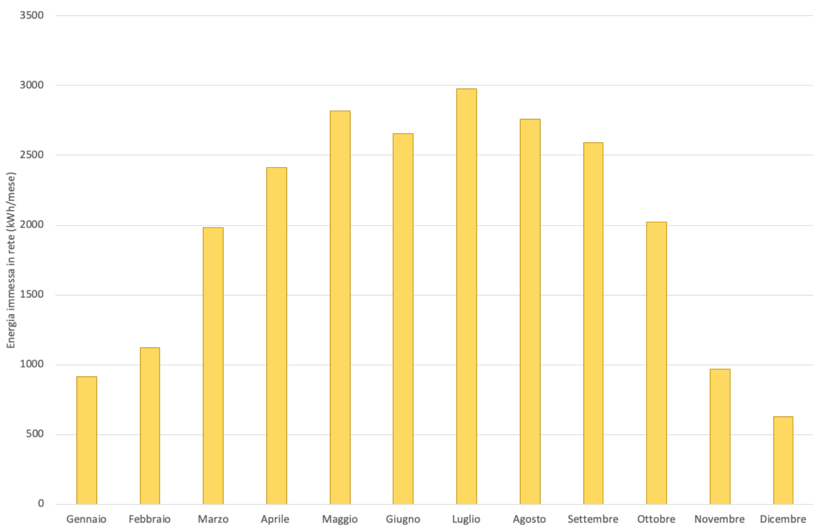


Figure 7-6: Feeding of electricity into the grid expected for the PV plant, downstream of self-consumption

(vii) REC Techno-Economic Analysis

Given the approximately **33,000 kWh/year fed into the grid**, the **maximum incentive obtainable** for energy exchanged within the REC amounts to just over **4,000 €/year**. Figure 7-76 shows how this result is achieved with about 100 users connected to the REC; however, given the trend of the curve, it is possible to reach 80% of this result with only 25 connected users.

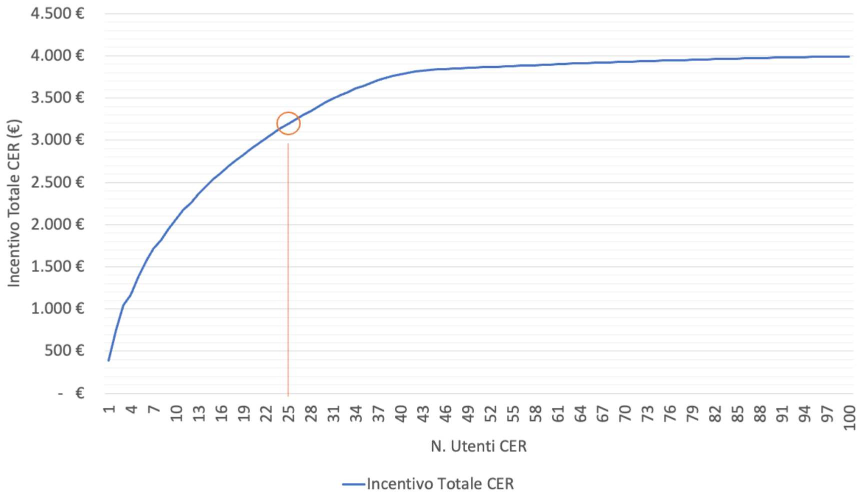


Figure 7-7: Trend in the value of the incentives envisaged for the Barberino REC according to the number of users. The point of achievement of 80% of the energy exchanged is indicated in red.

In fact, Figure 7-8 shows that as the number of users participating in the REC increases, the incentive given to the individual (and thus the savings in the bill) drops dramatically. This is due to the need to spread the incentive obtained from the ERC over an increasingly large pool of users. It is therefore necessary to find a compromise between collecting a sufficient percentage of the incentive compared to the maximum deliverable and a **minimum remuneration of individual users**. An ERC of about 25 users would pay out about **70-80€ per year** to the individual, which amounts to a percentage **saving of about 4-8%.**

The percentage difference is due to the fact that the standard user has significantly lower consumption and costs than the advanced user.

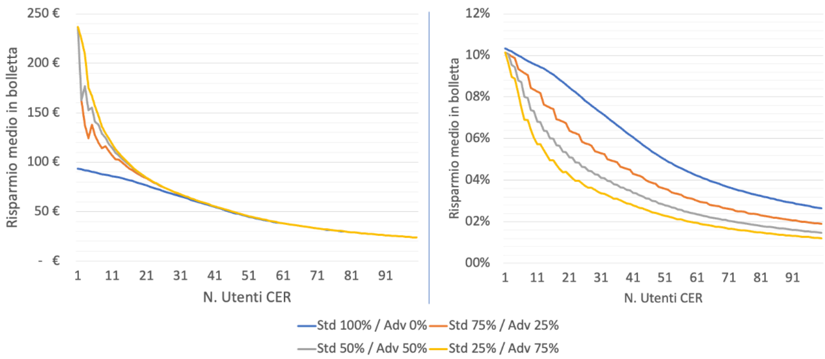


Figure 7-8: Trend of average savings on the bill (left: absolute, right: percentage) of consumers belonging to the REC, according to the number of users and the typological mix

Figure 7-9, on the other hand, shows the impact of REC on the economics of the PV system; it produces an improvement in NPV of more than 25%, or more than **€12,000 over 20 years**. The difference in situation between the single prosumer and the multiple consumer is thus highlighted.

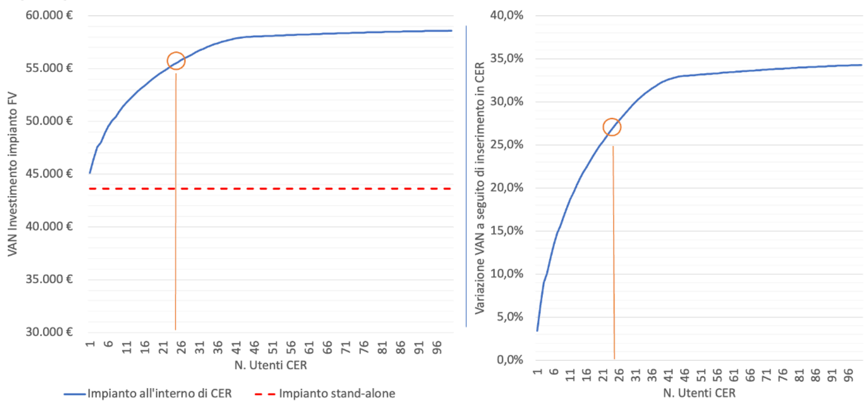


Figure 7-9: Left: trend of the NPV of the PV plant in the presence of RECs and as the number of users changes (in blue), compared with the pre-REC NPV (red). Right: Percentage change in NPV compared to the pre-REC case

Figure 7-10 shows the results of the sensitivity analysis on how incentives are distributed between prosumer and consumer, in the case of a REC with about 25 users. It can be seen that the greatest impact is always on the prosumer, again due to the greater number of consumers.

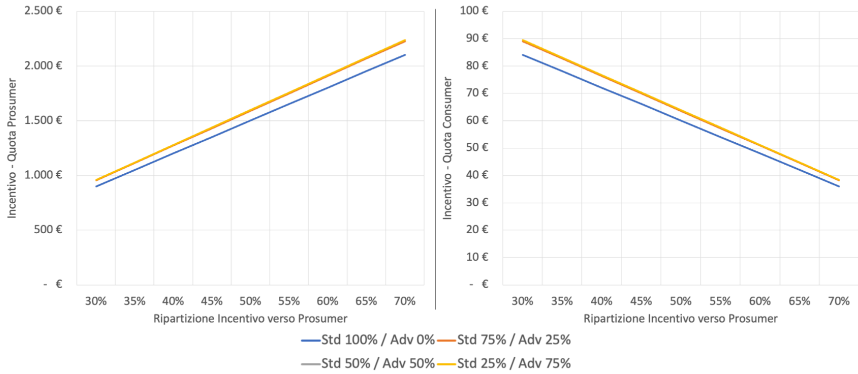


Figure 7-10: Sensitivity analysis of the value of the incentives paid to the individual prosumer (left) and consumer (right) according to the distribution of the incentive between them

In conclusion, Figure 7-11 shows the possible increase in the incentive collected by the REC if Demand-Response techniques were applied to maximise the overlap between the energy fed into the grid by the PV system and the energy withdrawn from user loads. It can be seen that the increase is maximum for a small number of users, and then decreases rapidly. This is due to a saturation effect of the energy fed in: the presence of many users alone maximises the energy shared.

The fact that the best result is obtained with the mix of only standard users is related to their much lower consumption, which leaves more room for manoeuvre. The presence of systems such as heat pumps, however, provides much better possibilities for action, so mixes with higher percentages of advanced users are certainly favoured at this juncture. It is emphasised, however, that the values given in the figure represent a theoretical maximum, and that already 30-40% of these values is an interesting target.

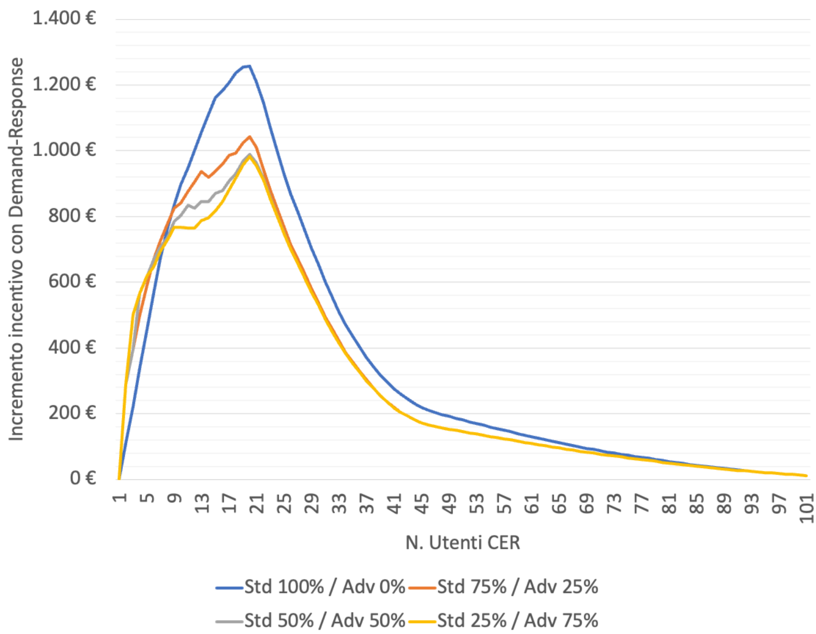


Figure 7-11: Mobilization of additional incentive volumes thanks to Demand-Response activities, based on the number and mix of users

7.3.2 Dicomano – Istituto Comprensivo Desiderio da Settignano

(i) Geolocalization

Below a summary of the main information on the side:

- Address: Via Leonardo da Vinci 1 - 50032 Borgo San Lorenzo Fi.
- GPS coordinates: 43.953869, 11.391301 (https://goo.gl/maps/Cowsi3e92Db1q1N87)

Figure 7-12: Plan (left) and satellite image of the roof of the Dante Alighieri Primary School (right)

The municipality of Borgo San Lorenzo is served by a single primary substation; within 500m from the headquarters of the Union of Mugello Municipalities (Figure 7-13) there are:

- An industrial area
- At least 10 commercial activities
- A football pitch
- A rugby field
- A primary school
- Villa Pecori Giraldi

Figure 7-13: Area considered for the assessment of commercial users and users belonging to the PA - Borgo San Lorenzo

(ii) PV plant design

In the first instance, a system whose preliminary design was already available to the administration was considered; the **peak power** is considered to be **19.5 kW** and the positioning on the roof is as described in Figure 16. The group of panels is oriented approximately 32° South, with the tilt following the inclination of the pitch of approximately 21°.

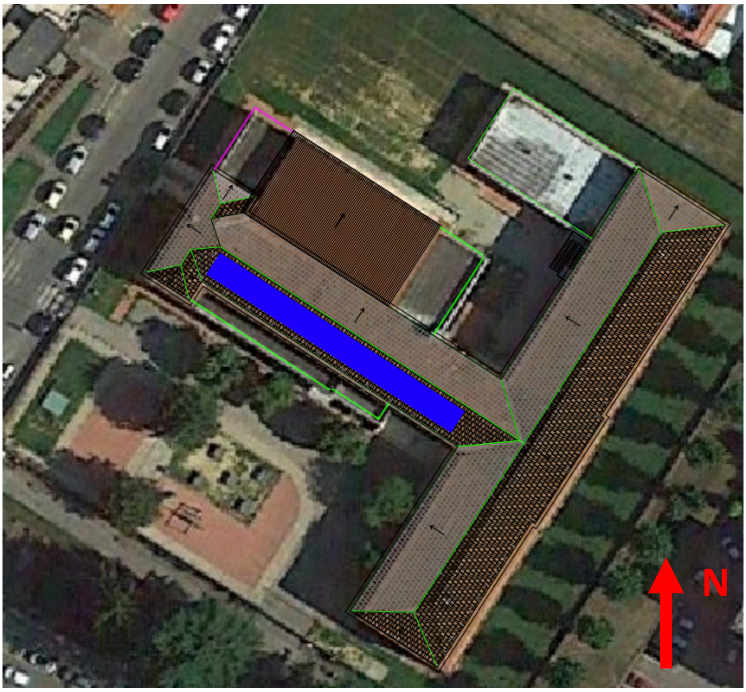


Figure 7-14:Roof plan of the Dante Alighieri Primary School, with the photovoltaic modules highlighted in blue

The **annual productivity** is about **26,200 kWh/year**, estimated using irradiation tables according to UNI 10349.

The **CAPEX** of the plant is estimated at **about €58,500** and the **OPEX** at about **€1,580**.

The main resulting economic indicators are as follows:

- Net Present Value at 20 years: €36,250
- Payback Time: 9 years
- Internal Return Rate of Investment: 11.6%.

The PV system has an estimated annual productivity of about 23% with respect to the detected consumption of the underlying utility; this allows this production to be almost completely used for local self-consumption, as summarised in Figure 7-15 (a); Figure 7-15 (b) shows the monthly profile of the remaining energy input to the grid.

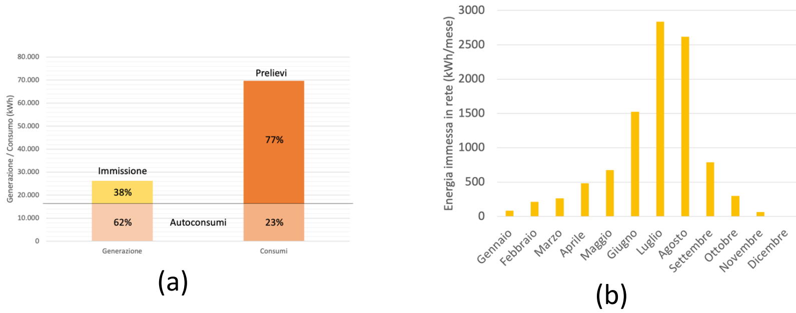


Figure 7-15: (a) Summary of the energy flows relating to the PV plant and the consumption user; (b) Grid injection profile downstream of self-consumption

The energy produced and fed into the grid by the plant, net of the expected self-consumption, amounts to approximately 9,845 kWh/year, mainly concentrated in the summer months. In any case, apart from the November-February period, the feed-in to the grid is sufficiently relevant and allows the characterisation of the REC to proceed.

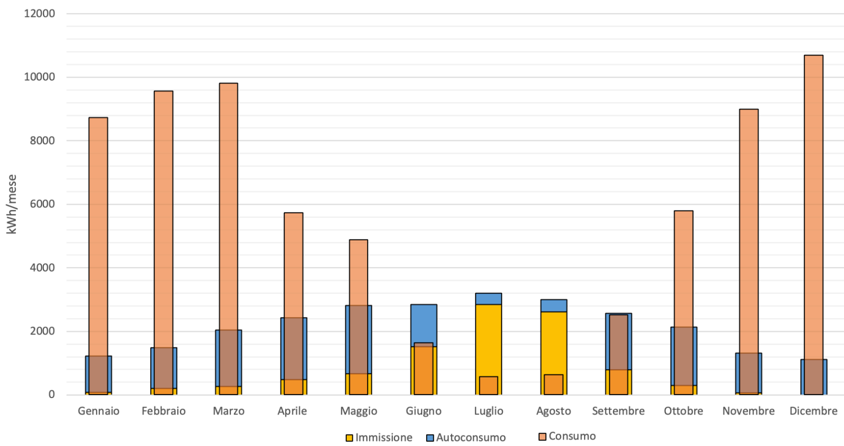


Figure 7-16: Trend of input and self-consumption profiles of the PV system and comparison with the total consumption profiles of the user relating to the Dante Alighieri primary school

(iii) REC Techno-Economic Analysis

Given the approximately **9,845 kWh/year fed into the grid**, the **maximum incentive obtainable** for energy exchanged within the REC is approximately **1,200 €/year**. This result is obtained with about 70 standard users connected to the REC; however, given the trend of the curve, it is possible to reach 80% of this result with only 21 connected users, as shown in Figure 7-17.

Given the concentration of the energy available for exchange mainly in a few summer months, the number of participating users could probably be slightly reduced without too high an impact on the total value of the incentives received.

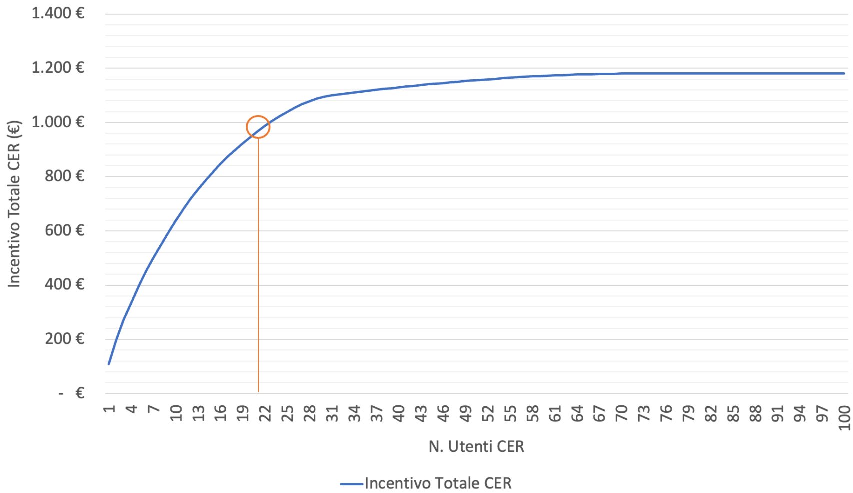


Figure 7-17: Trend in the value of the incentives envisaged for the REC of Borgo San Lorenzo according to the number of users. The point of achievement of 80% of the energy exchanged is indicated in red.

In fact, Figure 7-18 shows how as the number of users participating in the REC increases, the incentive given to the individual (and thus the savings in the bill) drops dramatically. This is due to the need to spread the incentive obtained from the ERC over an increasingly large pool of users. It is therefore necessary to find a compromise between collecting a sufficient percentage of the incentive compared to the maximum deliverable and a **minimum remuneration of individual users**. An ERC consisting of approximately 20-21 users would pay out approximately **EUR 30 per year to the individual**, corresponding to a percentage saving of approximately 3% for the standard user.

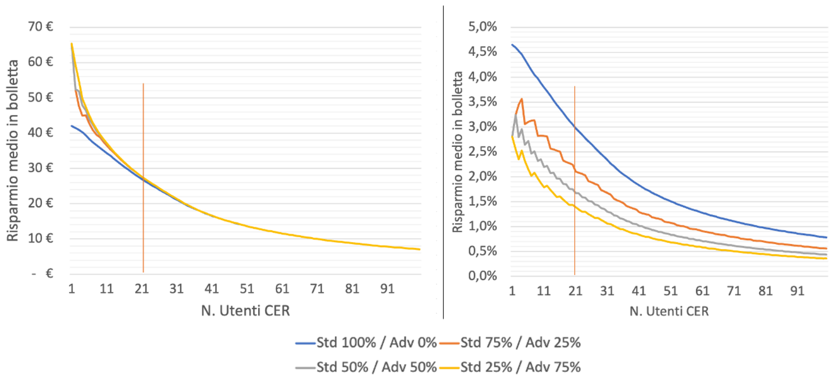


Figure 7-18: Trend of average savings on the bill (left: absolute, right: percentage) of consumers belonging to the REC, according to the number of users and the typological mix

Figure 7-19 shows the impact of REC on the economics of the PV system; it produces an **improvement in NPV of around 11%, or more than EUR 3,600 over 20 years**.

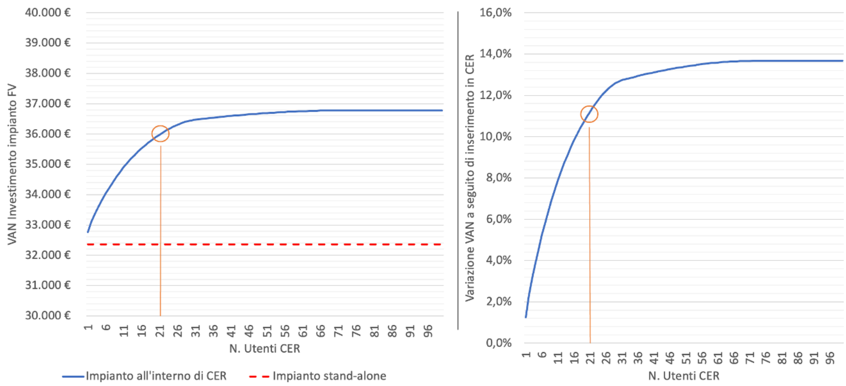


Figure 7-19: Left: trend of the NPV of the PV plant in the presence of RECs and as the number of users changes (in blue), compared with the pre-REC NPV (red). Right: Percentage change in NPV compared to the pre-REC case

7.3.3 Dicomano – Istituto Comprensivo Desiderio da Settignano: an alternative design for the PV plant and relative REC

In this section of the study, a 19.5 kW addition to the preliminary design was considered, which was already available to the administration and was analysed in the previous sections. This **15 kW addition** takes advantage of the recently constructed extension to the school building and the indicative positioning on this roof is as described in Figure 7-20. The panel assembly is oriented approximately 32° South, with a tilt of approximately 36°.

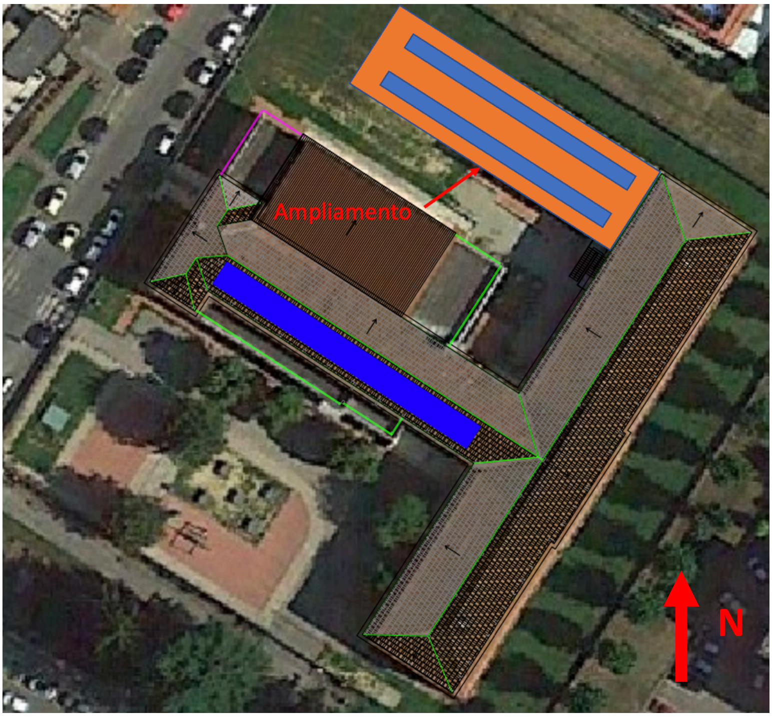


Figure 7-20: Plan of the roof of the Dante Alighieri Primary School, with the photovoltaic modules highlighted in blue and the extension of the structure in orange

The purpose of this further assessment is to verify the impact on the profitability of the REC of an increase in the output of the PV plant. The assumptions regarding the feasibility of the additional plant will have to be verified at a later date; on this occasion, the report focuses mainly on the energy-economic effects, with the aim of providing a basic idea of the possibilities related to an extension of the original plant design.

The annual productivity in this case increases to **approximately 46,300 kWh/year**, estimated using irradiation tables in accordance with UNI 10349.

The **CAPEX** of the plant thus composed is estimated at about **€88,500** and the **OPEX** at about **€2,400.**

The main resulting economic indicators are as follows:

- Net Present Value at 20 years: €73,150
- Payback Time: 8 years
- Internal Return Rate of Investment: 11.6%.

The PV system has an estimated annual productivity of about 36% compared to the detected consumption of the underlying utility, as summarised in Figure 7-21 (a); Figure 7-21 (b) shows the monthly profile of the remaining energy input to the grid.

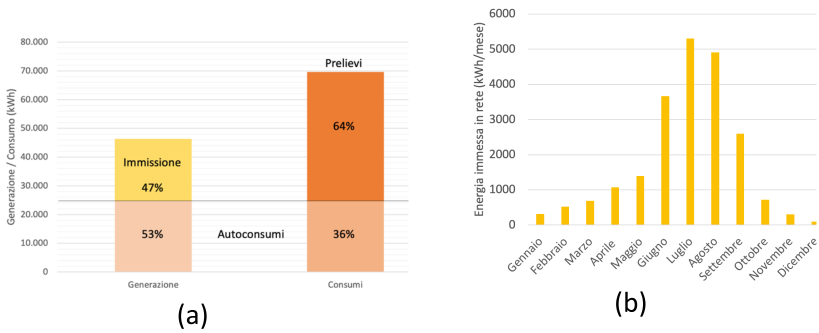


Figure 7-21: Trend of input and self-consumption profiles of the PV system and comparison with the total consumption profiles of the user relating to the Dante Alighieri primary school

The energy produced and fed into the grid by the plant, net of the expected self-consumption, amounts to **approximately 21,600 kWh/year**, mainly concentrated in the summer months. In any case, apart from the November-February period, the feed-in is sufficiently relevant and allows the characterisation of the REC to proceed.

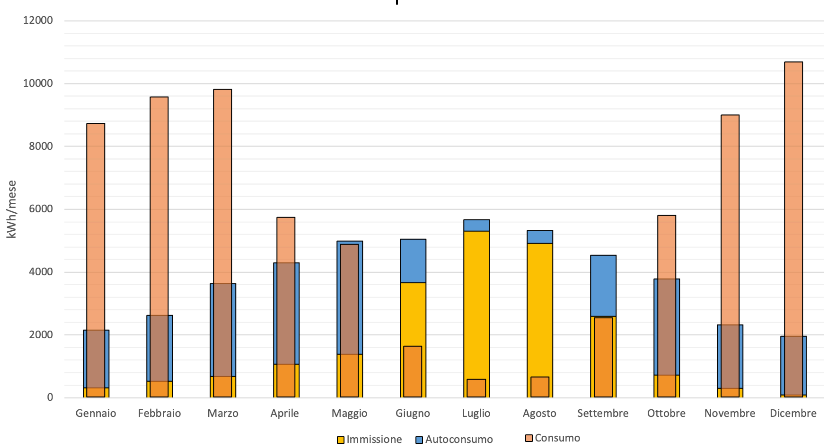


Figure 7-22: Trend of input and self-consumption profiles of the PV system and comparison with the total consumption profiles of the user relating to the Dante Alighieri primary school

Given the approximately **21,600 kWh/year fed into the grid**, the **maximum incentive obtainable** for energy exchanged within the REC is approximately **2,560 €/year**. This result is obtained with **about 100 standard** users connected to the REC; however, given the curve trend, it is possible to reach 80% of this result with only 33-34 connected users, as shown in Figure 7-23.

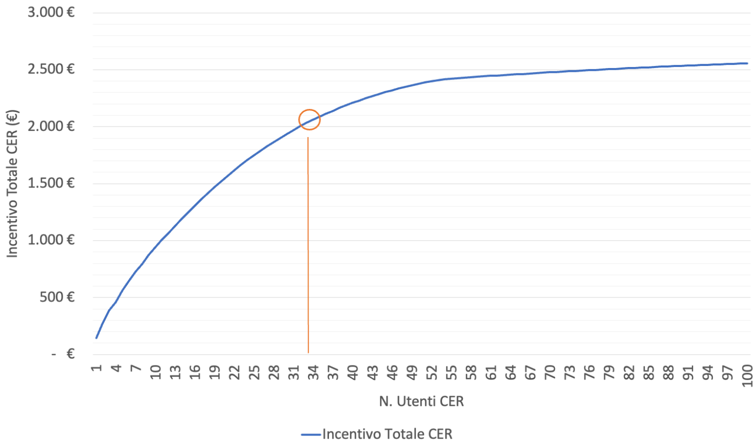


Figure 7-23: Trend of the value of the incentives provided for the Borgo San Lorenzo REC as a function of the number of users. In red is the point at which 80% of the exchanged energy is reached

In fact, Figure 7-24 shows that as the number of users participating in the REC increases, the incentive given to the individual (and thus the savings in the bill) drops dramatically. This is due to the need to spread the incentive obtained from the ERC over an increasingly large pool of users. It is therefore necessary to find a compromise between collecting a sufficient percentage of the incentive compared to the maximum deliverable and a minimum remuneration of individual users. An ERC of about 33-34 users would pay out about **35€ per year to the individual**, which equals a percentage saving of about 4% for the standard user.

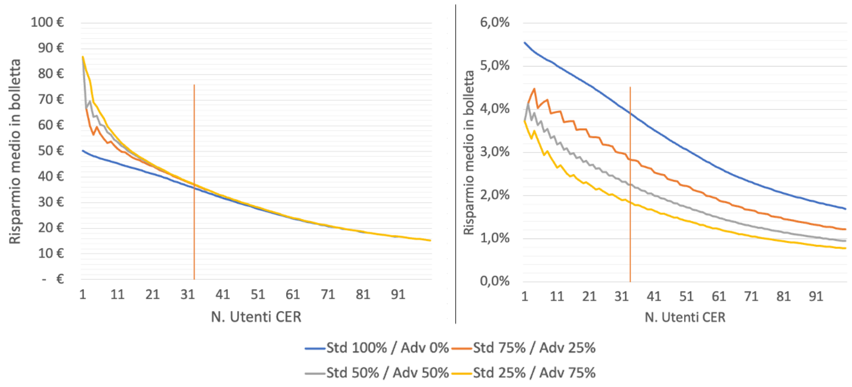


Figure 7-24: Development of average bill savings (left: absolute, right: percentage) of consumers in the REC, according to number of users and type mix

Figure 7-25 shows the impact of REC on the economics of the PV system; it produces **an improvement in NPV of around 12%,** or more than EUR 7,600 over 20 years.

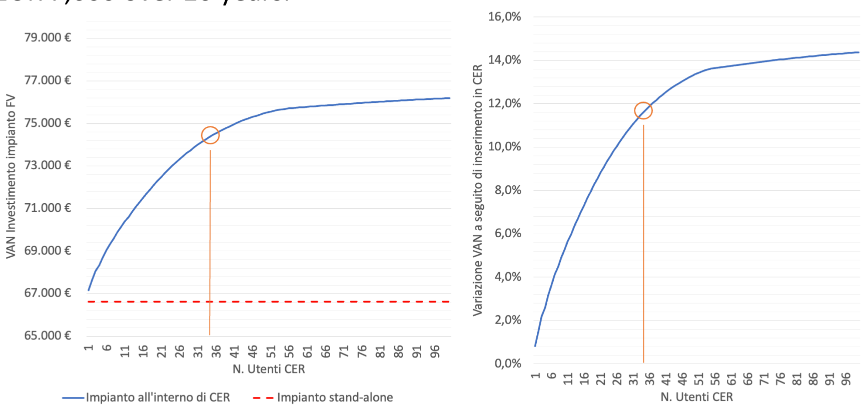


Figure 7-25: left: evolution of the NPV of the PV system in the presence of RECs and varying the number of users (blue), compared with the pre-REC NPV (red). Right: percentage change in NPV compared to pre-REC case

Chapter 8
Conclusion

This chapter summarizes the contribution of the Thesis and discusses the most promising pathways for future research

8.1 Summary of contribution

The MILP-based model developed during this research activity proved to be a versatile tool for REC management and evaluation. Several REC compositions were tested, together with different BESS parameters, in three different scenarios, to find the techno economic optimum for the analyzed REC. It emerged that:

- BESS implementation could help to improve both prosumer self-consumption and virtual energy exchanges within the REC. Anyway, only a careful charging and discharging scheduling allows to optimize its usage and the related revenues.

- By applying the MILP-based, forecast-based scheduling optimization presented in this work, a 10% average revenue increase could be obtained for the prosumer alone when compared to the non-optimized BESS usage scenario.

- Such revenue increase is obtained by reducing the BESS usage by around 30%, thus guaranteeing longer lifetime and, in perspective, the possibility to use the remaining overall capacity for providing different, non-energy-related services to the grid (i.e., flexibility and distributed balancing services).

The model can be complemented with the database of potentially controllable household loads realized from Pecan Street Dataport materials, providing, in perspective, a suitable tool for the simulation of demand-response activity at the residential level. The database has been structured to provide several possible uses within this framework:

- The average load profiles could be used as dummy for in-advance load scheduling (i.e. for day-ahead scheduling, under forecast assumptions)

- The raw load strips can be used in real-time management phase
- The database of single events, provided with actual timestamps, can be used randomly as an alternative in both the other previously described situations.

Finally, in this work, also the problem of optimal allocation of the prosumers in the communities has been faced. A metaheuristic Pareto optimization algorithm, in particular genetic algorithm, has been used to investigate the optimal number of RECs given a set of prosumers and consumers based on their allocation for both maximum and most uniform economic revenue. This multiobjective optimization problem produced a Pareto front in which it was possible to select more than one suitable solution, be it based on of the total economic revenue or on the distribution of it among the number of RECs.

It is worth noticing that in this case no REC management optimization has been carried out, for sake of simplicity; anyhow, the optimized RECs resulting from this activity are also the optimal starting point for further optimization processes, since generation and consumption are well “tuned”. This would allow to reduce i.e. BESS scheduling in order to obtain the same results.

A real case-study Techno-Economic assessment has been carried out, for a series of REC involving Public Administration users in a countryside environment. Several small PV generation systems to be installed on the roofs of buildings owned by the municipalities, such as theaters, schools, sport centers and others were considered as the main RES for the REC.

Objective of the work was to provide evidence of the possible benefits related to the REC, and to define a first-tentative optimal size for it. A Municipality-leaded (or at least participated) REC could provide several benefits: it would enhance citizens’ trust and will to participate, overcoming the existing uncertainties related to the rues and structure of the REC itself; it will open up to many dissemination and scale-up possibility.

8.2 Direction for future work

From a REC management perspective, the availability of a suited database for controllable household loads opens to a series of highly interesting research activities, involving demand-response flexibility exploitation. Such activities are well related to the work that Smart Energy Lab is carrying out in E-Earth project, the follow-up of E-CUBE; in that context, a trial case study for one or more really operating REC is envisaged, providing the perfect framework for experimental activity.

Moreover, the management of electrified thermal loads for space heating should be evaluated; research activities are already ongoing on that specific topic.

From a REC clustering perspective, a natural upgrading step for the model is to add links, in terms of constraints or premiums, to specific use of the existing distribution network, that allow to reduce the existing burden.

Chapter 9 Bibliography

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Appendix A
Publications

This research activity has led to several publications in international journals and conferences. These are summarized below (The author's bibliometric indices are the following: H-index = 6, total number of citations = 123 (source: Scopus on Month 1, 2023).

International journals

- Talluri G.; Lozito G.M.; Grasso F.; Iturrino Garcia C.; Luchetta A., Optimal battery energy storage system scheduling within renewable energy communities, ENERGIES, pp 8480 - 8503, 2021, Flore hdl: 2158/1283049
- Sospiro P.; Amarnath L.; Di Nardo V.; Talluri G.; Gandoman F.H., Smart grid in China, EU, and the US: State of implementation, in ENERGIES, pp 5637-5652, DOI: 10.3390/en14185637, ISSN 1996-1073, Flore hdl: 2158/1245000
- Grasso F.; Talluri G.; Giorgi A.; Luchetta A.; Paolucci L., Peer-to-Peer Energy Exchanges Model to optimize the Integration of Renewable Energy Sources: the E-Cube Project. Energia Elettrica Supplement, 2020, 1–8, https://doi.org/10.36156/ENERGIA06_02, FloRe id number hdl: 2158/1189977
- Garcia Cl.; Grasso F.; Luchetta A.; Piccirilli M.C.; Paolucci L.; Talluri G., A Comparison of Power Quality Disturbance Detection and Classification Methods Using CNN, LSTM and CNN-LSTM, Applied Science, 2020, 1-22, https://doi.org/10.3390/app10196755, FloRe id number hdl: 2158/1208546
- Talluri G.; Grasso F.; Chiaramonti D., Is Deployment of Charging Station the Barrier to Electric Vehicle Fleet Development in EU Urban Areas? An Analytical Assessment Model for Large-Scale Municipality-Level EV Charging Infrastructures, Applied Sciences, 2019, 1-29, https://doi.org/10.3390/app9214704, FloRe id number hdl: 2158/1179381

International Conferences and Workshops

- Grasso, F; Lozito, GM; Fulginei, FR; Talluri, G, Pareto Optimization Strategy for Clustering of PV Prosumers in a Renewable Energy Community, 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON), pp 703 - 708, 2022, Flore hdl: 2158/1283179

- Grasso, F; Iturrino Garcia, C; Lozito, GM; Talluri, G, Artificial Load Profiles and PV Generation in Renewable Energy Communities Using Generative Adversarial Networks, 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON), pp 709 - 714, 2022, Flore hdl: 2158/1283054
- Bindi M.; Talluri G.; Lozito G.M.; Luchetta A.; Piccirilli M.C.; Grasso F., Smart monitoring of DC-DC converters, 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), pp 1 - 6, 2022, Flore hdl: 2158/1282900
- Talluri, G.; Bindi, M.; Luchetta, A.; Grasso, F.; Luchetti, L.; Paolucci, L., 2021. Analysis of Power Losses due to Magnetic Shielding for Electric Vehicle Wireless Charging. DOI:10.1109/CPE-POWERENG50821.2021.9501223. pp.1-6. In IEEE CPE-POWERENG 2021 - ISBN:978-1-7281-8071-7, Flore: hdl:2158/1244672
- F. Grasso, A. Reatti, P. A. Scarpino, G. Talluri, G. Cafaro, Importance of arc flash analysis in e-mobility, in 2020 AEIT International Annual Conference - Special Session 6- e-mobility & shipboard applications DOI: 10.23919/AEIT50178.2020.9241087, Flore hdl: 2158/1239186
- Grasso. F.; Paolucci. L.; Bacci. T.; Talluri. G.; Cenghialta. F.; D'Antuono. E.; De Giorgis S., “Simulation Model and Experimental Setup for Power Quality Disturbances Methodologies Testing and Validation,” in 5th International Forum on Research and Technologies for Society and Industry: Innovation to Shape the Future, RTSI 2019 - Proceedings, pp. 359–363, doi: 10.1109/RTSI.2019.8895585, FloRe id number hdl: 2158/1181807
- Grasso F.; Abdollahi M.; Talluri G.; Paolucci L., Power Control and Energy Management of Grid-Scale Energy Storage Systems for Smart Users, in 2019 AEIT International Annual Conference,