Politecnico di Torino

Laurea magistrale in ingegneria energetica e nucleare
A.a. 2021/2022
Sessione di laurea novembre/dicembre 2022

Effects of Synchronism between Photovoltaic Generation and Energy Demand in a Residential Energy Community

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Abstract

According to many future scenarios, a high penetration of renewable electricity in the electricity mix will be needed in order to limit global warming. To accomplish this, in most countries the share of renewable electricity will need to drastically increase from its present values. Energy communities may be one of the enablers of this growth, due to their potential to support the development of distributed infrastructures and to increase grid flexibility.

This work analyses the impacts that yearly energy demand, synchronism between photovoltaic (PV) energy generation and energy demand, PV inclination and orientation, and the presence of energy storage systems have on a residential energy community's key performance indicators (KPIs). These impacts are assessed through simulations performed with an open-source Python-based program adapted from the literature.

In the first part of this thesis, a literature review on energy communities is conducted, with a particular focus on their definitions, their possible activities, their typologies, their current state in Italy, and on their modeling approaches.

The method utilized in this work to represent the yearly demand and synchronism (with PV production) of users' demand profiles is the so-called "PCC-demand plane", which utilizes the Pearson Correlation Coefficient (PCC) to represent the synchronism between energy demand and PV generation. The potential of the PCC-demand plane is first demonstrated by showing that the presence of demand profiles in different areas of the plane has a significant effect on the KPIs of a simulated energy community.

Secondly, the impacts of the inclination and orientation of PV systems are analyzed. The effects of different PV inclinations are found to be mostly limited to changes in the yearly PV-produced energy, with very limited effects on PCCs. Different PV orientations can have a strong impact on both PV energy production and PCCs; however, the eventual improvements of synchronism produced by orientations different from South appear to be generally not enough to compensate for the reduced energy production.

Thirdly, a tool to create custom distributions of demand profiles, based on normal distributions for the values of yearly demand and PCC, is developed. Performing simulations with different custom distributions, it is found that the means of PCC and yearly demand significantly affect the KPIs (whose trends are analyzed and discussed) of the simulated energy communities, while the standard deviation of demand does not.
Moreover, two distributions of demand profiles derived from different sources but with similar averages and standard deviations of both PCC and yearly demand are used in simulations. The latter produce similar KPIs, suggesting that demand profiles with similar distributions of PCC and yearly demand may cause similar performances of the energy communities.

Finally, an analysis is conducted on the effects of the presence of batteries in an energy community, analyzing the variations of KPIs and PCC, comparing several distributed batteries installed in some households and a single centralized battery usable by all of the community's households. Batteries are found to be an effective way to increase the PCC of an energy community and consequently its KPIs; in particular, a centralized battery appears to be the most effective way of doing this.

Acknowledgments

Voglio ringraziare tutte le persone che mi hanno accompagnato e sostenuto durante il mio percorso universitario e non solo.

Grazie ai miei relatori, il prof. Andrea Lanzini, il prof. Francesco Demetrio Minuto e il dott. Daniele Salvatore Schiera, per tutto l'aiuto, il supporto e i consigli che mi hanno dato durante lo sviluppo di questa tesi.

Grazie ai miei compagni di corso, per tutte le esperienze condivise e il supporto reciproco.

Grazie ai miei amici, quelli nuovi e quelli di sempre, per tutti i bei momenti passati insieme e per essere sempre stati pronti a consigliarmi e aiutarmi.

Grazie alla mia famiglia e ai miei parenti, in particolare ai miei genitori, a mia nonna, a mio zio e alle mie zie, per avermi dato l'opportunità di studiare e per aver condiviso con me ogni gioia e ogni fatica.

Grazie ad Alice, per tutto.

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Main acronyms

CEC: Citizen Energy Communities

CI: Confidence Interval

DER(s): Distributed Energy Resource(s)

DSM: Demand Side Management

EC: Energy Community

KPI(s): Key Performance Indicator(s)

P2P: Peer-to-peer

PCC: Pearson Correlation Coefficient

PV: Photovoltaic

RES: Renewable Energy Sources

Q1: Quadrant 1 (of the PCC-demand plane)

Q2: Quadrant 2 (of the PCC-demand plane)

Q3: Quadrant 3 (of the PCC-demand plane)

Q4: Quadrant 4 (of the PCC-demand plane)

REC: Renewable Energy Community

SC: Self-Consumption

SS: Self-Sufficiency

1 Introduction

1.1 Relevance and definitions of energy communities

The Paris Agreement poses as the common objective of its signatory countries the limitation of global warming to a temperature increase, compared to pre-industrial times, well below 2 °C [1]. In order to reach this target, a significant growth of the share of renewable electricity in the electricity mix is needed. The International Energy Agency (IEA) estimates in the World Energy Outlook 2021 that the share of renewable electricity in the world in 2050 would need to be more than 80% in the Sustainable Development scenario, which describes a "well below 2 °C" pathway to reach the objectives established by the Paris Agreement. Even considering a more conservative scenario, such as the Announced Pledges scenario (which considers the ambitions and targets currently announced and is expected to lead to a temperature increase of 2.1 °C by 2100), the share of renewable electricity is forecasted to be more than 70% by 2050 [2].
However, most of the current electrical grids and related technologies are built to accommodate a share of renewable electricity in the range of 20% - 40%, resulting inadequate for the energy transition and creating the need for more flexibility and balancing options to allow for the amount of renewable electricity generation needed for the decarbonization of the energy system [3].

Energy communities could be a part of the solution to this issue since they can contribute to increasing grid flexibility locally and supporting the development of distributed infrastructures [3], thus decreasing and/or deferring the traditional network upgrades [4]. The possible importance of energy communities in the energy transition is highlighted by some estimates done by the European Commission in 2016 that envisioned the possibility of around 21% of the installed solar capacity and 17% of the wind capacity (corresponding to 50 GW of solar power and 50 GW of wind power) in the European Union being owned by energy communities by 2030 [5]. It is worth noting that this prediction is quite dated and could result too ambitious nowadays, considering that in the European Union (EU) the estimated installed renewable capacity in energy communities in 2021 was *"at least 6.3 GW"* according to the European Commission [6], which is a small percentage of the total renewable capacity installed in the EU, which was almost 500 GW in 2019 [7]. However, the prediction made in 2016 highlights the future potential of energy communities and the interest that the EU is showing toward them. Therefore, it is possible to infer the relevance of the concept of energy communities, but an accurate definition of it is necessary to further analyze it.

Many definitions of energy communities have been developed in the last decade, highlighting different aspects of the concept and defining more in particular sustainable energy communities, renewable energy communities, and clean energy communities [8]. However, it was only recently that clear legislative definitions were given in the EU legal framework, in the European Commission's Clean Energy Package [4]. These definitions are the ones considered and analyzed in this thesis and they are two, one contained in the revised Renewable Energy Directive (EU) 2018/2001 (also known as RED II) and one introduced by the revised Internal Electricity Market Directive (EU) 2019/944. The former is the definition of "renewable energy communities" (RECs), which concerns energy communities in whose activities only renewable energy is used, while the latter is the definition of "citizen energy communities" (CECs), for which no restriction on the kind of energy (renewable or not) is posed [4].

Before analyzing these definitions, it is important to note that they are definitions of energy communities as legal entities, therefore they do not focus primarily on the energy systems that are present in an energy community and on their functioning. Lowitzsch et al. argue that energy communities can be seen as the governance model of energy clusters, the latter being the technical concept describing the emerging energy systems managed by the energy communities' members. In their own words, they conceive energy communities and energy clusters as *"mirror images, governance and technological, of the same concept"* [3].

The complete definitions are not reported here for sake of brevity and can be found for example in [9]. The main aspects of RECs and CECs that emerge from the Clean Energy Package, highlighting the differences and similarities between the two concepts, are presented in Table 1.1 (own elaboration from [3], [4]).

Table 1.1: Differences and similarities between the definitions of RECs and CECs.

	Renewable Energy Communities	**Citizen Energy Communities**
Purpose	Primarily *"environmental, economic or social community benefits for its shareholders/members or for local areas"*, not financial profits.	
Participation	Open and voluntary.	
Allowed Participants	Only natural persons, local authorities, and enterprises of micro, small and medium size.	All types of entities.
Control	RECs can be controlled by the members located in the proximity of the renewable energy project.	The members can exercise control but excluding medium and large enterprises.
Autonomy	RECs must be autonomous from individual members (whose stock ownership is limited to 33% of the total) and from other market actors.	Autonomy is not directly referenced in the definition, but members or shareholders involved in large-scale commercial activity and in energy as a primary area of activity are excluded from decision-making.
Geographical Scope	RECs must be located in the proximity of the renewable energy project.	CECs have no requirement of proximity to the energy project; generation and consumption can occur in different locations.
Activities	Activities are in the electricity and heating sectors and involve renewable energy, in all its forms.	Activities are in the electricity sector, the use of any energy source, including fossil fuels, is allowed.

1.2 The activities of energy communities

Analyzing the legal framework of energy communities in the EU is necessary but insufficient to fully understand their current and possible future impacts on energy systems. Indeed, energy communities can perform many different activities in the energy field, which the legal definitions do not completely describe. The Joint Research Centre (JRC) identified such activities in [4], through a combination of literature review and analysis of real, operative energy communities in the EU. Their findings describe energy communities as actors that can partake in one or more of the following activities:

- electricity generation for sale to a supplier,
- supply of energy in various forms to retail customers,
- sharing and individual and collective self-consumption of locally produced electricity,
- ownership and/or management of a local distribution network,
- energy storage and flexibility provision,

- electric mobility,
- other energy services (such as energy efficiency and/or energy savings, smart grid integration, and energy monitoring and management for network operations),
- other various activities, not necessarily directly connected to energy (such as financial or consultation services) [4].

Electricity sharing and self-consumption and energy storage are the most relevant activities for the focus of this thesis and are therefore further analyzed, even if they are not necessarily the most frequent activities of existing energy communities (indeed, the analysis performed by the JRC on operative energy communities suggests that other activities, such as electricity generation for sale and energy supply are significantly more common [4]).

1.2.1 Peer-to-peer electricity trading

Electricity users that not only consume electricity but also produce it, through distributed energy resources (DERs), are called prosumers. They can utilize the electricity produced by the DERs they own to reduce their energy costs in two ways: self-consuming the produced electricity instead of buying it and sharing the surplus electricity produced in local energy markets [10]. The activities of electricity sharing and self-consumption in energy communities are simply more prosumers doing this, with the peculiarity that electricity sharing mainly occurs locally, amongst members of the energy community [4].

Prosumers of an energy community can decide to sell energy to other members in a specific quantity and at a certain price to which both parties agree, thus performing what is called peer-to-peer (P2P) trading [10]. More specifically, article 2 of RED II defines peer-to-peer trading as *"the sale of renewable energy between market participants by means of a contract with predetermined 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"* [3]. It is important to specify that even if a third party can act as an intermediary, it has no right to directly control the trade among prosumers, even if it could partially influence their decision-making, for example by imposing some constraints [10].

Despite potentially having great importance in energy communities, peer-to-peer energy trading is not the only possible way of coordinating prosumers, in fact, it has been described as one of three possible ways of doing so, the other two being an optimization approach and considering only the energy management of the single user (not coordinating the prosumer community as a whole) [10].

1.2.2 Energy storage and demand side management

With the increasing diffusion of renewable energy sources (RES), energy storage has attracted more and more interest, being considered a possible solution to the variable generation of photovoltaic (PV) and wind energy systems [11]. It is also one of the technologies that are being prominently considered for deployment at the community scale, due to its modular nature and the possibility of connecting energy storage systems to distributed RES owned by residential users. In this way, energy storage could help to increase the diffusion of distributed RES, for example by storing surplus generation for later use (thus increasing electricity self-consumption), contributing to maintaining grid stability, and procuring economic revenues to owners by allowing them to take part to some electricity markets [12].

Energy storage in an energy community could be installed at the community level, having a size of tens or hundreds of kWh and being connected to the community distribution network. Alternatively, it could be located “behind the meter” of single proprieties, with a size of generally less than 20 kWh in the case of residential users [12].

Different kinds of energy storage are suitable to be installed in energy communities: electrochemical batteries (in particular Lithium-ion batteries thanks to their high efficiency and lifetime), flow batteries (which are interesting for their flexibility due to their energy and power being decoupled), hydrogen obtained through electrolysis (one of the best options for medium and long term energy storage), and thermal energy storage (which can range from simple hot water tanks to latent heat storage using phase change materials) [12].

Demand side management (DSM) is the ensemble of various ways to alter the pattern and magnitude of the electricity consumption by end-users by increasing, reducing, or rescheduling the energy demand [11]. DSM could be implemented in energy communities, alongside energy storage, to improve the responsiveness to demand variations, allowing users to assume a more active role through their responsive loads [13]. This could allow active participation in energy communities even for users not owning DERs, for example for a lack of financial availability. DSM could be a useful resource to better match energy demand and supply in energy communities with a high amount of variable renewable energy generation [13].

1.3 Typologies and legal structures of energy communities

Multiple forms of energy communities have emerged over the years, with differences in underlying objectives, supporting business models, and utilized technologies. Gui and MacGill defined clean energy communities and identified three typologies of them. It is important to specify that their definition of "clean energy communities" is quite broad, as it is *"social and organizational structures formed to achieve specific goals of its members primarily in the cleaner energy production, consumption, supply, and distribution"* [8]. Due to the generality of this definition not all of the communities respecting it will also adhere to how the EU legal framework describes renewable energy communities or citizen energy communities. However, Gui and MacGill's identification of three categories of clean energy communities could be extended to energy communities in general.

Firstly, the authors identify centralized clean energy communities as constituted by a cohesive network of members that collectively own energy-related assets or participate in energy-related programs (such as energy efficiency or demand side management). Due to the high level of cohesion and the common goals of the members, these communities are generally not difficult to integrate into the existing centralized electrical system. Community power plants belong to this typology of clean energy community [8].

Secondly, Gui and MacGill define distributed clean energy communities as those communities in which members:

- individually own DERs with which they generate energy,
- are connected through a controlling entity,
- share the same rules for electricity supply and consumption.

For this typology of communities, the authors envision two possible approaches: P2P trading and the virtual power plant model (which consists in aggregating and controlling controllable energy generators, storage units, and loads, so that the complex behaves similarly to a single power plant) [8].

Thirdly, Gui and MacGill distinguish decentralized clean energy communities which have the characterizing aspect of generating and locally consuming energy for their own self-sufficiency. These communities have a particular focus on self-sufficiency and autonomy from the main electrical grid, to which they may be connected or not. The authors consider community microgrids (local electricity supply systems independent from the main electrical grid) and integrated community energy systems (i.e. integrated urban resource management systems) to be part of decentralized clean energy communities [8].

The Joint Research Center reviewed the different legal structures for energy communities, differing in governance, decision-making, and responsibilities, that are present in European countries. They identified as possible legal structures [4]:

- Energy cooperatives: enterprises that allow citizens to possess and manage (through a democratic governance model) renewable energy projects; the aim is to benefit members by reinvesting profits in favor of the community.
- Limited partnerships: partnerships (usually done for large projects) that redistribute the responsibilities of individuals through a limited liability company; participants can buy different shares and their voting rights are proportional to the owned shares.
- Community trusts and foundations: a community group owns the energy project, funded through grants and loans, and invests profits in the local community.
- Housing associations: non-profit associations that, to reduce energy poverty, invest in energy projects to offer some benefits (such as lower energy prices) to inhabitants of social housing.
- Non-profit customer-owned enterprises: this kind of legal structure can be used by communities that manage their independent energy networks (such as district heating).
- Public-private partnerships: created when local authorities stipulate contracts with private enterprises to provide energy and benefits to a citizen community.
- Public utility companies: companies that are managed and invested in by municipalities on behalf of citizens.

1.4 Impacts of energy communities on the energy system

Studying energy communities "in a vacuum" is not sufficient to fully understand their importance and their impact, it is also necessary to analyze the effects they have or may have on the energy system as a whole.

If DERs are not adequately controlled and coordinated, they may cause effects that are negative for the electrical network, such as the inversion of the power flow direction in electric lines, voltage rises (where normally voltage drops are expected and considered in the design phase) and greater fault currents [10].

However, if DERs are coordinated they can actually produce positive effects on the electricity network, for example by reducing power losses and costs of distribution and transmission systems [10], as well as by allowing to postpone improvements of the latter [4]. These advantages can occur only if prosumers play an active role by providing energy services [10], therefore energy communities

can help to decentralize the energy system and to adequately operate distributed renewable energy systems [4].
Moreover, P2P sharing (which can occur in energy communities) can also produce other benefits through the reduction of the electricity demand peak, operating costs, and reserve requirements and by improving the reliability of the electrical grid [10].

1.5 Renewable energy communities and collective self-consumption in Italy

In Italy, some projects related to renewable energy communities had already started at the beginning of this century, well before the formulation of the EU framework for RECs in RED II. In the most recent years, further steps have been made for the promotion of renewable energy self-consumption and RECs in Italy [14]. In particular, the Decree-Law 162/19 (which partially transposed the RED II directive [14]) defined the conditions and modes for the realization of renewable energy collective self-consumption initiatives (composed of at least two jointly-acting self-consumers located in the same building) and of renewable energy communities [15]. The effect of the RED II directive in Italy has led to a considerable acceleration in the development of RECs and collective self-consumption initiatives [14]. This can for example be seen considering how 59 of the 100 RECs and self-consumption initiatives mapped by Legambiente in 2022 were registered from June 2021 to May 2022 [16].
To promote the diffusion of Italian RECs and collective self-consumption initiatives, some economic incentives have been introduced for the so-called "shared electricity", which is defined as the minimum, on an hourly basis, between the electricity injected in the electrical grid and the electricity withdrawn from the connection points of the REC or jointly acting self-consumers [14]. The GSE (*Gestore dei Servizi Energetici,* the institution which manages the Italian energy sector) will remunerate (for 20 years from the commercial beginning of operation) the shared electricity with the sum of:

- 8.37 €/MWh, for both REC and collective self-consumption initiatives,
- an additional contribution for avoided energy losses in the grid (which depends on the hourly zonal price and on the voltage level of the network to which self-consumers are connected), only for jointly acting self-consumers,
- a premium tariff, equal to 100 €/MWh for self-consumers groups and to 110 €/MWh for RECs [15].

Additional Italian incentives that members of RECs or of collective self-consumption initiatives could have access to are the so-called Ecobonus and Superbonus. The Ecobonus is a tax deduction in 10 years of 50% of the expense incurred for the installation cost of a photovoltaic system of peak power up to 200 kW. The Superbonus allows a tax deduction in 5 years of 110% of the initial cost of PV systems and of energy storage systems, as long as their installation is accompanied by other main interventions on the building (such as the improvement of its thermal insulation) and as the latter's energy class improves by at least two classes. However, the tax deduction from the Superbonus is valid only for the expense of up to 20 kW_p of PV systems (which can have total power up to 200 kW, but the power exceeding 20 kW is non-deductible through the Superbonus) and prevents the users that benefit from it from also having access to the premium tariff of 100 or 110 €/MWh described above [14], [17].

1.6 Energy communities modeling

The previous sections showed how energy communities are a promising concept, but also how they are still in the initial phases of diffusion and development, making further research on them necessary. Modeling and simulating energy communities are important tools for studying them, allowing to gather data that could be used for various purposes, such as for helping decision-making during the operational or design phase of an energy community, for evaluating how the energy community would fare in different scenarios, and for designing policies [18].

Two possible approaches for modeling the energy system of an energy community are the simulation of different scenarios and the formulation of an optimization problem [19]. The first approach consists in evaluating the performances of an energy system in certain given conditions, while the second consists in finding the optimum of an objective function (which describes the optimization aim, for example to identify the optimal design of a system), imposing certain constraints to the latter, by changing certain decision variables [20]. Another possible distinction is between modeling approaches that are heuristic (performable using software like HOMER, TRNSYS, EnergyPlus, *Caliope*…), meta-heuristic (through genetic algorithms and particle swarm or radial movement optimization), and mathematical optimization (using various methods, with the most frequently used being Mixed-integer linear programming) [19].

Modeling energy communities (like modeling any energy system) requires making various choices, such as which technologies to include, what input data to use, and the purpose/objective of the model [20].

With regard to the technologies considered in the literature when modeling energy communities, a literature review conducted by Gjorgievski et al. in 2021 revealed the presence of four technology clusters:

- shared PV systems, sometimes associated with individually owned batteries,
- energy storage owned by the community,
- hybrid energy systems,
- district heating and cooling [19].

Another crucial step of modeling energy communities is the selection or gathering of the input data, which is crucial for both the operation and the design phase but may prove to be challenging. The availability of open-source datasets may be helpful and allow the authors of energy community simulations to avoid directly collecting data. Several of these datasets are presented in the review conducted by Kazmi et al. in 2021, which presents open data on the energy demand of residential and commercial buildings, on weather conditions, and on forecasts for climate change [21].

For what concerns modeling goals considered in the literature, the findings of Gjorgievski et al. revealed that they are mainly economic when an optimization approach is used, with a cost function used to represent and pursue such objectives. Other possible objectives are technical and environmental, even if, compared to the economic ones (which were found to be pursued in the great majority of cases), they were considered in a significantly lower percentage of the reviewed studies [19].

The focus that the current Italian incentives for renewable energy communities, illustrated in section 1.5, pose on shared electricity is a way to reward energy self-consumption [14]. Therefore, energy self-consumption can be a relevant aspect to be taken into consideration when deciding the modeling goals. Indeed, the relevance of the self-consumption of energy communities is shown by the presence in the literature of studies that aim to increase or optimize it. For example, De Grève et al. utilized Machine Learning techniques to develop data analytics modules that aim to help members of energy communities to increase the coordination between their energy consumption and the renewable power generation of the community [22]. Giordano et al. developed an optimization model for the energy management of energy communities that utilizes Internet-of-Things technology that has the increase of self-consumption as one of its advantages [23]. Barone et al. proposed a method to increase the self-consumption of energy communities utilizing smart metering and smart charging of electric vehicles [24].

The presented studies all employ some methods to improve the self-consumption of energy communities and measure its improvements. However, none of these studies quantify the main

underlying cause for the increase in self-consumption: the increase in synchronism between energy demand and renewable energy production. Indeed, an increase in this synchronism causes an increase in self-consumption [25].
To the best of my knowledge, no methods for quantifying the synchronism between energy demand and renewable energy production in energy communities have been presented in the literature and studied, other than the method introduced by Minuto and Lanzini in [18], which is the method used and further analyzed in this thesis. The method is explained in more detail in section 2.4, but in synthesis, it constitutes in representing the demand profiles of the members of energy communities in a plane based on their synchronism with renewable generation and their yearly demand. This method was applied by Minuto and Lanzini in [18] for evaluating various mechanisms to share the profits of energy communities.
Therefore, the effects that the synchronism between energy demand and renewable energy production can have on the self-consumption and other techno-economic parameters of energy communities remain to be quantified and studied. This literature gap is the focus of this thesis, and it is tackled as outlined in the following section.

1.7 Contribution and structure of this work

The contribution of this work is using for new objectives the method introduced by Minuto and Lanzini in [18] for characterizing demand profiles of energy users belonging to energy communities based on their synchronism with PV generation (which is the kind of renewable generation analyzed in this work) and their yearly demand.
The synchronism of such demand profiles is quantified and studied with the goal of better characterizing its link with the self-consumption and other techno-economic parameters of energy communities. This study is performed by analyzing several aspects of energy communities, to establish the impacts that these aspects have on the synchronism of the demand profiles and in turn on the considered techno-economic parameters of energy communities. The evaluation of the techno-economic parameters of energy communities is done through simulations performed with an open-source Python-based program adapted from the literature, presented in section 2.1.
The characterization of demand profiles of users belonging to energy communities considering their synchronism with PV generation and their yearly demand is therefore the main novelty in the approach of this work. Differences in synchronism and yearly demand of such demand profiles are considered in the various sections of this work and related to the performances (quantified through

key performance indicators) of simulated energy communities. The differences in synchronism and yearly demand analyzed in this work are those caused by three factors: different characteristics of PV systems, different characteristics of the demand profiles, and the presence of battery systems for energy storage.

The main results obtained in this thesis are briefly summarized in the following.
It is shown that differences in synchronism and yearly demand of the demand profiles of users belonging to energy communities do indeed cause significant differences in the techno-economic parameters of simulated energy communities composed by these users.
The effect of changing the inclination of PV systems is shown to have a limited impact on both the synchronism of demand profiles and the performance of energy communities, while differences in the orientation of PV systems are shown to be more impactful on both the synchronism of demand profiles and the performance of energy communities.
A tool for creating custom datasets of demand profiles with given characteristics of yearly demand and synchronism is developed and utilized. The comparison of two datasets of demand profiles with similar characteristics of yearly demand and synchronism is performed, resulting in similar performances in energy communities using them as inputs. Several custom datasets of demand profiles are created and utilized in simulations, quantifying the effects on the performances of energy communities of changing the characteristics of synchronism and yearly demand of the demand profiles of users belonging to energy communities.
Batteries are analyzed as a way to increase the synchronism of demand profiles with PV generation. This increase in synchronism is quantified for an example of energy community and the changes, due to the presence of batteries, in the performances of this energy community are presented and analyzed.

The structure of this work can be summarized as follows.
In section 2, the main methodologies followed in this work, regarding the simulations of energy communities, the model of PV systems, the datasets of demand profiles, and the PCC-demand plane are presented.
In section 3, the relevance of the PCC-demand plane as a tool to represent and describe the demand profiles of energy communities is preliminarily investigated through some simulations.
In section 4, the effects that the inclination and orientation of PV systems can have on the distribution of demand profiles in the PCC-demand plane and on the key performance indicators of energy communities are studied.

In section 5, a tool for creating new custom datasets of demand profiles with given characteristics with regard to yearly demand and PCC is presented and utilized to investigate the effects on energy communities of certain characteristics of the datasets of demand profiles.

In section 6, the effects that batteries have on energy communities are analyzed in more detail, considering the cases of multiple distributed batteries and of a single centralized battery.

In section 7, the main conclusions of this work are summarized, and possible future work is presented.

2 Methodology

In this section, the main methodologies followed in this work, regarding the simulations of energy communities, the model of PV systems, the datasets of demand profiles, and the PCC-demand plane are presented.

2.1 Setup of the simulations of energy communities

The simulations of energy communities performed in this work are based on the code developed by Pena-Bello et al. presented in [26]. This is an open-source Python-based code that is available on GitHub at [27]. The code is not presented in detail in this work, since it is already explained by its original developers in [26] and since only slight modifications have been made to it. These modifications were simple changes to allow the code to accept inputs relative to Italy (which was not one of the originally implemented countries). The novelty of this work is not constituted by modifying the original code but by using it for new objectives and with different input data regarding PV systems, described in section 2.2, and households' demand profiles, described in sections 2.3.1 and 5.1.

The code simulates a residential energy community in which some of the households have installed PV systems and some of these households also have installed batteries for energy storage. It is possible to choose the number of households present in the energy community as well as the shares of households that have PV systems and batteries. The energy communities simulated in this work are composed of 60 households out of which 30 have installed PV systems. Batteries are present in only some of the communities simulated, their eventual usage is specified when introducing each simulated scenario.

The structure of energy community just described is the one considered in all of the sections, except for part of the simulations conducted in section 6.1. In this section, for comparison, an energy community with a single large PV system and a single centralized battery, both jointly owned and used by the whole community, is considered.

It is important to highlight that all of the simulations conducted in this work consider a whole year and have an hourly resolution, meaning timesteps of one hour each.

In section 2.1.1, the power flows that are simulated within each household and in the whole energy community are described.

The pricing systems applied to the energy exchanges of the simulated energy communities are explained in section 2.1.2.
Section 2.1.3 explains in more detail how each simulation works, highlighting which factors are fixed and which are randomized.
Section 2.1.4 explains how the Monte Carlo method is applied to obtain the desired results from the simulations.
Section 2.1.5 describes the key performance indicators utilized in this work, explaining how they are calculated and their relevance.

2.1.1 Technologies and power flows present in the simulated energy communities

In this section, the power flows of the simulated energy communities are presented. The power flows relative to energy communities with multiple PV systems and batteries are explained first, then in the end the power flows relative to an energy community with a single PV system and a single battery, which was simulated only in section 6.1, are explained.
In the energy communities with multiple PV systems and batteries, the power flows for each household that has a PV system and a battery are illustrated in Figure 2.1, which is taken from the documentation of prosumpy [28], an open-source Python-based code that was used by Pena-Bello et al. as a starting point for developing the code used in [26] and in this work.

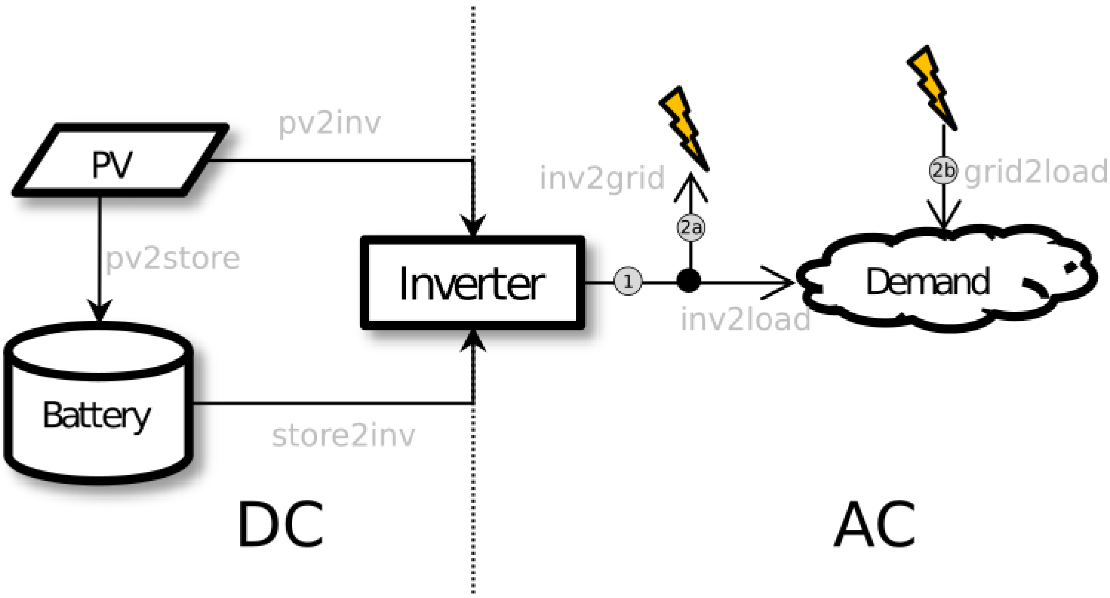

Figure 2.1: Technologies and power flows present in a household with a battery and a PV system [28].

The technologies shown in Figure 2.1 are a PV system, a battery, an inverter, the household's loads (represented by the cloud with "Demand" written on it), and the electrical grid (represented by the two lightning symbols). The model and characteristics of the batteries considered in this work are equal to those used in [26], in particular, the round-trip efficiency is 91%. The efficiency of the inverter has been considered equal to 94% in [26] and in this work. The letters "DC" and "AC" on the bottom highlight how the inverter converts the power from direct current (DC), relative to PV systems and batteries, to alternating current (AC), used by the household's loads and by the electrical grid.

Figure 2.1 shows how the power produced by the PV systems can go in two directions. The first direction (the flow pv2store) represents the storing of energy in the battery system, which occurs if there is a surplus of PV generation (i.e. the amount of PV-generated power is greater than the power demand of the household's loads) and the battery is not fully charged. If these two conditions are both verified, the surplus PV-produced energy, which is not utilized by the household's loads, is stored in the battery. On the other hand, the flow pv2inv represents the part of PV-produced power that goes to the inverter. This power then flows towards the household's loads (shown by the flow inv2load) to satisfy their demand and, in case of surplus of PV generation, part of the pv2inv (after going through the inverter) is exported to the electrical grid, through the flow inv2grid.

The flow grid2load represents the power imported by the household from the electrical grid to satisfy the demand of the loads when the flow inv2load is not enough to do so.

Finally, the flow store2inv represents the power flow of the battery discharging itself. After going through the inverter, the power coming from the battery first of all satisfies as much of the loads' demand as possible through the flow inv2load.

If the power discharged from the battery can only fulfill the demand of the loads of the single household or it can also be exported to the electrical grid depends on the considered "strategy" of battery management.

In the code developed by Pena-Bello et al., there are two possible strategies, called "self-consumption maximization" or "SC" and "peer-to-peer" or "P2P", both explained in [26]. In this work, it is always specified which of the two strategies is considered when batteries are present in the community.

In summary, in the case of the SC strategy, each battery can be discharged only to fulfill the demand of the loads of the household in which the battery is installed.

On the other hand, in the case of the P2P strategy, it is possible for the owners of batteries to choose to sell part of the energy stored in their batteries when there is no PV surplus and the charge present in their batteries is more than needed to satisfy the demand of their loads. When these two conditions are verified, the sale of part of the energy stored in the batteries can happen, but if it actually occurs depends on the preferences of the users that own the batteries, who choose whether to sell or not. These preferences are simulated in the code based on the preferences of real German homeowners that Pena-Bello et al. investigated in [26] through a poll that asked the interviewed homeowners if they would sell the energy stored in their batteries in various cases that considered different combinations of electricity price, state of charge of the battery and time until the next PV surplus. The considered cases and other details on the poll and on the implementation of the preferences of users in the code are presented in [26]. The customer preferences that were found and used by Pena-Bello et al. in [26] are also used in the simulations of this work that consider the presence of batteries managed with the P2P strategy.

Figure 2.1 presents a household that has installed both a PV system and a battery in its premises, however not all of the households in the simulated energy communities have these technologies. Houses with only PV systems have the setup presented in Figure 2.1 but without the battery, therefore the energy flows are the same except for pv2store and store2inv, which are not possible. Houses without PV systems and batteries can be simply represented by their loads, which can only import electricity from the electrical grid, therefore only the power flow grid2load is possible in these cases.

Considering the whole energy community, in the case of multiple PV systems and batteries, the code models all of the households of the community as being behind the same point of common coupling. The surplus PV-generated power (inv2grid) is injected by households with PV systems in the local electrical grid of the energy community and this power is considered to be consumed within the energy community (i.e. self-consumed by the community) if there is energy demand from some of the households that belong to the community. If the injected PV power is more than the demand of all of the households belonging to the community, then the part of the injected PV power that is not consumed within the community is exported to the main electrical grid, “external” to the community. The power imported by the various households from the electrical grid (grid2load) can come from three different sources. The first is the previously described surplus PV power injected into the local grid and consumed within the energy community. The second source, possible only if batteries are present and the P2P strategy is followed, is energy sold by the users that own batteries that inject power from the batteries to the local grid. The third source is importing energy from outside of the energy community, i.e. from the main electrical grid, this is done only when the first two sources are not enough to fully satisfy the overall energy demand of the community.

It is important to specify that the trades of energy within the community occur “automatically”, meaning that they are not due to specific agreements between two users (i.e. inhabitants of households that belong to the energy community), therefore there is no peer-to-peer electricity trading. The energy trades within the community occur when one user independently injects power into the local electrical grid (due to either a surplus of PV generation or a battery discharge, the latter being possible only in the case of the P2P strategy) and another user independently imports power from the local electrical grid to satisfy its energy demand. The prices of the energy trades are regulated by the pricing mechanisms described in section 2.1.2.

The considerations made in this section until this point were relative to an energy community with multiple PV systems and batteries. However, as previously mentioned, in part of the simulations conducted in section 6.1 a second type of energy community is considered: an energy community with a single large PV system and a single centralized battery.
The power flows relative to this second kind of energy community are the same presented in Figure 2.1, but in this case, the PV system, inverter, and battery represented in that figure are the only ones present in the community and the cloud with “Demand” written on it represents the aggregate energy demand of all of the households of the energy community. The only strategy considered for the centralized battery of this case is the SC strategy, therefore the battery is discharged only to satisfy loads of the community’s households. The power flows inv2grid and grid2load in this case are always exchanges of power with the main electrical grid external to the energy community.

Finally, it is important to specify that all of the simulations conducted in this work consider a total period of one year and that all of the power flows and relative energy balances are considered with an hourly resolution, meaning that the power values in each timestep (of one hour) are average values of power over the duration of the timestep.

2.1.2 Pricing mechanisms used for the simulated energy communities

The prices and pricing mechanisms of electricity considered for the energy communities in this work are the same ones used by Pena-Bello et al. in [26].

The first pricing mechanism is the one that Pena-Bello et al. used in [26] for energy communities in which the SC strategy for batteries, introduced in section 2.1.1, is used. In this pricing mechanism, the prices for buying energy from the grid and selling energy to the grid are constant and assumed equal to 0.28 €/kWh and 0.04 €/kWh respectively. These prices, used by Pena-Bello et al. in [26], are also the ones considered in this work because they cannot be changed in the case of the second pricing mechanism (due to the reasons explained below) and they are then kept equal for all of the pricing mechanisms to allow for comparisons of the relative energy bills. These prices for the energy exchanges with the grid are not realistic in the current Italian energy crisis, however, it is important to note that they are not prices that are unrealistic in general. For example, the average total price of purchase of electricity for residential customers in the so-called *regime di maggior tutela* in Italy in the last four months of 2021 was 0.297 €/kWh [29], not far from 0.28 €/kWh. Moreover, it is important to note that the community electricity bill, the only KPI considered in this work that is influenced by the electricity prices, is always considered in this work only in terms of comparisons between different bills and the main results of these comparisons should be generally valid even for different prices.

The first pricing mechanism just described is the one used in this work in the simulations of energy communities with multiple PV systems but without batteries and of energy communities with multiple PV systems and multiple batteries managed with the SC strategy.

The second pricing mechanism, used by Pena-Bello et al. in [26] for energy communities with the P2P strategy for batteries, is a pricing mechanism that considers a dynamic internal price within the energy community and is based on the price model developed by Liu et al. in [30]. This was the pricing mechanism considered in this work for the simulations of energy communities with multiple PV systems and multiple batteries managed with the P2P strategy.

The details of this pricing mechanism are explained in [26] and [30] and are not reported in this section, however, its basic concept is explained in the following.

This pricing mechanism considers fixed prices for the energy exchanges with the main electrical grid external to the energy community (assuming a lower price for the sale of electricity to the main grid than for the purchase) and a variable/dynamic internal price for energy exchanges that occur among households of the energy community. This variable internal price is always equal for all of the members of the energy community, all of the energy exchanges that occur within the community are associated with this same price.

The dynamic internal price varies in time depending on the ratio between the total power supply internal to the community and the total power demand of the community. The lower this ratio is in a certain timestep and the higher the internal price is in that timestep, since the scarcity of energy supply compared to the amount of energy demand makes electricity more valuable. The maximum value of the internal price is reached when the ratio becomes equal to zero, meaning when there is no power supply internal to the community, in this case, the internal price (which is not relevant when there is no internal supply, since no internal energy exchanges can occur) becomes equal to the price at which electricity is bought from the main electrical grid. On the other hand, the minimum value of the internal price is reached when the ratio between internal supply and demand becomes greater than one, when this occurs the internal price becomes equal to the price at which electricity is sold to the main electrical grid. For values of the ratio between internal supply and demand that are greater than zero and lower than one, the internal price varies between its minimum and maximum values just described, becoming higher for lower values of the ratio.

The internal dynamic price of the second pricing mechanism is constrained to be a step function in the code developed by Pena-Bello et al. and used in this work. This is done because the experimental interview conducted by Pena-Bello et al. in [26] only considered some values of electricity price when investigating the preferences of homeowners with regard to selling part of the energy stored in their batteries. The values that the internal price can assume are thus only €0.04, €0.12, €0.20, and €0.28 per kWh.

As described before, the minimum and maximum of the internal price are, respectively, the price of sale to the main electrical grid and the price of purchase from the main electrical grid. The former was considered to be constant and equal to 0.04 €/kWh, and the latter was also considered to be constant and equal to 0.28 €/kWh. These prices, used by Pena-Bello et al. in [26], are also the ones considered in this work. This is done because choosing different prices for the energy exchanges with the grid or for the values of the step function of the internal price would not allow using the customer preferences found by Pena-Bello et al. for the sale of energy stored in batteries (since these preferences depend also on the electricity price), which are used in this work in the simulations that consider the presence of batteries managed with the P2P strategy.

Finally, the third pricing mechanism is used for an energy community with a single large PV system and a single centralized battery, which is considered in part of the simulations conducted in section 6.1. The pricing mechanism for this kind of community is very simply composed only of the price of sale to the main electrical grid, considered equal to 0.04 €/kWh, and of the price of purchase from the electrical grid, considered equal to 0.28 €/kWh. These prices are the same previously introduced in order to allow for a comparison of the bills of the two different kinds of communities. In this kind of community, the single PV system and the single centralized battery are considered to be jointly owned and used by the whole community, therefore energy produced by the PV system or discharged from the battery is simply freely used by all the households of the community.

2.1.3 Input data and randomized factors of each simulation

Each simulation of an energy community conducted in this work requires certain input data, the main input data is presented in this section. The first inputs to give are the number of households that are present in the community, the share of these households that have PV systems, and the share of households with PV systems that also have batteries. The timestep can be chosen to be equal to 15 minutes, 30 minutes, or 1 hour; 1 hour was always chosen in this work due to producing a significant decrease in the time needed for the simulations. If batteries are present, their size also needs to be inserted as an input, as well as the strategy (SC or P2P) with which they are managed. The code of the country to simulate needs to be specified since based on this code, the input files of PV production and households' demand profiles and the distribution of PV systems' sizes are chosen. The input files of PV production and demand profiles are .csv files that contain power trends with at least an hourly resolution and that are the power trends used in the simulations. The input power trend of the PV production is only one, relative to a peak power of 1 kW, and it is rescaled for each PV system simulated by multiplying it by the peak power of each PV system. On the other hand, multiple demand profiles are contained in the input file, and each household of the simulated energy community is randomly assigned one of these demand profiles.

Considering the two countries for which simulations are made in this work, meaning Italy (considered in all of the sections of this work) and Germany (simulations for Germany are made only in section 5.2), the input files of PV production and demand profiles and the distribution of PV systems' sizes are different. The data relative to Germany is the one used by Pena-Bello et al. in [26], which includes a dataset of demand profiles (better presented in section 2.3.1), a PV generation profile, and a custom distribution of PV sizes that is followed by the code when assigning the peak powers of the simulated PV systems. The data relative to Italy was added in this work and includes a dataset of demand profiles (better presented in section 2.3.1), a PV generation profile, and a truncated normal distribution of PV sizes, the latter two obtained as explained in section 2.2.

Finally, a crucial input of each simulation is the seed, which is an integer number that fixes the random factors of the simulation, making each simulation reproducible. The use of the seed is necessary since various factors are randomized in each simulation. Indeed, each simulation of energy communities with multiple PV systems (and eventually multiple batteries) randomizes:

- Which demand profiles, out of the ones contained in the input dataset of demand profiles, are assigned to the households of the simulated energy community;
- To which households the PV systems and the batteries (if present) are assigned;

- The peak power of each PV system, choosing the sizes according to the set distribution of PV sizes;
- In the case of batteries managed with the P2P strategy, which decision profile (out of the ones obtained by Pena-Bello et al. in [26]) regarding when to sell energy contained in batteries to assign to each user with batteries.

In the case of an energy community with a single PV system and a single centralized battery (simulated only in section 6.1), the only randomized factors are which demand profiles to assign to the households and which size to assign to the PV system. The size of the only PV system is chosen as the sum of the sizes of PV systems (that are extracted randomly) that would be present in an energy community with multiple PV systems with the same input parameters and seed.

In any case, the randomized factors are present in order to introduce some variations between simulations. Through the use of different seeds, different energy communities are simulated, allowing to obtain results based on the Monte Carlo method, as explained in section 2.1.4. Moreover, if some input parameters of the simulated energy communities change while others do not, as it is done in various sections of this work to investigate the effect of varying some input parameters, the use of seeds allows for better comparisons. The reason for this is that the same seed fixes the randomized factors tied to certain input data if the latter is not changed, making these factors equal between different cases and allowing the elimination of their effects in the comparisons. For example, this means that if in two simulations the input PV profile is changed but the same seed is used, then the chosen PV sizes and the assigned demand profiles will be the same in the two simulations, so the results will be influenced only by having different input PV profiles, not by having different demands or total PV power.

2.1.4 Monte Carlo method

In order to increase the robustness of the results obtained through the code they developed, Pena-Bello et al. utilized the Monte Carlo method in [26], performing 1000 different simulations with the same input data, randomizing in each simulation the factors described in section 2.1.3, and presenting the means of the performed simulations, along with the relative 95% confidence intervals, as their final results.

The same approach was used in this work to obtain the various results presented, with the only difference being that 100 simulations were performed with each set of input data, instead of 1000. This difference derives from the fact that many different sets of input data are simulated in this work and performing 1000 simulations for each of them would require too much time for the simulations to complete. Performing 100 simulations instead of 1000 caused the 95% confidence intervals that are reported with the means to be wider, but they were not generally too large to prevent making relevant considerations on the results. Therefore, each of the results presented in this work for a certain set of input data is obtained by performing 100 simulations (always corresponding to the values of seed comprised between 0 and 99) and finding the mean values over the 100 simulations, along with the relative 95% confidence intervals.

The 95% confidence intervals were found following [31], which explains how the confidence interval (CI) can be found as shown in equation (2.1), where $\bar{x}$ is the sample mean, z is the statistic associated with a certain confidence interval (z is equal to 1.95996 for a 95% CI [32]), s is the sample standard deviation and n is the sample size.

$$CI = \left(\bar{x} - z\frac{s}{\sqrt{n}}, \bar{x} + z\frac{s}{\sqrt{n}}\right) \tag{2.1}$$

2.1.5 Key performance indicators

The key performance indicators (KPIs) that are found through the simulations of energy communities and presented as results in this work are described in this section. They are part of the KPIs presented by Pena-Bello et al. in [26] and are calculated following the same methods followed by Pena-Bello et al.

The first two KPIs are the self-consumption (SC) and the self-sufficiency (SS) of the energy community. The SC is a ratio (usually expressed in percentage) that expresses how much of the energy generated by the community's PV systems (E_{PV}) is consumed locally within the community (either by households' loads or by storing it in batteries), without exporting it. The part of the energy that was produced by the PV systems of the energy community that is consumed locally is called self-consumed energy ($E_{self\text{-}consumed}$), therefore the SC (in percentage) can be expressed through equation (2.2).

$$SC = \frac{E_{self-consumed}}{E_{PV}} \cdot 100 \tag{2.2}$$

The SS is a ratio (usually expressed in percentage) that expresses how much of the local energy demand (E_{demand}) is satisfied through the self-consumption of energy produced by the local PV systems. Therefore, the self-consumed energy ($E_{self\text{-}consumed}$) is at the numerator of SS, which can be expressed (in percentage) through equation (2.3).

$$SS = \frac{E_{self-consumed}}{E_{demand}} \cdot 100 \tag{2.3}$$

Both the SC and SS of the energy community are calculated at the point of common coupling, which is considered to be only one for the whole energy community. Therefore the self-consumed energy at the numerator of SC and SS is the PV-produced energy that is consumed locally by any of the members of the energy community, without exporting it to the main electrical grid. The PV-produced energy is considered to be self-consumed in the part for which there is energy demand from any of the households that belong to the community. Moreover, since the values of SS and SC reported in this work are always referred to the whole community, the amounts of energy demand and PV generation at their denominator are those of the whole community. All of the values of SC and SS reported in this work are referred to the whole year simulated.
Higher values of SC and SS are generally desirable, if the values of PV-generated energy and energy demand are fixed, since they indicate a higher amount of self-consumed energy and self-consuming energy is generally convenient for PV owners since the cost of importing energy is generally higher than the profit obtained exporting it. Moreover, in actual settings, incentives may be given for self-consumed energy, for example, the incentives that have been devised for Italian renewable energy communities, presented in section 1.5, reward “shared electricity”, which is a concept analogous to self-consumed energy.

The PV-produced energy that is not self-consumed within the energy community is exported to the main electrical grid. The yearly total of this exported energy is another KPI considered in this work, which is for example useful in cases that consider an increase in PV energy production, to understand how much of this additional energy is self-consumed and how much is exported.

Two other KPIs considered are the demand peak and the injection peak, which are both referred to the only point of common coupling of the energy community. They are found as the maximum values that the power flows of demand and injection reach in the point of common coupling in a timestep of the simulated year. These two KPIs are significant for the sizing of the electrical distribution system of the community since both electrical lines and substations’ transformers have to be sized considering the maximum power that can pass through them [33]. Therefore, having lower values of the demand peak and of the generation peak would generally be positive, since it would reduce the needed sizes, and therefore the costs, of transformers and electrical lines.

Finally, the last KPI considered is the yearly electricity bill of the whole energy community. In the cases of the energy communities with multiple PV systems (and eventually multiple batteries), it is calculated as the sum of all of the electricity bills of the members/users of the energy community. The electricity bill of each user ($Bill_{user}$) is simply found as the sum of all the money flows that are relative to that user in each timestep, as expressed by equation (2.4).

$$Bill_{user} = \sum_{i=0}^{t} E_{imp,i} \cdot p_{imp,i} - E_{exp,i} \cdot p_{exp,i} \tag{2.4}$$

In equation (2.4) i is the timestep, $E_{imp,i}$ and $E_{exp,i}$ are respectively the amount of energy imported and exported at that timestep (in kWh), while $p_{imp,i}$ and $p_{exp,i}$ are respectively the prices of importing and exporting energy (in €/kWh).

In the case of the energy community with a single PV system and a single centralized battery, the yearly electricity of the community is simply found by applying equation (2.4) but considering the energy imports and exports that the whole community does with the main electrical grid external to the energy community.

The electricity bill is a useful KPI to perform comparisons between different cases, seeing which one produces lower values of electricity bill, which are desirable. The magnitude of one electricity bill by itself is never commented on in this work since it depends on the pricing mechanism and on the prices of energy, which are subject to changes and can be different in real settings.

2.2 Model of PV systems

As anticipated in section 2.1.3, the input data used when energy communities are considered in Italy (which is the case for all of this work except in part of section 5.2) was not present in the work conducted by Pena-Bello et al. in [26] and is introduced in this thesis. This section describes how the yearly power profiles of PV generation and the distribution of sizes of PV systems of the energy communities are obtained for Italy in this work.

The PV generation profile that is required as an input of the code needs to be referred to a system with a peak power of 1 kW and be relative to one year, with a resolution of one hour (since one hour is chosen as the timestep of the simulations in this work). In order to obtain a profile of this kind, a Python script that utilized the Python package pvlib was developed. The script utilizes the procedural code provided in the pvlib documentation [34] and creates a PV generation profile relative to a typical meteorological year (which is retrieved by pvlib from the PVGIS data source). The script developed considers the PV module “Hanwha HSL60P6-PA-4-250T”, which is implemented in the library of pvlib and is obtained by the library of “Sandia modules”, provided by the American National Renewable Energy Laboratory and available on GitHub at [35]. The obtained power profile is the output of the PV system in direct current (so before the inverter) since this is what is required as input by the code developed by Pena-Bello et al. available at [27]. Since the peak power of the considered PV model is 250 W, the obtained power profile is multiplied by 4 to obtain the needed power profile relative to a peak power of 1 kW.
Some inputs are then required by the script that models the PV system. The first input is constituted by the geographical coordinates of the PV system, which in this work are always a latitude equal to 45.056° and a longitude equal to 7.651°, which correspond to a point in the city of Turin. Then, the altitude of Turin, equal to 239 m, is also inserted and kept constant for all of the PV profiles created for this work. Finally, the script requires the orientation and the inclination of the PV system. The convention that pvlib utilizes for the azimuth angle (relative to the orientation of PV systems) is also the one used in this work, and it is the following:

- Azimuth = 0° for a North orientation,
- Azimuth = 90° for an East orientation,
- Azimuth = 180° for a South orientation,
- Azimuth = 270° for a West orientation

The orientation and inclination of PV systems are the only inputs of this script that are varied in this work. The “base case” of the PV profile is considered to be an inclination of 25° and a South orientation. These are the parameters of the PV systems that are considered in all of this work except for section 4, in which various cases of different inclinations and orientations are investigated.

The distribution of the sizes of PV systems for the energy communities located in Italy simulated in this work is a normal symmetrically truncated distribution. This means that the average PV power of the energy community is provided as an input, and a normal distribution with this average power ($P_{PV\ average}$) is created and truncated at a minimum power ($P_{PV\ min}$) of 1 kW and at a maximum power ($P_{PV\ max}$) determined through equation (2.5).

$$P_{PV\ max} = 2 \cdot P_{PV\ average} - P_{PV\ min} \tag{2.5}$$

Equation (2.5) makes it so that $P_{PV\ min}$ and $P_{PV\ max}$ are equidistant from $P_{PV\ average}$ so that the normal distribution is symmetrically truncated.
The PV sizes for the simulated PV systems are then randomly extracted in each simulation according to the probabilities related to the normal symmetrically truncated distribution just described. If the normal distribution was not truncated symmetrically then the PV powers extracted according to it would not have an average tending to the chosen average of the distribution.

2.3 Datasets of residential demand profiles

This section describes the datasets of residential demand profiles that are used in this work and the Pearson correlation coefficient that is calculated for each demand profile.

2.3.1 German and Italian datasets of residential demand profiles

Two datasets of residential demand profiles are considered in this work. The first, called “German dataset of demand profiles” is a dataset of real German residential demand profiles that is the same used by Pena-Bello et al. in [26].

The second dataset, called “Italian dataset of demand profiles” is a dataset of synthetic Italian residential demand profiles that were obtained through the tool developed by Bottaccioli et al. presented in [36].

Further descriptions and analyses of these two datasets of residential demand profiles are reported in section 2.4.1.

2.3.2 The Pearson correlation coefficient

In this work, the Pearson correlation coefficient (PCC) is utilized to represent the synchronism between the trends of demand profiles and PV generation. The PCC is calculated, through the function “corrcoef” of the Python package NumPy [37], for each of the residential demand profiles that are used as input of a simulation, together with the PV generation profile used for that same simulation.

The PCC is a number that can range from -1 to +1 and that indicates the nature of the correlation between two variables, with -1 indicating a perfectly negative linear relationship and +1 indicating a perfectly positive linear relationship [38].

A negative value of PCC between demand and PV generation means that they tend to be negatively correlated (i.e. that the demand tends to increase when the PV generation tends to decrease and vice versa), while a positive value of PCC between demand and PV generation means that they tend to be positively correlated (i.e. that demand and PV generation tend to both increase or decrease at the same time). The higher the module of PCC is and the stronger the correlation, be it negative or positive, tends to be.

In this work, in order to use intuitive expressions, demand profiles that have a positive PCC with the PV generation are sometimes said to be more “synchronous” with the PV generation, while demand profiles that have a negative PCC with the PV generation are sometimes said to be more "asynchronous" with the PV generation. In the same way, a higher PCC is said to mean that there is a greater synchronism between demand and PV generation, while a lower PCC is said to mean that a lower synchronism is present.

2.3.3 Normality of the PCC and yearly demand distributions of the Italian and German datasets of demand profiles

In this section, three methods to establish if a distribution is close to being normal are applied to the Italian and German datasets of demand profiles, to check if their values of yearly demand and PCC follow a normal distribution or not.

The first test conducted is the Shapiro-Wilk test, which is done through the Python function scipy.stats.shapiro [39]. This function implements the algorithm described by Royston [40], which modifies the original procedure introduced by Shapiro et al. in [41] to allow for the correct calculation of the P-value for a number of samples ranging from 3 to 5000 [40]. The results of the Shapiro-Wilk test are reported in Table 2.1.

Table 2.1: Results of the Shapiro-Wilk test applied to the Italian and German datasets of demand profiles.

	Test statistic (W)	**P-value**
Germany - Demand	0.99	0.847
Germany - PCC	0.986	0.596
Italy - Demand	0.928	$2.34 \cdot 10^{-21}$
Italy - PCC	0.983	$2.09 \cdot 10^{-9}$

The null hypothesis of the Shapiro-Wilk test is that the distribution is normal [42]. The lower the P-value is and the more evidence there is against the null hypothesis, the P-value of 0.05 is often considered the cutoff point, considering P-values below 0.05 to be a sign of evidence that the null hypothesis can be rejected [43].
Considering the results reported in Table 2.1, for both the cases of yearly demand and PCC, the null hypothesis of normality cannot be rejected for the German dataset, since the P-value is much greater than 0.05, but it can be rejected for the Italian dataset since the P-value is much lower than 0.05.

Therefore, this test seems to indicate that the demand profiles of the German dataset have a normal distribution of PCC and yearly demand, while the considered Italian profiles do not.

The second normality test conducted is the Anderson-Darling test, introduced by Stephens in [44]. This test is performed through the Python function scipy.stats.anderson, which returns the test statistic and the critical values for certain significance levels (S.L.). If the test statistic is larger than a critical value then the null hypothesis that the distribution is normal can be rejected for the S.L. relative to that critical value [45]. The results of the Anderson-Darling test are reported in Table 2.2.

Table 2.2: Results of the Anderson-Darling test applied to the Italian and German datasets of demand profiles.

	Test statistic	**Critical value for 15% S.L.**	**Critical value for 10% S.L.**	**Critical value for 5% S.L.**	**Critical value for 2.5% S.L.**	**Critical value for 1% S.L.**
Germany, Demand	0.267	0.549	0.625	0.750	0.875	1.041
Germany, PCC	0.366	0.549	0.625	0.750	0.875	1.041
Italy, Demand	15.604	0.574	0.653	0.784	0.914	1.088
Italy, PCC	4.341	0.574	0.653	0.784	0.914	1.088

In Table 2.2, the cases in which the test statistic is lower than the critical values and thus the null hypothesis of the distribution being normal cannot be rejected, are highlighted in green. On the other hand, the cases highlighted in red are those in which the test statistic is higher than the critical values, and thus the null hypothesis of the distribution being normal can be rejected.
Therefore, the Anderson-Darling test seems to indicate that the distributions of PCC and demand for the German dataset are not significantly different from normal distributions, while those for the Italian dataset significantly differ from normality.

A different kind of normality test is also conducted, performing a graphical check of normality through a quantile-quantile plot or Q-Q plot, in which the quantiles of a data distribution are compared with the quantiles of a standardized theoretical distribution (in this case a normal distribution). In the case of a data distribution that is similar to the theoretical distribution, the plotted dots represented in the Q-Q plot approximately lie on the diagonal line with equation y=x [46].

A Q-Q plot is plotted for each distribution of the two datasets through the Python function statsmodels.graphics.gofplots.qqplot [47] and the resulting plots are reported in Figure 2.2.

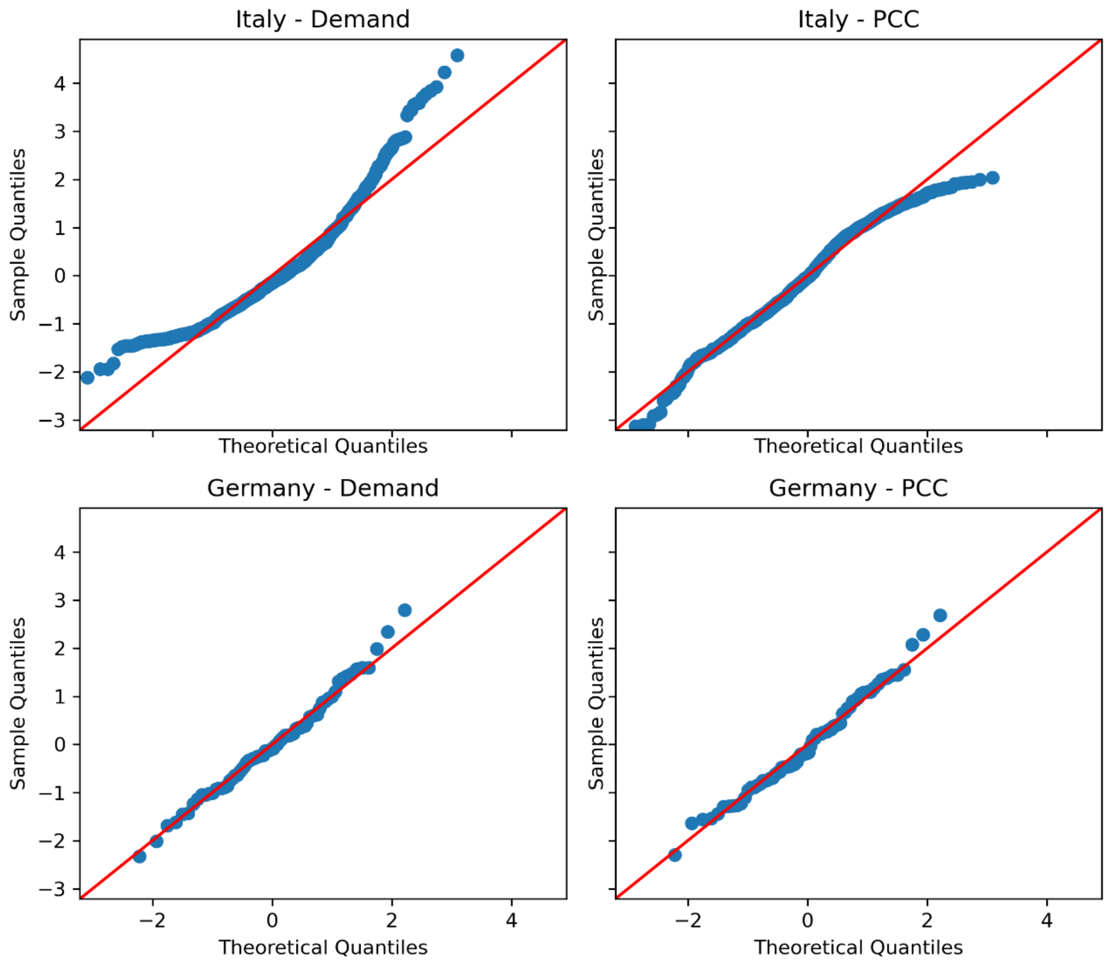

Figure 2.2: Q-Q plots for PCC and yearly demand of the Italian and German datasets.

The Q-Q plot of a normal distribution tends to have the points (in blue in Figure 2.2) quite close to the straight line (in red in Figure 2.2). The Q-Q plots for the German dataset seem to present this characteristic, suggesting the normality of the distributions for the German dataset. The Q-Q plots for the Italian dataset, on the other hand, seem to suggest the non-normality of the distribution of demand, while the distribution of PCC seems to be closer to normality, even if not quite as close as the distributions of the German distribution.

In conclusion, considering the results of the three normality tests performed, it is reasonable to say that the distributions of PCC and yearly demand of the German dataset do not appear to significantly differ from normality, while the distributions of the Italian dataset do.

2.4 Characterization of the PCC-demand plane

The main focus of this work is the analysis of the effects that the magnitude of households' yearly energy demand and the synchronism between photovoltaic (PV) energy generation and energy demand can have on residential energy communities. These two factors (yearly demand and synchronism) are considered for each household composing the energy community. The households of the energy communities simulated in this thesis have, in each simulation, demand profiles randomly extracted from an input dataset of demand profiles. Therefore, using an effective way to represent the yearly demand and synchronism with PV generation of the demand profiles contained in such datasets would be helpful to quickly identify the characteristics of the used demand profiles. This is done by representing all of the demand profiles in the so-called "PCC-demand plane", whose concept was introduced by Minuto and Lanzini [18]. The PCC-demand plane is a plane having the yearly energy demand (eventually normalized considering the PV generation, as explained in section 2.4.2) as its horizontal axis and the Pearson correlation coefficient (PCC) between energy demand and photovoltaic production as its vertical axis. Each demand profile can then be represented on this plane as a point, with coordinates equal to its yearly demand and its PCC.

Four quadrants can be defined on the PCC-demand plane, considering an axis corresponding to PCC equal to zero and one corresponding to the average demand of the demand profiles present in the dataset. In this way the following four quadrants are defined:

- Quadrant 1 (Q1), in which users have yearly energy demand below average and PCC lower than zero,
- Quadrant 2 (Q2), in which users have yearly energy demand above average and PCC lower than zero,
- Quadrant 3 (Q3), in which users have yearly energy demand below average and PCC higher than zero,
- Quadrant 4 (Q4), in which users have yearly energy demand above average and PCC higher than zero.

In this thesis, when talking about distributions of demand profiles on the plane, sometimes the term "user" is used for short in place of the term "residential demand profile". This is done for brevity and since every residential demand profile does indeed belong to a household, which can be seen as a whole as an energy user. Therefore, distributions of demand profiles in this work are also called "distributions of users" and points in the PCC-demand plane, representing demand profiles of households, are also called "users".

2.4.1 Analysis of the datasets of Italian and German demand profiles

In this section, the two datasets of demand profiles described in section 2.3 are graphically represented on the PCC-demand plane and some observations on these representations are made.

The dataset of 74 real German residential demand profiles belonging to the German dataset used by Pena-Bello et al. in [26] is represented in the PCC-demand plane in Figure 2.3.

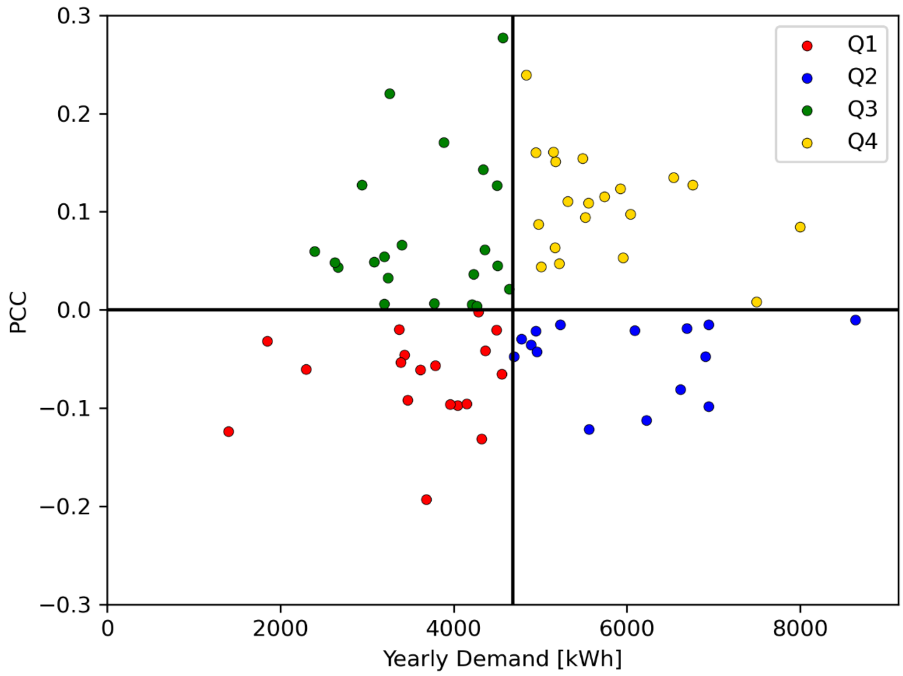

Figure 2.3: Representation of the German dataset of demand profiles on the PCC-demand plane.

The minimum yearly demand of the demand profiles present in the German dataset is 1398.5 kWh, the maximum is 8635.1 kWh and the mean (represented by the vertical axis in Figure 2.3) is 4685.1 kWh.

The PCC of these demand profiles was found considering the PV generation profile originally used by Pena-Bello et al. together with the dataset of German profiles in [26].

Observing the values of PCC of the different demand profiles, it is noticeable how there are not particularly high absolute values of PCC, indicating a generally low degree of correlation between demand and PV generation profiles. Indeed, many profiles have an absolute value of PCC quite close to zero, with 52 profiles (out of 74) having PCC between -0.1 and 0.1 and 31 profiles having PCC between -0.05 and 0.05.

The average PCC value is 0.0238, in part due to the presence of more profiles with PCC greater than zero (41 profiles) than profiles with negative PCC (33 profiles). Moreover, there are significantly more profiles that tend to be more synchronous (17 profiles have PCC > 0.1) than profiles that tend to be more asynchronous (5 profiles have PCC < -0.1). It is important to keep in mind that "synchronous" and "asynchronous" are intended with the meanings explained in section 2.3.2.

The Italian dataset of 992 synthetic residential demand profiles is represented in the PCC-demand plane in Figure 2.4.

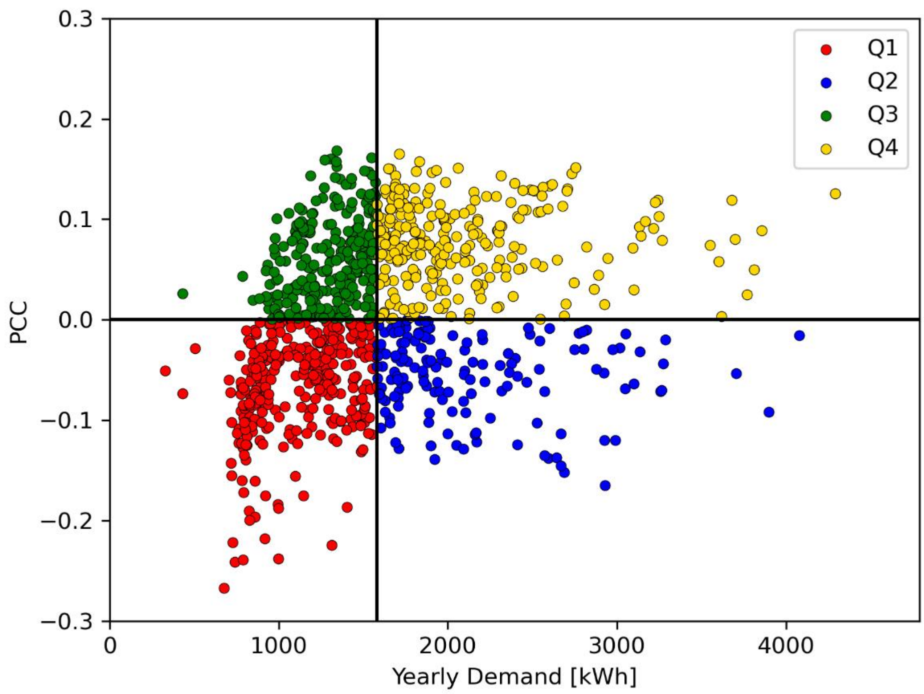

Figure 2.4: Representation of the Italian dataset of demand profiles on the PCC-demand plane.

The minimum yearly demand of the demand profiles present in the Italian dataset is 328.8 kWh, the maximum is 4288.5 kWh and the mean (represented by the vertical axis in Figure 2.4) is 1579.9 kWh. It is noticeable that the average yearly demand of these profiles is significantly lower than the mean of the German profiles (the latter being equal to 4685.1 kWh). This indicates a significative difference between the two datasets, suggesting that energy communities using the two different datasets as inputs (with other inputs staying the same) would present significantly different KPIs.

The values of PCC of the demand profiles represented in Figure 2.4 are referred to a PV generation profile defined according to the methodology illustrated in section 2.2, considering a South orientation and a 25° inclination of the PV system.

Considering the values of PCC of the different demand profiles, it is noticeable how, like in the case of the German profiles, there are not particularly high absolute values of PCC, indicating a low degree of correlation between demand and PV production. Indeed, many profiles have an absolute value of PCC quite close to zero, with 766 profiles (out of 992) having PCC between -0.1 and 0.1 and 394 profiles having PCC between -0.05 and 0.05. The shares of profiles in these ranges of PCC are not far from those of the German dataset, with the profiles having an absolute value of PCC lower than 0.1 being the 77.2% for the Italian dataset and 70.3% for the German dataset, while the profiles with an absolute value of PCC lower than 0.05 are 39.7% for the Italian dataset and 41.9% for the German dataset.

The average PCC value is very close to zero, being equal to 0.0067. There are slightly more profiles with positive PCC (520 profiles) than profiles with negative PCC (472 profiles). Moreover, there are more profiles that tend to be more synchronous (135 profiles have PCC > 0.1) than profiles that tend to be more asynchronous (91 profiles have PCC < -0.1), but the disproportion between these two groups is less (relatively to the total number of profiles) than for the German dataset.

2.4.2 The PCC-demand plane with normalized demand

The PCC-demand plane with the yearly demand as its horizontal axis does not take into account the amount of energy produced by the PV systems installed in the energy community. However, considering this factor could be useful since it is likely to have a strong influence on the KPIs of energy communities.

In order to consider the magnitude of the PV energy generation in the PCC-demand plane, it is possible to normalize the yearly demand, by dividing it by the PV generation allocated to one user. This ratio is then chosen as the new quantity plotted on the horizontal axis of the PCC-demand plane and is called "normalized demand".

As explained in section 2.2, in the simulations performed in this work the distribution of PV power is a normal distribution truncated in a way that it remains symmetrical with respect to the average power. Therefore, the average of many random PV sizes chosen according to this distribution will be close to the chosen average power. For this reason, when considering average results over many simulations (which is what is done in this work), the PV energy generation in the whole community ($E_{\text{PV tot community}}$) is close to being equal to the energy produced by PV systems all with power equal to the set average PV power. This means that $E_{\text{PV tot community}}$ can be approximated with equation (2.6).

$$E_{PV\ tot\ community} \cong E_{PV\ P=1kW} \cdot P_{PV\ average} \cdot N_{PV} \tag{2.6}$$

In (2.6) $E_{PV\ P=1kW}$ is the energy generated by a PV system with peak power equal to 1 kW, $P_{PV\ average}$ is the input average PV power and N_{PV} is the number of PV systems installed in the community.
The validity of equation (2.6) was also checked *a posteriori* for one example by finding the average energy generated by the PV systems over 100 simulations. In this example, the PV average power was equal to 5 kW and the average PV energy production across all the simulations was found to be roughly equal to 221883 kWh (95% CI (218979 kWh, 224787 kWh)). The annual PV energy production of the PV system's (with an inclination of 25° and South orientation) generation profile used as input is 1483.63 kWh. Considering that 30 PV systems were considered to be installed in the energy community of this example, then applying equation (2.6) $E_{PV\ tot\ community}$ for this example would be approximated as 222544.5 kWh. This value is a good approximation of the average total PV energy generation obtained in the performed simulations, differing from it only by 0.3% and being well within the 95% confidence interval of the simulation result.
Considering equation (2.6), the quote of PV energy generation "allocated" to one user ($E_{PV\ one\ user}$), defined as the PV energy generation of the whole community divided by the number of users present in the community (N_{users}), can be approximated as shown in equation (2.7).

$$E_{PV\ one\ user} = \frac{E_{PV\ tot\ community}}{N_{users}} \cong E_{PV\ P=1kW} \cdot P_{PV\ average} \cdot \frac{N_{PV}}{N_{users}} \tag{2.7}$$

Since the demand is normalized by dividing it by the PV-generated energy allocated to one user, the higher the latter is and the lower the normalized demand will be, thus moving towards the left all the points representing the demand profiles in the PCC-demand plane with normalized demand. Analyzing the formula (2.7) used to approximate $E_{PV\ one\ user}$, the latter could increase if the average PV power is increased, if the energy generated by a PV system of 1 kW peak power becomes higher (such as due to a better orientation or inclination of the PV panels) or if the number of PV systems in the community increases (with the total number of users being fixed).
In conclusion, through equation (2.7) the PV-generated energy allocated to one user is approximated (in a way that is independent from the single simulation) as the average value to which the simulations tend to after enough have been conducted. Therefore, equation (2.7) is deemed a good way to find the PV-generated energy allocated to one user to normalize the yearly demand, allowing to estimate the normalized demand without performing any simulations.

Considering the PV model introduced in section 2.2, which is the one used in this work for simulations set in Italy, a PV system with South orientation and 25° inclination, an average PV power of 5 kW, and an energy community with 30 users with PV systems out of a total of 60 users, equation (2.7) can be applied as follows.

$$E_{PV\ one\ user} \cong E_{PV\ P=1kW} \cdot P_{PV\ average} \cdot \frac{N_{PV}}{N_{users}} = 1483.6 \cdot 5 \cdot \frac{30}{60} = 3709\ kWh \tag{2.8}$$

Therefore, to pass from the PCC-demand plane with yearly demand to the PCC-demand plane with normalized demand it is sufficient to divide for 3709 kWh the yearly demand of each demand profile, obtaining the representation of the Italian dataset of demand profiles shown in Figure 2.5. It is important to keep in mind that this representation, unlike the representation in the PCC-demand plane with yearly demand, depends on the average PV power.

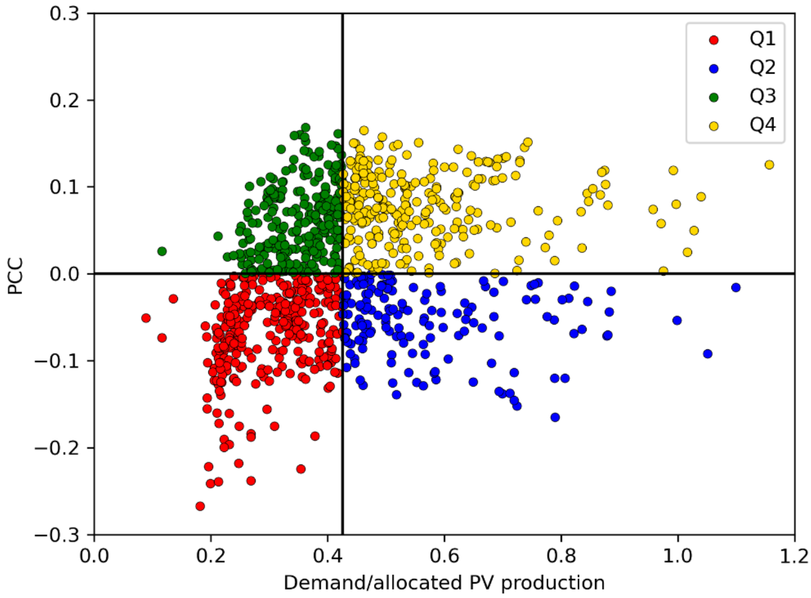

Figure 2.5: Distribution of the Italian dataset of demand profiles in the PCC-demand plane with normalized demand.

On the other hand, applying equation (2.7) with the values used by Pena-Bello et al. for the German energy community simulated in [26], meaning an annual PV energy generation of 1535.8 kWh and an average PV power of 5.9 kW, the allocated energy per user is found to be 4530.7 kWh. The simulations conducted in [26] considered 100 users instead of the 60 users considered in this work, but this difference does not affect the result of equation (2.7), since the latter depends on the PV penetration in the energy community (i.e. the ratio N_{PV}/N_{users}), which is equal to 0.5 in both cases (since the number of PV systems is equal to 50 in [26] and 30 in this thesis). For the German dataset of demand profiles, the representation in the PCC-demand plane with normalized demand can be obtained by dividing for 4530.7 kWh the yearly demand of each demand profile, obtaining the representation shown in Figure 2.6.

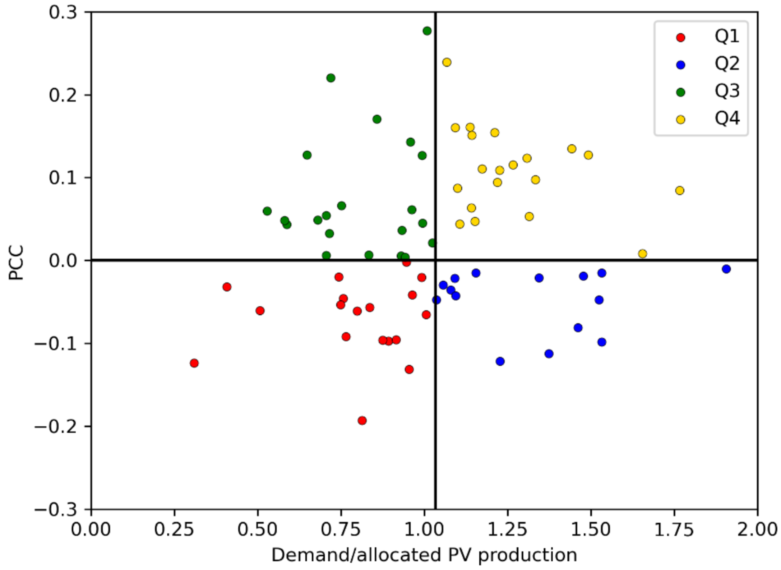

Figure 2.6: Distribution of the German dataset of demand profiles in the PCC-demand plane with normalized demand.

The PCC-demand plane with the normalized demand can be used to compare the Italian and German datasets of demand profiles while taking into account also the amount of PV production.
Considering the PV average power of 5 kW (and a South orientation, 25° inclination, and 50% PV penetration in the energy community) the obtained distribution of Italian demand profiles, plotted in Figure 2.5, has values of normalized demand that are quite different from those of the German dataset plotted in Figure 2.6. In particular, the values of normalized demand of the German dataset are higher, with a maximum of 1.91 compared to a maximum of 1.16 for the Italian profiles.
However, since the demand is normalized by dividing it by the PV-generated energy allocated to one user, a distribution's values on the horizontal axis of the PCC-demand plane with normalized demand can be "rescaled" by simply considering a different average PV power. In this case, to make the maximum values of normalized demand of the two datasets of demand profiles comparable, it is possible to consider the maximum yearly demand ($E_{\text{yearly demand, maximum}}$) of the Italian profiles, equal to 4288.5 kWh, and calculate the average PV power needed for this maximum demand to be equal, after normalization, to the maximum value of normalized demand ($E_{\text{normalized demand, maximum}}$) of the German dataset, equal to 1.91. This can be done by simply finding first the amount of PV-produced energy that has to be allocated to one user ($E_{\text{PV one user}}$) to satisfy the condition described above, through equation (2.9), and then the PV average power relative to this allocated energy, through

equation (2.10). In the latter equation, all of the terms have the same meanings introduced for equation (2.7), since equation (2.10) is simply an inverse form of equation (2.7).

$$E_{PV\ one\ user} = \frac{E_{yearly\ demand,maximum}}{E_{normalized\ demand,maximum}} = \frac{4288.5}{1.91} = 2245.3\ kWh \tag{2.9}$$

$$P_{PV\ average} \cong \frac{E_{PV\ one\ user}}{E_{PV\ P=1kW}} \cdot \frac{N_{users}}{N_{PV}} = \frac{2245.3}{1483.6} \cdot \frac{60}{30} = 3.03\ kW \tag{2.10}$$

The result of equation (2.10) indicates that if an average PV power of roughly 3 kW is considered (without changing the other PV parameters such as PV orientation or inclination), then the distribution of Italian profiles is rescaled to be comparable to the distribution of German profiles for what concerns the maximum values of normalized demand.

These two distributions are then plotted together in Figure 2.7 for a visual comparison, considering an average PV power of 3 kW for Italy. In this figure, yellow points represent Italian demand profiles while red points represent German demand profiles, the yellow axes represent the average normalized demand and the average PCC for Italy and the red axes represent the average normalized demand and the average PCC for Germany.

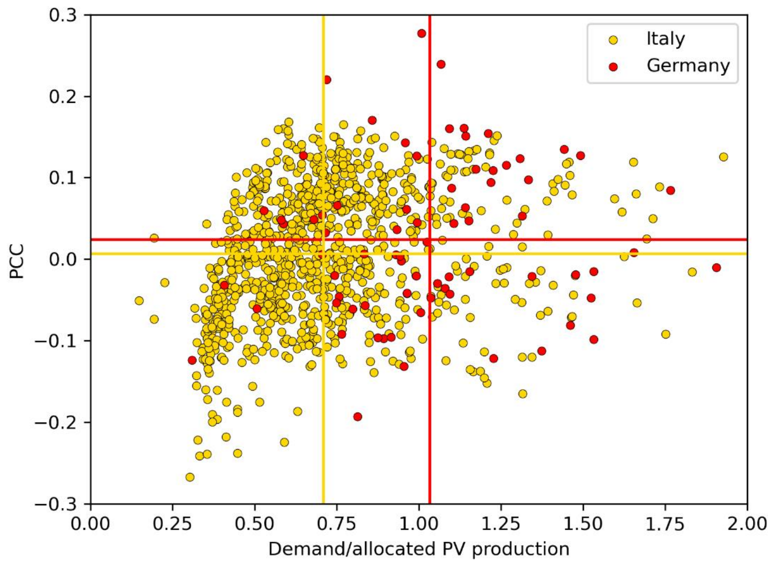

Figure 2.7: Representation on the PCC-demand plane with normalized demand of the German dataset and the Italian dataset, considering an average PV power of 3 kW for the latter.

It is also interesting to find the average PV power that should be considered for the Italian profiles' average normalized demand to be close to the one of the German profiles. This can be found considering that the average yearly demand ($E_{mean\ yearly\ demand}$) for the Italian profiles is 1579.89 kWh, while it is 4685.07 kWh for the case of Germany. Considering the PV penetration in the energy community to be equal for Italy and Germany, equation (2.11) needs to be respected for the average normalized demands to be equal for the two countries.

$$\frac{E_{mean\ yearly\ demand\ Italy}}{E_{PV\ P=1kW\ Italy} \cdot P_{PV\ average\ Italy}} = \frac{E_{mean\ yearly\ demand\ Germany}}{E_{PV\ P=1kW\ Germany} \cdot P_{PV\ average\ Germany}} \tag{2.11}$$

Consequently, the average PV power needed for the Italian average normalized demand to be equal to the German one can be found with equation (2.12).

$$P_{PV\ average\ Italy} = \frac{E_{mean\ demand\ Italy} \cdot E_{PV\ P=1kW\ Germany} \cdot P_{PV\ average\ Germany}}{E_{PV\ P=1kW\ Italy} \cdot E_{mean\ demand\ Germany}} = \\ = \frac{1579.89 \cdot 1535.83 \cdot 5.9}{1483.63 \cdot 4685.07} = 2.06\ kW \tag{2.12}$$

Therefore, considering an average PV power of 2.06 kW the average normalized demands of Italy and Germany will be similar, making the two relative distributions of demand profiles similar in the PCC-demand plane with normalized demand, as shown in Figure 2.8.

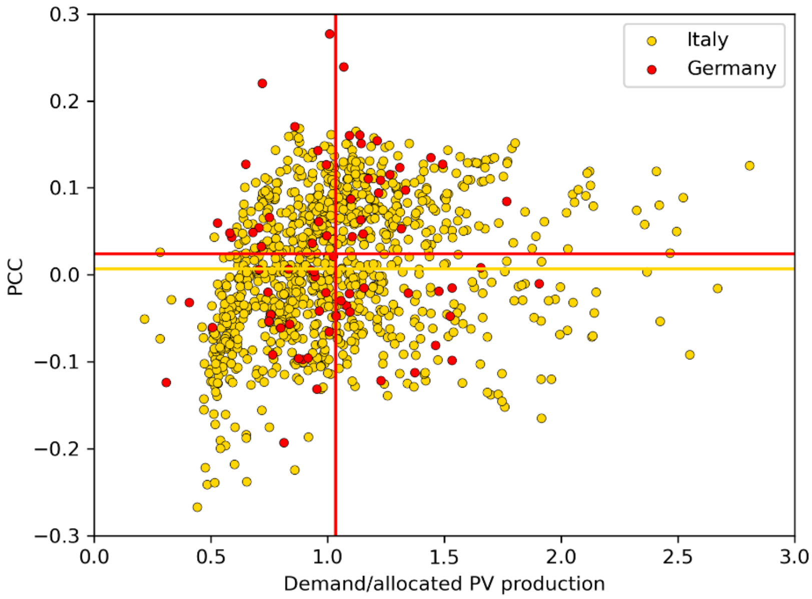

Figure 2.8: Representation on the PCC-demand plane with normalized demand of the German dataset and the Italian dataset, considering an average PV power of 2.06 kW for the latter.

Figure 2.8 (with the yellow axes corresponding to the means for Italy and the red axes corresponding to the means for Germany) shows that the distributions of the demand profiles of Germany and Italy, with Italy having an average PV power of 2.06 kW, present indeed very similar average normalized demands, shown by the fact that the two vertical axes, representing the average normalized demands of the two distributions, are superimposed.
These calculations suggest that if the Italian and German datasets were to be used in simulations with the goal of comparing their results, a sensible choice for the average PV power of the Italian energy communities could be 2.06 kW since it would make the average normalized demands of the two datasets equal. However, comparisons of this kind are not reported in this work, since the two datasets are not composed to be a statistically significant sample of the general populations of Germany and Italy, they are simply two collections of real (in the case of Germany) or realistic (in the case of Italy) residential demand profiles. Therefore, comparing results obtained using the two datasets without further elaborations would not yield noteworthy results.

2.5 Application of the methodology: setups of case studies

The methodology described in the previous sections is applied in this work to four "case studies", whose results are presented in section 3, section 4, section 5, and section 6.
Each of these case studies is independent of the others and has the goal of investigating the effects that some of the "components" of energy communities can have on the communities. The main methods used in all of the case studies are the PCC-demand plane and the simulations performed through the code developed by Pena-Bello et al. and available at [27]. The "components" of energy communities studied are the demand profiles (investigated in section 3 and section 5), the PV systems (investigated in section 4), and the batteries (investigated in section 6).
In the rest of this section, the main aspects of the setups of the various case studies are presented. These setups are in any case described in more detail in the sections corresponding to the case studies.

In section 3, the objective is to provide preliminary proof that demand profiles being in different areas of the PCC-demand plane causes the KPIs of energy communities to be different. The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops, while no users have batteries installed in their houses. The choice of not considering batteries in these simulations is made to avoid introducing the influence of an additional factor (batteries) in this preliminary analysis, leaving the analysis of the impact of batteries to other sections of this work.

The differences between the various energy communities simulated in this section are the demand profiles considered. Indeed, simulations are performed for four scenarios, one for each quadrant of the PCC-demand plane. Each scenario considers demand profiles of the Italian dataset that belong all to one quadrant, different for each scenario, of the PCC-demand plane.

In section 4, the objective is to analyze the effects that the inclination and the orientation of PV systems can have on the distributions of demand profiles on the PCC-demand plane and on the performances of energy communities. The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops, while no users have batteries installed in their houses. The choice of not considering batteries in these simulations is made to "isolate" the impact of the variations of the parameters of PV systems, without including the influence of batteries that could potentially alter the impact that changes in the PV systems by themselves cause.
The differences between the various energy communities simulated in this section are the inclination and the orientation of the PV systems. When investigating the effects of the inclination of PV systems the latter is varied and the orientation is always considered towards South; when investigating the effects of the orientation of PV systems the latter is varied and the inclination is always considered equal to 25°.

In section 5, the energy communities simulated are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops. Three subcases regarding batteries are considered: one without any batteries, one with batteries managed with the SC strategy, and one with batteries managed with the P2P strategy.
In section 5.2, the objective is to compare the performances of energy communities using demand profiles from two different datasets with similar characteristics of yearly demand and PCC. The two compared datasets are then used in simulations for each of the three subcases regarding batteries.
In section 5.3, the objective is to analyze the impacts of changing some characteristics of the datasets of demand profiles on the performances of energy communities. To do this, several custom datasets of demand profiles are created and used in simulations for each of the three subcases regarding batteries.

In section 6, the objective is to study the effects of batteries on energy communities. The energy communities simulated are each composed of 60 residential users. Three setups of energy communities are simulated and confronted: in one case 30 users own PV systems and there are no batteries, in another case 30 users own PV systems and 15 of these users also own batteries, and in the last case, there are a single PV system and a single battery jointly owned by the whole energy community. The energy communities confronted all have the same demand profiles and PV generation parameters to better confront the effects caused only by batteries.

3 Results: effects of the presence of demand profiles in different quadrants of the PCC-demand plane

The goal of this section is to analyze the effects on the KPIs of an energy community of the presence of demand profiles in a certain quadrant of the PCC-demand plane, using the demand profiles of the Italian dataset introduced in section 2.3.1. The rationale behind this is to have a preliminary verification that users (meant as another way of calling the residential demand profiles, as explained at the beginning of section 2.4) belonging to different quadrants do indeed cause the community KPIs to change significantly. This is tested by considering four scenarios representing “limit cases”, in which the community is composed solely of users belonging to one of the quadrants of the PCC-demand plane, considering the quadrants defined for the Italian dataset of demand profiles.

3.1 Selection of demand profiles

In order to increase the difference between the KPIs of the four different scenarios to better observe the trends, not all the demand profiles of the Italian dataset belonging to each quadrant of the PCC-demand plane have been included in the four scenarios. In fact, the profiles closest to the quadrants’ borders have been excluded, utilizing only profiles with:

- Absolute value of PCC > 0.05 for all the quadrants,
- Yearly demand < (average yearly demand – 200 kWh) for quadrants Q1 and Q3,
- Yearly demand > (average yearly demand + 200 kWh) for quadrants Q2 and Q4.

These restrictions lead to the selection of the demand profiles shown in Figure 3.1, which clearly shows how the demand profiles that were closer to the quadrants’ borders have been excluded.

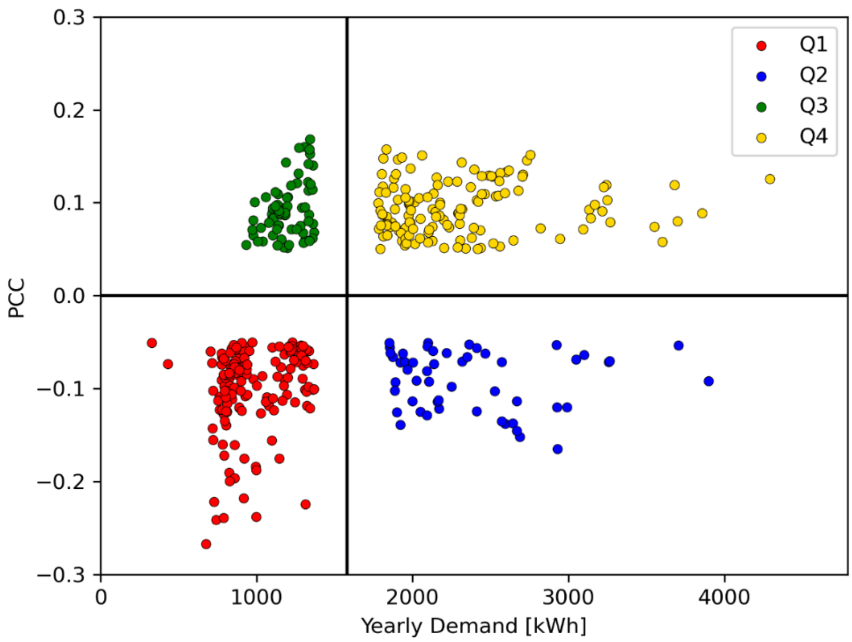

Figure 3.1: Demand profiles initially selected for the investigation of the effects of belonging to the four different quadrants of the PCC-demand plane.

In order to better analyze the profile distributions for the different quadrants that were obtained following the criteria just described, the average PCC and average yearly demand of the selected demand profiles are presented in Table 3.1.

Table 3.1: Average PCC and yearly demand of the demand profiles initially selected for the comparison of the four quadrants.

Quadrant	**Average PCC**	**Average yearly demand [kWh]**
Q1	-0.098	980.9
Q2	-0.091	2381.8
Q3	0.092	1191.9
Q4	0.094	2295.3

It is noticeable that the absolute values of the average PCC are not so different among the demand profiles selected for the different quadrants, this should allow for a more general comparison between quadrants since the average degree of correlation between demand profiles and PV generation is similar for the different quadrants.

Regarding the average yearly demand, the difference among the quadrants with low demand (Q1, Q3) is not high but neither negligible, with Q3 having a higher demand on average. Instead, among the quadrants of high demand (Q2, Q4) the difference is quite low compared to the average demands.

Therefore, to make the simulation results more comparable between Q1 and Q3, the set of profiles selected for Q1 is modified, removing some profiles with low yearly energy demand in order to have an average yearly demand of the considered profiles in Q1 closer to that of the profiles in Q3. The new considered profiles for Q1 after this change are represented in the updated graph of Figure 3.2.

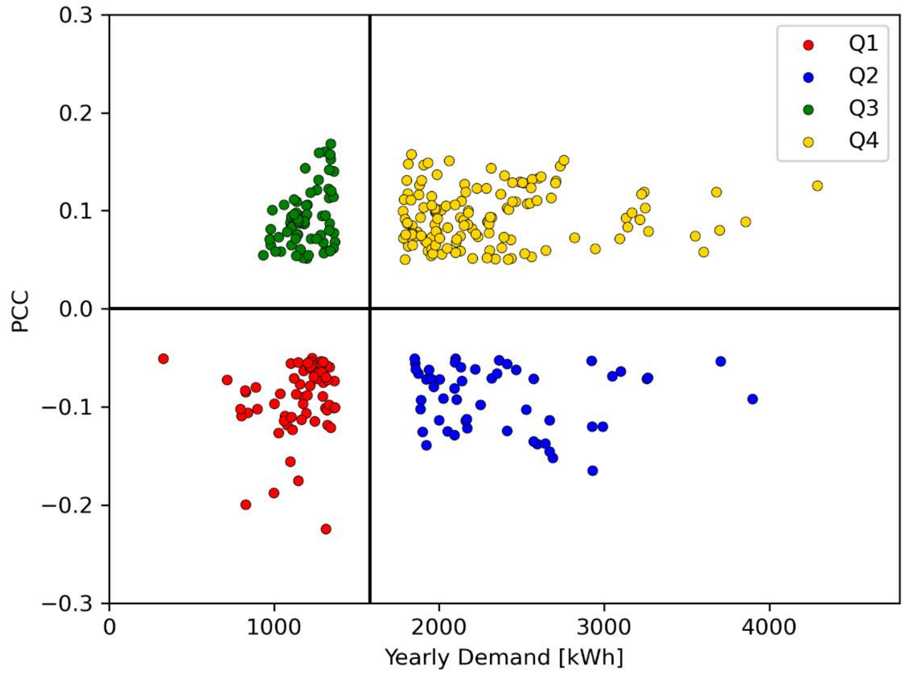

Figure 3.2: Demand profiles selected for the investigation of the effects of belonging to the four different quadrants, after the removal of some profiles from Q1.

The updated data regarding the average PCC and average yearly demand of the demand profiles selected after this change are shown in Table 3.2.

Table 3.2: Average PCC and yearly demand of the demand profiles selected for the comparison of the four quadrants, after the remotion of some profiles from Q1.

Quadrant	**Average PCC**	**Average demand [kWh]**
Q1	-0.089	1153.4
Q2	-0.091	2381.8
Q3	0.092	1191.9
Q4	0.094	2295.3

These data are considered adequate for producing comparable results since the differences among absolute values of PCC and values of yearly average demand (between Q1 and Q3, Q2 and Q4) are low enough and further lowering them proves to be problematic since lowering the differences in demand can increase the differences in PCC and vice versa. In any case, the goal of this section is to provide a simple proof of the change of KPIs due to demand profiles belonging to different quadrants of the PCC-demand plane and a qualitative observation of these effects. The similarity of the average yearly demands and absolute values of average PCC are deemed acceptable for this objective, the effects of varying the average yearly demand and the average PCC are analyzed more in detail in section 5.

3.2 Simulation setup and results

The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops, while no users have batteries installed in their houses. The choice of not considering batteries in these simulations is made to avoid introducing the influence of an additional factor (batteries) in this preliminary analysis, leaving the analysis of the impact of batteries to other sections of this work.
The PV parameters utilized in these simulations are a South orientation and an inclination of 25°. Moreover, the sizes of the PV systems of the community members are randomly selected in each simulation according to a normal distribution with average PV power of 5 kW, symmetrically truncated at 1 kW and 9 kW.
Four scenarios are simulated, one for each quadrant of the PCC-demand plane. These scenarios all utilize the demand profiles selected in section 3.3.1 that belong to the quadrant corresponding to the scenario, of which they take the name. For example, scenario Q1 considers users only belonging to quadrant Q1. It is important to keep in mind that not all of the profiles previously defined are utilized in each simulation. In fact, for each of the 100 simulations performed for each scenario, 60 (equal to the number of households in the community) demand profiles are randomly extracted from the dataset of available profiles (which are those represented in Figure 3.2) and attributed to the households of the simulated energy community.
The KPIs presented further below are the means of the KPIs obtained from the 100 simulations performed for each scenario, with the 95% confidence interval reported alongside the means.

The first KPI analyzed is the community self-consumption (SC), which is reported in Figure 3.3.

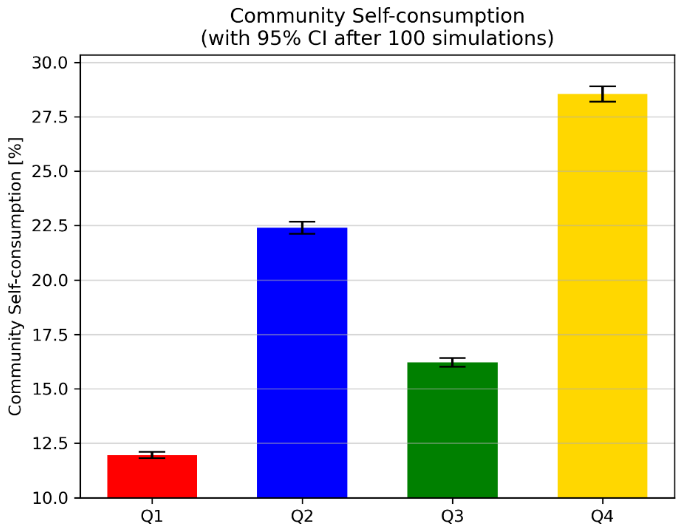

Figure 3.3: Community self-consumption in the four different scenarios.

Comparing the different scenarios, it is possible to notice significant differences in the values of SC (as well as in self-sufficiency (SS), analyzed in more detail further below), which suggest the significance of analyzing the impact that different demand profiles distributions on the PCC-demand plane have on SS and SC.

As expected, the SC is greater in scenarios with higher demand (scenarios Q2 and Q4), and, when average demands are similar, in case of higher synchronism with PV generation (e. g. scenario Q3 has greater SC than Q1 and scenario Q4 has greater SC than Q2). The effect of demand seems to be prevailing on the effect on synchronism, as shown by the fact that scenario Q2 (with large demand and low PCC) has a significantly higher SC than Q3 (with low demand and high PCC). It has to be noted that such prevalence of the effect of demand is valid for the degree of demand and PCC differences considered in this analysis, it is likely that a higher difference in synchronism and/or a lower difference in demand would make synchronism the prevalent effect. However, the obtained trend results from the use of synthetic but realistic profiles of Italian residential users and should therefore be based on realistic demand and PCC differences among users.

With regards to the cause of these results, the reason why an increase in yearly average demand causes an increase in SC is due to allowing for greater consumption of the PV-produced energy, since the greater the demand is and the lower the PV surplus that is injected into the net is. Similarly, a higher synchronism of the demand with the PV generation allows for a greater SC by allowing greater use of the PV-produced energy thanks to higher demand in periods with PV generation.

These observations are confirmed by the value of energy exported by the community in one year in the different scenarios (which is affected only by the consumption trends, since the PV generation and sizes are identical in all these scenarios), shown in Figure 3.4. The exported energy is, indeed, lower in the scenarios with higher demand and higher synchronism. For comparison, the total energy produced by the PV systems in one year is 221883 kWh (95% CI (218979 kWh, 224787 kWh)) in the simulations performed for all the scenarios.

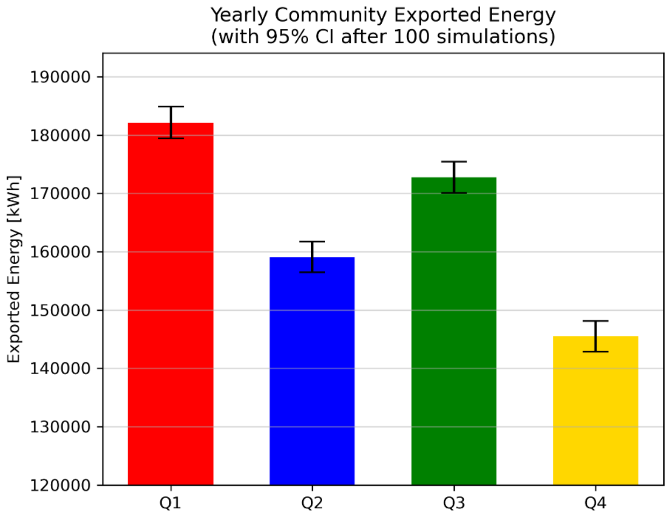

Figure 3.4: Energy exported by the energy community in one year in the four different scenarios.

Analyzing the community self-sufficiency (SS), shown in Figure 3.5, it is notable that it tends to increase with higher synchronism and lower demand. This was expected, since a higher synchronism allows to consume a greater share of the PV-generated energy, thus decreasing the reliance of the community on the external electrical grid, and a lower demand (with a fixed PV generation) reduces the need to import energy from outside of the community, since the share of demand that the PV systems are able to satisfy increases.

The prevailing effect on SS appears to be synchronism, as shown by the fact that the scenario Q4 (with large demand and high PCC) has a higher SS than Q1 (with low demand and low PCC). The observation on the prevailing effect on SS has the same limitations explained for the prevailing effect on SC, meaning that it is likely to be dependent on the magnitude of differences in PCC and demand between quadrants.

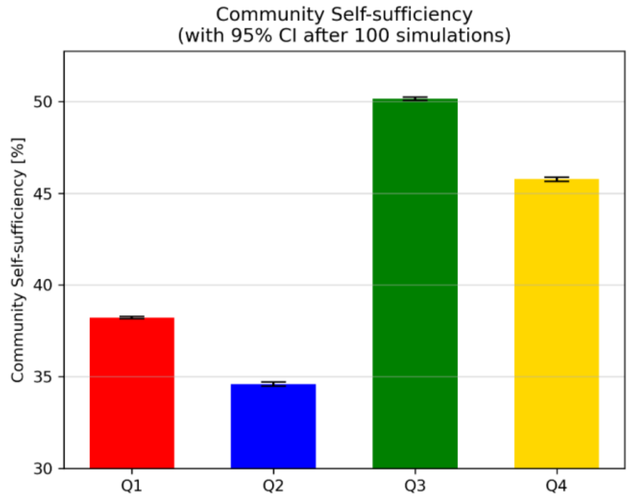

Figure 3.5: Community self-sufficiency in the four different scenarios.

The demand peak and injection peak are reported in Figure 3.6.

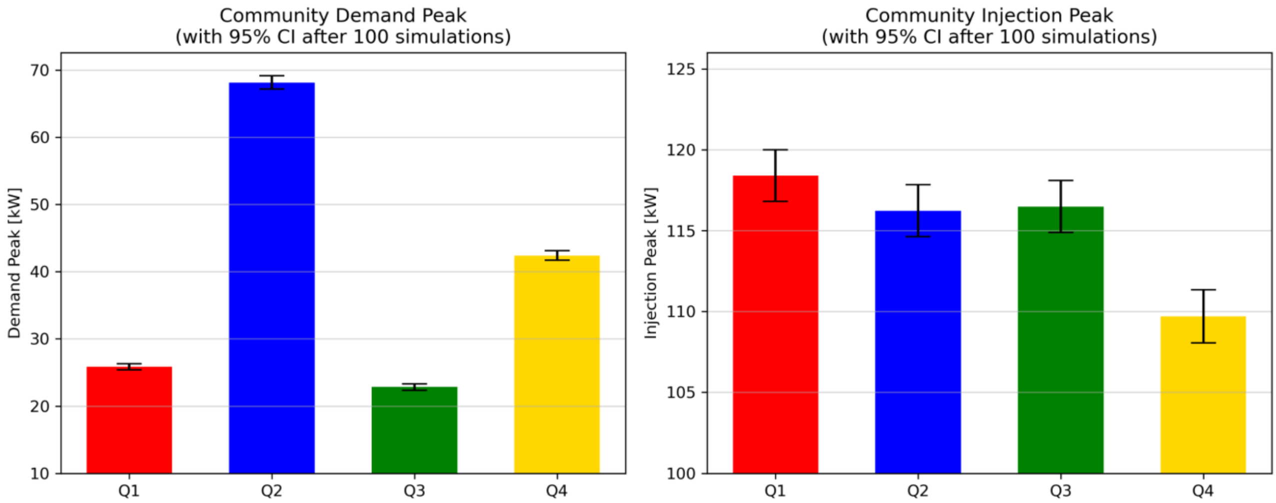

Figure 3.6: Demand peak and injection peak of the community in the four different scenarios.

As expected, the demand peak is significantly greater in the cases in which the average demand of the users is greater, i.e. scenarios Q2 and Q4. It is also interesting to note how greater synchronism causes a decrease in the demand peak. This decrease is limited for the scenarios with low demand (Q1 and Q3), causing a demand peak decrease of just 11.5%, but much more significant for the scenarios with high demand, in which a demand peak decrease of 38.2% is observed comparing Q4 to Q2.

However, it is clear from the results that the injection peak of the community is barely affected by changes in average yearly demand and PCC, with the only significant reduction occurring in the

scenario Q4. The cause for this limited change is likely that in all the scenarios there is a moment in which the PV generation (which is exactly the same in the four scenarios) far exceeds the energy demand, causing a significant injection peak.
Based on these results, it seems that greater demand and synchronism can reduce the injection peak but only by a limited amount. However, it is to be noted that the reduction could potentially be greater if the generation was lower or the demand and/or synchronism was higher, therefore the reduction could be more relevant in other cases and shouldn't be ignored *a priori*.
Another point to consider is that the injection and demand peaks are mainly relevant for the sizing of the lines and of the transformer, which have to be designed taking into account the greater between the two peaks. Thus, a decrease in the demand peak can result ineffective in this regard if the injection peak remains greater and thus the limiting factor to consider in sizing, making its reduction the relevant point to consider. However, in a real setting, it is likely that there is not a transformer connected only to the energy community but that it is connected to other users as well. In this case, the injected power may be consumed by other users not belonging to the energy community before getting to the transformer, thus decreasing the injection peak at the transformer, and possibly making the demand peak (to be calculated considering all the users connected to the transformers, not only those belonging to the energy community) the limiting factor instead of it.

The last KPI analyzed for these scenarios is the community yearly electricity bill (reported in Figure 3.7).

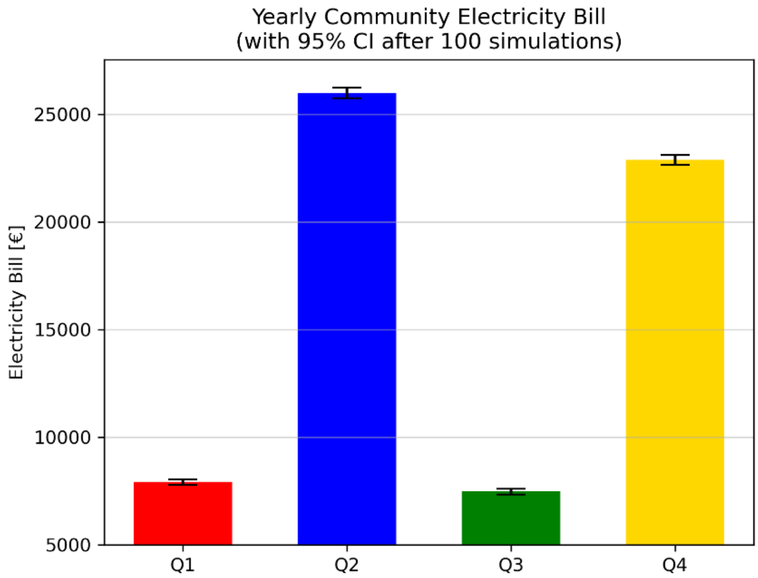

Figure 3.7: Yearly electricity bill of the energy community in the four different scenarios.

Aside from the obvious result of a lower energy demand causing a much lower electricity bill, it is notable that a greater synchronism can also cause a decrease in the electricity bill. This latter effect is due to the increase in self-consumption caused by a higher synchronism. This decreases the bill because it is more economically convenient for owners of PV systems to self-consume the PV-generated energy than to sell it, due to the cost of importing energy being higher than the profit from exporting it, considering the first pricing mechanism explained in section 2.1.2, which was used in these simulations (since they do not consider batteries).

In conclusion, the simulations performed and the analyses on the obtained KPIs clearly show an influence of the position of demand profiles in the PCC-demand plane on several KPIs of the simulated energy communities. Consequently, these preliminary findings show a possible relevance of the PCC-demand plane as a tool to represent the demand profiles of energy communities in a way that could help to partially predict some effects that the demand profiles may have on the communities' KPIs.
Therefore, the results presented in this section suggest the possible usefulness of the further analyses based on the PCC-demand plane that are presented in the rest of this thesis.

4 Results: effects of the parameters of PV systems on energy communities

When analyzing energy communities using the PCC-demand plane, the importance of PV energy generation should not be forgotten. Indeed, demand profiles are what is represented in the plane (in the form of dots), but both the PCC and the normalized demand of each demand profile are affected by the PV production. The PCC is influenced by the trend of the PV generation profile, while the yearly sum of the latter, determining the yearly PV-generated energy, influences the normalized demand.

The PV production profile's trend and sum can be influenced by various factors, such as the model of PV panels used, the geographical location in which the PV systems are installed, the inclination, and the orientation of the PV systems. In this section, the effects of the latter two parameters (PV systems' inclination and orientation) are investigated, fixing all of the other factors. This decision is made because the other factors, which are supposed to be fixed in this section, are either not subject to choice, such as the geographical location of the energy community, or are usually chosen following criteria that are not the focus of this thesis, for example, the model of PV panels used could be chosen following economic criteria. Therefore, the geographical coordinates and the model of PV panels are fixed parameters in this section, and both are as explained in section 2.2, meaning the same used in all of this work.

Another constant parameter in this section is the average PV power of the energy community, which is arbitrarily fixed equal to 5 kW, except for a set of simulations performed in section 4.2.3, in which an average PV power of 2.06 kW is also considered. The effects that the variation of average PV power has on the PCC-demand plane with normalized demand are not investigated in detail in this thesis, since they are quite obvious: a change in average PV power would simply result in a horizontal shift of all the profiles in the plane towards the right (in case of a decrease of average PV power) or towards the left (in case of an increase of average PV power). This shift was already shown in Figure 2.7 and Figure 2.8 when discussing how the maximum or average normalized demand of the Italian dataset could be made similar to that of the German dataset simply by changing the average PV power.

The dataset of demand profiles considered in this section is the Italian one introduced in section 2.3.1. The "base case" for PV systems' inclination and orientation, considered in this work outside of this section, is constituted by an inclination of 25° and a South orientation. Therefore, in this section

particular attention is given to these cases of inclination and orientation and when considering one of the two fixed, it is fixed equal to its value in the base case. This means that the PV systems' orientation is always towards South in section 4.1, in which the effects of inclination are analyzed, while the inclination is always equal to 25° in section 4.2, in which the effects of orientation are analyzed.
In this section, the impacts of changing the inclination and orientation of PV systems are assessed considering the variations of the distribution of demand profiles in the PCC-demand plane and of the KPIs of the simulated energy communities. The calculations of KPIs are performed considering their values relative to 100 simulations for each case and finding the relative means and 95% confidence intervals. It is important to keep in mind that the 100 simulations have been performed with the same set of seeds (ranging from 0 to 99, included) for each case. This means that, as explained in section 2.1.3, all of the randomized factors have been randomized in the same way for each case, when the relative input data remained unvaried. In the case of this section, this mainly means that all the cases for which 100 simulations were performed selected the same demand profiles and the same PV sizes, increasing the comparability between different cases. For example, the 60 demand profiles that are chosen for the simulation with a seed equal to 0 are the same in the case of a South PV orientation and a West PV orientation, and the same goes for the sizes of the 30 PV systems installed in the energy community. In this way, the input factors that are fixed and are not analyzed in this section, such as demand profiles and sizes of PV systems, do not randomly alter the results.

4.1 Inclination of PV systems

The goal of this section is to investigate the effects that the inclination of PV systems has on an energy community. As previously mentioned, all of the PV systems have the general characteristics introduced in section 2.2 and are supposed to be South-oriented. The only change considered in the PV parameters between the different cases analyzed in this section is the inclination, which, for sake of simplicity and to better analyze its effect, is supposed for each case to be equal for all of the PV panels present in the energy community.

The values analyzed in this section for the inclination (also known as tilt angle) of PV systems are 20°, 25°, 30°, 35° and 40°. These values were chosen to represent some possible realistic values of the tilt angles of rooftop PV panels, which generally lie directly on the roof or have little additional structural support and therefore generally present an inclination similar to that of the rooftop. The value of the "base case" was arbitrarily chosen as 25°, while the maximum inclination of 40° is the one that PVGIS 5.1 (a tool developed by the Joint Research Center of the European Union, available online at [48]) indicated as the optimal value for maximizing the energy produced in one year at the geographical coordinates considered in this work.

In section 4.1.1, some considerations are made on the effects that the inclination of PV systems has on the synchronism between energy demand and PV generation and on the amount of yearly energy produced. These considerations do not depend on the simulation of an energy community, being based on methods, such as the PCC-demand plane with normalized demand, that allow to preliminarily analyze the demand and supply of an energy community without simulating it.

On the other hand, in section 4.1.2, energy communities with different inclinations of PV systems are simulated, to analyze the values of KPIs in the different cases and to compare them.

4.1.1 Energy production, normalized demand and PCC

The inclination of PV systems is known to impact their power generation profile and thus their yearly energy production. An inclination that generally maximizes the yearly energy generation can be found, but it is important to keep in mind that such inclination is the optimum considering the whole year, but not during each time of the year. Indeed, PV production during Summer tends to be higher for tilt angles lower than the yearly optimum, while during Winter PV systems tend to generate more energy for tilt angles higher than the yearly optimum [49].

These facts are coherent with the power differences that were found between the generated PV production profiles (all corresponding to a peak power equal to 1 kW) corresponding to different inclinations that are reported in Table 4.1. For clarity, it is necessary to specify the nomenclature followed by Table 4.1: each column considers differences between two hourly PV production profiles with peak power equal to 1 kW (obtained as illustrated in section 2.2), with one inclination being always the base case of 25°, whose power profile is subtracted from the power profile of the compared tilt angle. For example, in the column "20° - 25°" the differences between the PV production profile corresponding to a tilt angle of 20° and the one corresponding to 25° are considered.

Table 4.1: Power differences between PV generation profiles (with peak power = 1 kW) corresponding to different inclinations.

Inclination	**20° - 25°**	**30° - 25°**	**35° - 25°**	**40° - 25°**
Max positive power difference [W]	24.90	55.82	106.45	149.48
Max negative power difference [W]	-59.34	-26.34	-53.44	-80.34
Average power difference [W]	-2.91	2.03	3.17	3.36

Indeed, Table 4.1 shows how inclinations that are closer than 25° to the optimal tilt angle of 40° present a positive average power difference, meaning an overall increase in yearly energy production, while 20°, being farther from 40° than the base case, presents a negative average power difference. However, as previously mentioned, different inclinations are better in different periods of the year. This is shown by the fact that all of the inclinations present both moments in which their corresponding power production is significantly higher than that of the base case (highlighted by the maximum positive power difference) and moments in which, on the opposite, their corresponding power production is significantly lower (highlighted by the maximum negative power difference).
In any case, since this work considers simulations of the duration of a whole year, the most important (and synthetic) parameter to consider when comparing the power production of PV systems is the total yearly energy generated, which is reported in Table 4.2, considering a peak power of 1 kW.

Table 4.2: Comparison of the yearly energy generation values corresponding to different inclinations of PV systems (with peak power = 1 kW).

Inclination	**20°**	**25°**	**30°**	**35°**	**40°**
Yearly generated energy [kWh]	1458.1	1483.6	1501.4	1511.4	1513.0
Decrease in energy compared to 40° [%]	3.63	1.94	0.77	0.11	0.00

Observing Table 4.2, it is clear how 40° is indeed the best inclination from the point of view of the yearly energy production, as suggested by PVGIS. However, it is important to notice how the values of energy production have only a slight decrease when considering the other inclinations. This is important when considering rooftop PV systems since the easiest solution for their installation is having their tilt angle be equal to that of the rooftop, which was often chosen before of the installation of PV panels on it. Therefore, the results of Table 4.2 suggest that following the inclination of the rooftop, at least in the range of analyzed inclinations, could be a sensible choice. Moreover, the base case (a tilt angle of 25°) considered as inclination in the rest of this work does not cause an excessive decrease in energy production compared to 40° and should therefore be an adequate reference value. Considering the PCC-demand plane with normalized demand, the effect of a change in the yearly PV-produced energy is a change in the PV-produced energy allocated to each user, which then causes a variation of the values of normalized demand and therefore a horizontal shift of the demand profiles along the horizontal axis. To quickly visualize the different distributions of normalized demand corresponding to the different inclinations, a joyplot (also known as Ridgeline plot) has been realized by utilizing the Python package JoyPy [50] and it is reported in Figure 4.1.

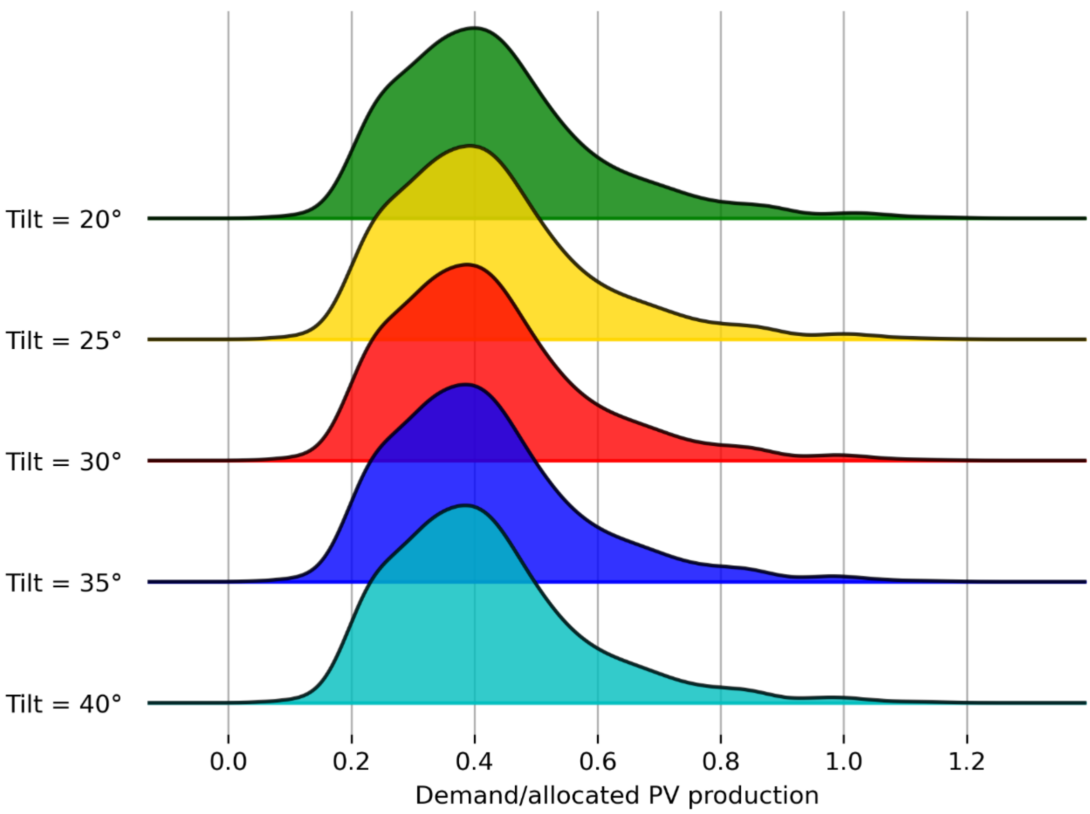

Figure 4.1: Joyplot representing the distributions of normalized demand corresponding to different inclinations of PV systems

Observing Figure 4.1, it is noticeable how the changes between the distributions of normalized demand are very limited, coherently with the slight changes in the yearly energy production reported in Table 4.2. However, it can be noticed that the lower the inclination is and the more the distribution is moved towards the right of the plot, meaning that the values of normalized demand are higher. This is what was expected, since lower inclinations are further from the optimal inclination of 40° and cause a lower yearly energy generation, thus reducing the denominator of the normalized demand and therefore increasing the values of normalized demand.

Besides the yearly energy production, the changes in PCC considering different inclinations of the PV systems are also analyzed. Five different values of PCC were calculated for each of the 992 demand profiles present in the Italian dataset, considering the synchronism with the five different PV generation profiles corresponding to the five different inclinations.
Table 4.3 considers the differences between PCCs corresponding to the same demand profile, for the five different inclinations of the PV systems, comparing each inclination to the base case of a tilt angle of 25°. For example, in the column "20° - 25°" the differences between the PCCs of demand profiles calculated with the PV production profile corresponding to a tilt angle of 20° and the PCCs of demand profiles calculated with the PV production profile corresponding to 25° are considered. Each of the reported differences is a difference between PCCs relative to a same demand profile, whose PCC is calculated with different PV production profiles. For example, if one profile has a PCC of 0.1247 for an inclination of 20° and a PCC of 0.1241 for an inclination of 25°, the relative value of difference taken into account for the column "20° - 25°" is 0.0006.

Table 4.3: PCC differences considering different inclinations of PV systems.

Inclination	**20° - 25°**	**30° - 25°**	**35° - 25°**	**40° - 25°**
Max positive difference of PCC	0.0022	0.0030	0.0058	0.0085
Max negative difference of PCC	-0.0032	-0.0020	-0.0038	-0.0056
Average difference of PCC	-0.0007	0.0006	0.0012	0.0018

Analyzing Table 4.3, it is clear that different inclinations in general produce very limited changes in PCC. The average variations from the base case are close to being negligible and even the maximum variations are very low.
This result was expected since the value of PCC depends on the trends of the demand and PV generation profiles that are confronted, not on the magnitude of their values. For example, the PCC of a certain demand profile with a PV generation profile is the same regardless of the peak PV power considered, since the latter only causes a "rescaling" of the PV profile, by multiplying it for the same value in all of its timesteps, changing, therefore, the magnitude of the values of the PV profile without changing its trend. The change of inclination acts in a similar way: the trend of the PV generation profile remains mostly the same regardless of the inclination, what changes is the magnitude of the

values of power of the profile. This can be seen for example considering the average daily profiles of PV generation with different tilt angles, reported in Figure 4.2.

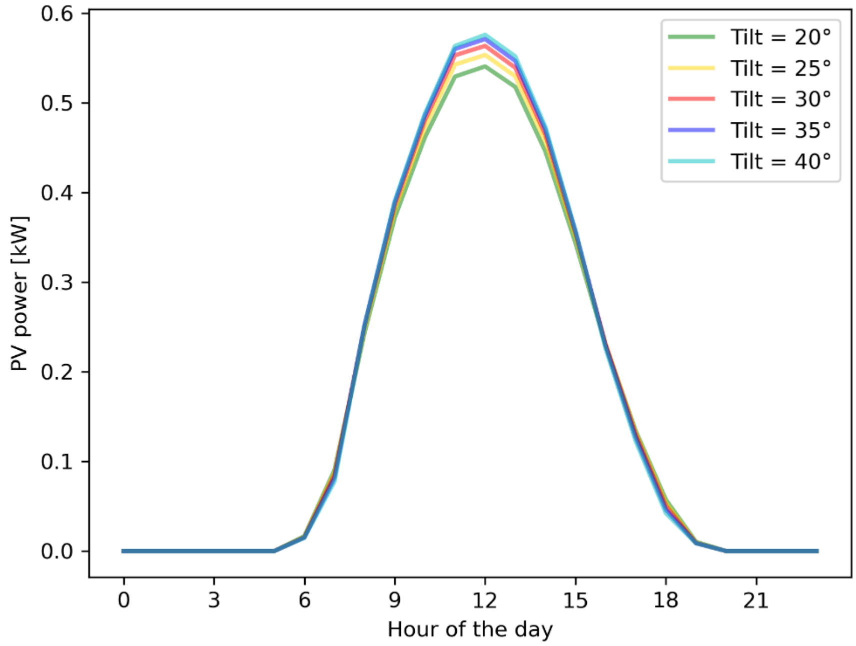

Figure 4.2: Average (over the whole year) daily profiles of PV generation with different inclinations, considering a peak power of 1 kW.

Figure 4.2 was obtained performing averages of power over the whole year for each hour of the day, considering PV generation profiles with a peak power of 1 kW. For example, the value of power plotted for 9 a.m. is the average of all the values of power that the profiles had at 9 a.m. on each day of the year. Figure 4.2 shows how the average trend of the PV generation profiles remains mostly the same regardless of the inclination, all of the profiles have their peak at the same hour, start and end power production at similar times and the profiles even superimpose for a significant part of the day. Similar considerations can be made considering the average daily PV production profiles over only a certain month, for example, the daily averages across January are represented in Figure 4.3 (which was obtained in the same way as Figure 4.2, but considering averages only of the values of power relative to January).

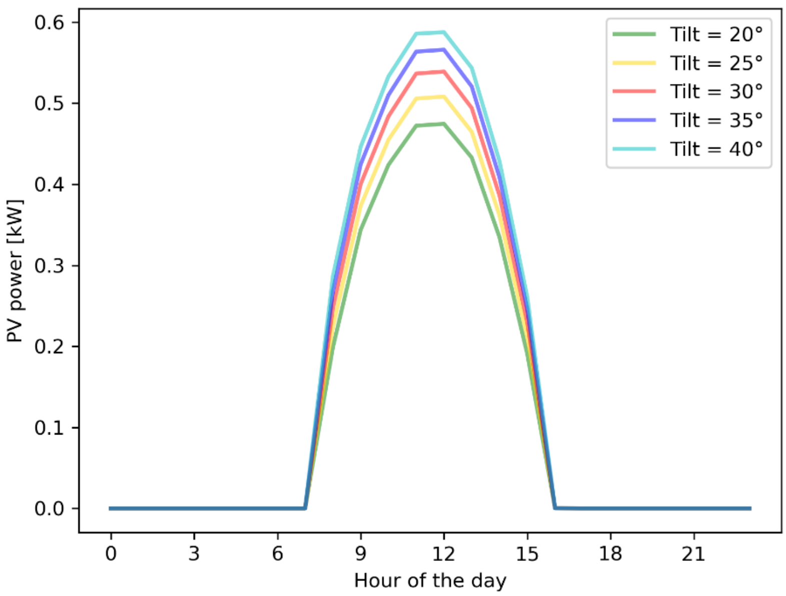

Figure 4.3: Average (over the month of January) daily profiles of PV generation with different inclinations, considering a peak power of 1 kW.

It is important to observe that what Figure 4.2 and Figure 4.3 show is not a perfect rescaling of PV generation profiles (like the one caused by a change in the peak power), a rescaling occurs but it is not even over all of the hours of the day, causing the trend of PV profiles to be altered slightly, enough to produce some changes in the values of PCC, but not enough for these changes to be drastic.

The effects of the different inclinations on both PCC and normalized demand can be quickly visualized in the PCC-demand plane with normalized demand. In order to perform a comparison with the base case of a tilt angle equal to 25°, each other inclination was compared to it through an arrow plot in the PCC-demand plane with normalized demand (in which an average PV power of 5 kW was considered). These plots, reported in Figure 4.4, Figure 4.5, Figure 4.6, and Figure 4.7, represent each demand profile with an arrow (which has a color that depends on the quadrant of the PCC-demand plane in which its starting point is) which starts from the point relative to the PV profile with inclination equal to 25° and ends at the point relative to the PV profile with the inclination that is compared. This means that the coordinates in the plane of the start of an arrow represent the PCC and normalized demand of the relative demand profile when considering an inclination of 25°, while the coordinates of the end of the same arrow are the PCC and normalized demand of the same demand profile but considering a different inclination of the PV system.

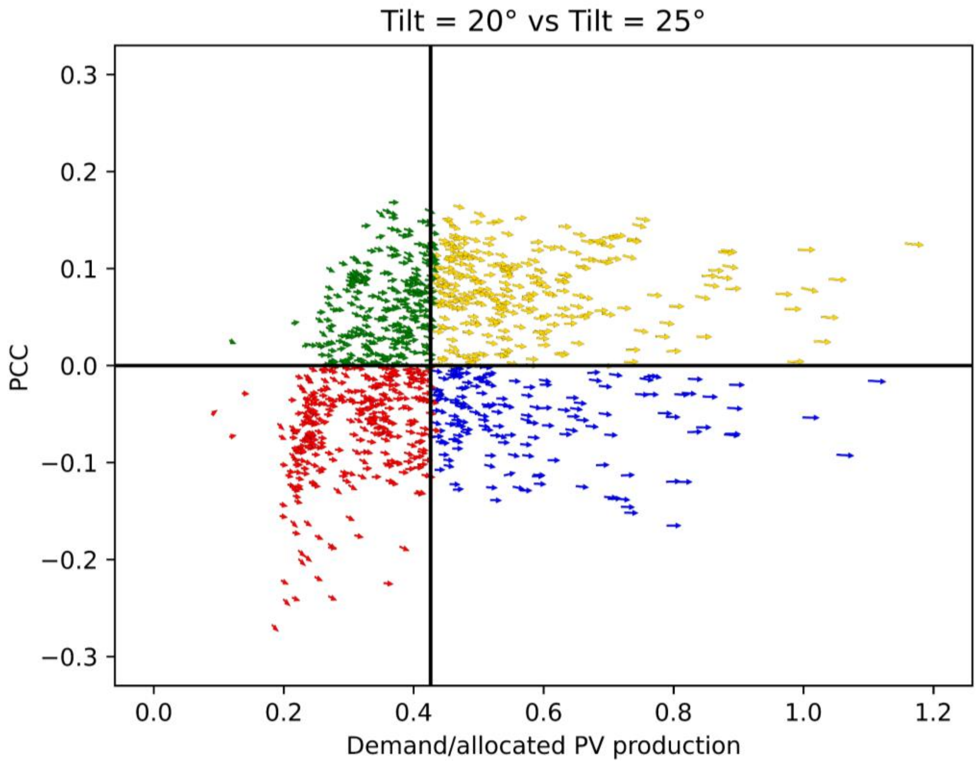

Figure 4.4: Arrow plot in the PCC-demand plane with normalized demand, comparing an inclination of 25° (at the start of the arrows) and an inclination of 20° (at the end of the arrows).

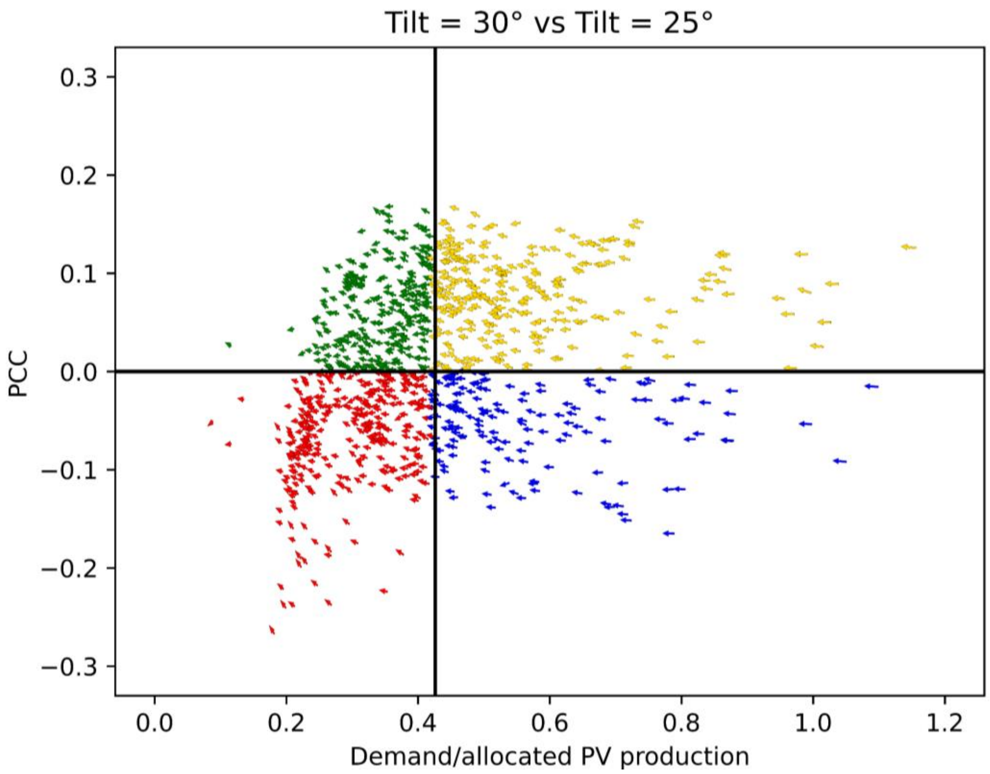

Figure 4.5: Arrow plot in the PCC-demand plane with normalized demand, comparing an inclination of 25° (at the start of the arrows) and an inclination of 30° (at the end of the arrows).

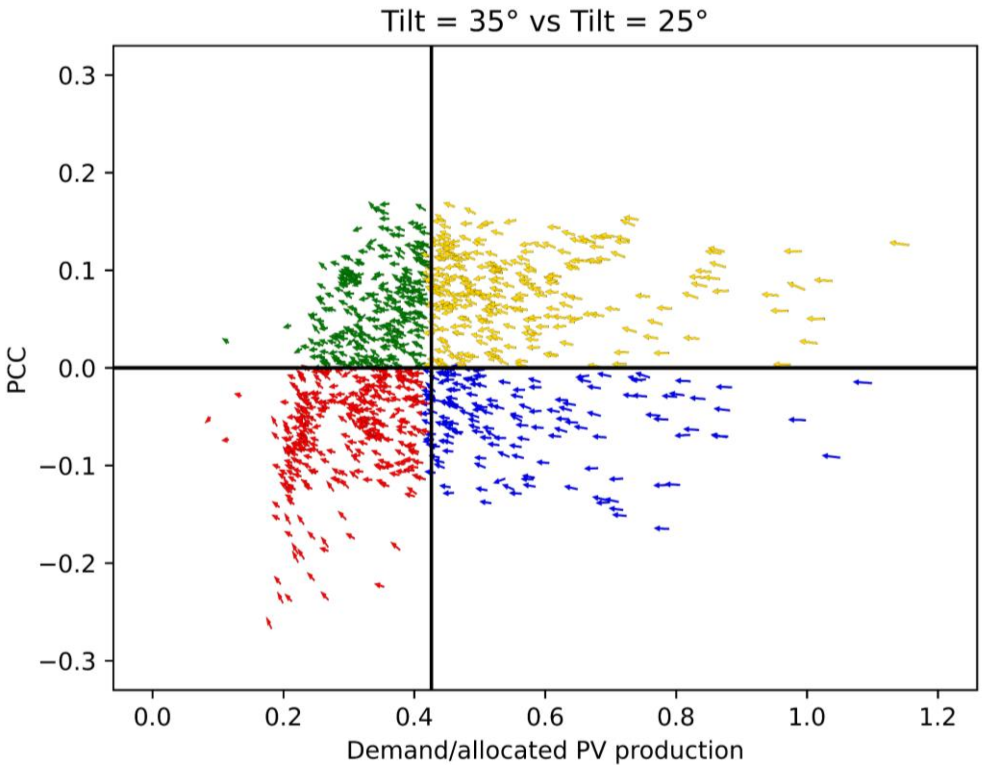

Figure 4.6: Arrow plot in the PCC-demand plane with normalized demand, comparing an inclination of 25° (at the start of the arrows) and an inclination of 35° (at the end of the arrows).

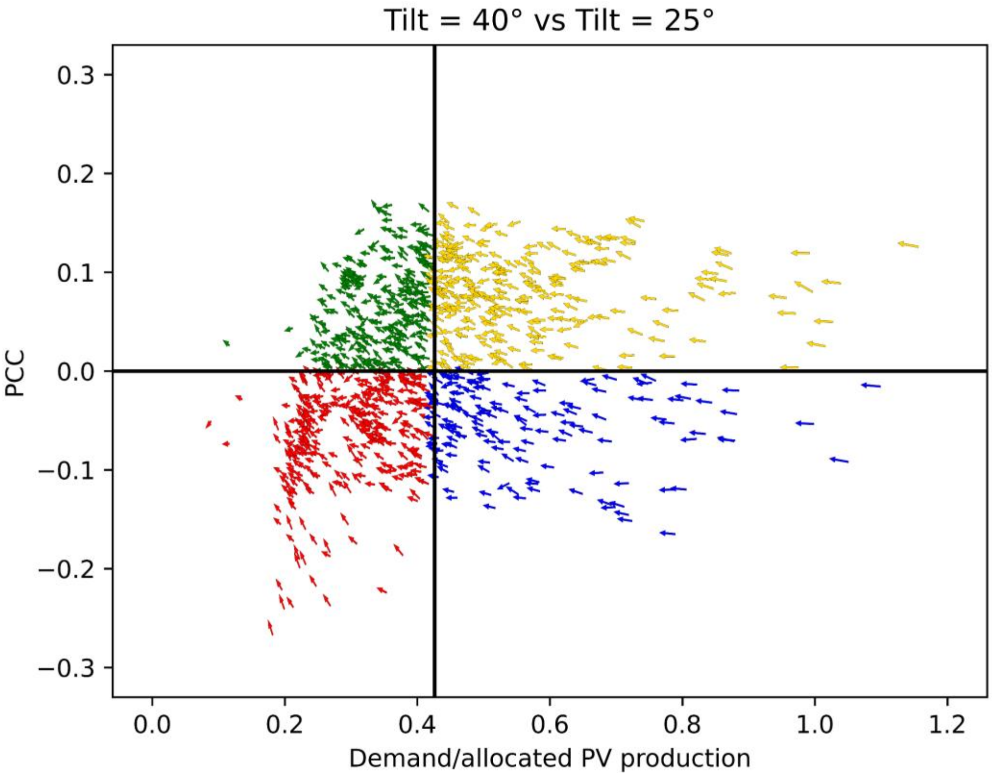

Figure 4.7: Arrow plot in the PCC-demand plane with normalized demand, comparing an inclination of 25° (at the start of the arrows) and an inclination of 40° (at the end of the arrows).

Figure 4.4, Figure 4.5, Figure 4.6, and Figure 4.7 show arrows that are coherent with what was previously observed:

- An inclination of 20° causes a decrease in PV production compared to a tilt angle of 25°, therefore increasing the normalized demand and making all the arrows point toward the right,
- Inclinations of 30°, 35° and 40° cause an increase in PV production compared to a tilt angle of 25°, therefore decreasing the normalized demand and making all the arrows point toward the left,
- The variations of the values of PCC (represented by the differences between the vertical coordinates of the beginnings and ends of the arrows) are limited and no significant general trends of arrows shifting towards the top or bottom emerge.

4.1.2 KPIs of energy communities

The changes in the distributions of demand profiles in the PCC-demand plane with normalized demand due to different inclinations of PV systems are expected to produce some differences between the KPIs of simulated energy communities whose PV systems have different inclinations. However, since differences in values of both PCC and normalized demand were shown to be quite low in section 4.1.1, the differences between the KPIs relative to different inclinations are expected to be low as well.

The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops, while no users have batteries installed in their houses. The choice of not considering batteries in these simulations is made to "isolate" the impact of the variations of the parameters of PV systems, without including the influence of batteries that could potentially alter the impact that changes in the PV systems by themselves cause.

The PV parameters utilized in these simulations are a South orientation and an inclination different for each case, in order to investigate its impact. Moreover, the PV sizes of the community members are randomly selected in each simulation according to a normal distribution with average PV power of 5 kW, symmetrically truncated at 1 kW and 9 kW.

100 simulations were conducted for five energy communities, each with all the PV systems having one of the five inclinations analyzed in this section. The means of the KPIs found from these simulations, along with their 95% confidence intervals, are reported in Figure 4.8, Figure 4.9, and Figure 4.10.

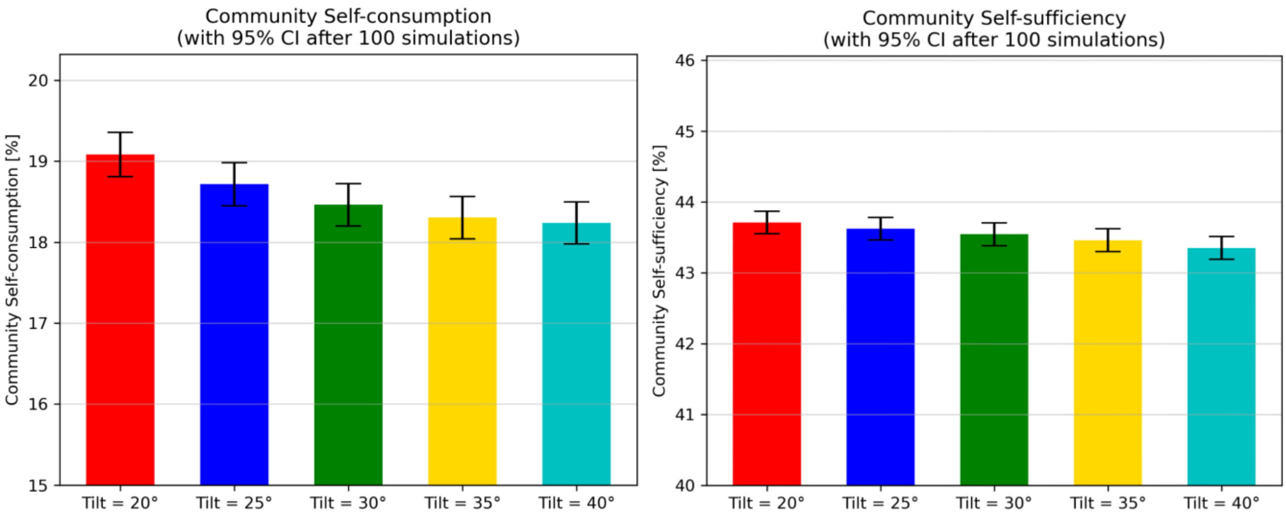

Figure 4.8: Self-sufficiency and self-consumption of the energy community, comparing five different inclinations of PV systems.

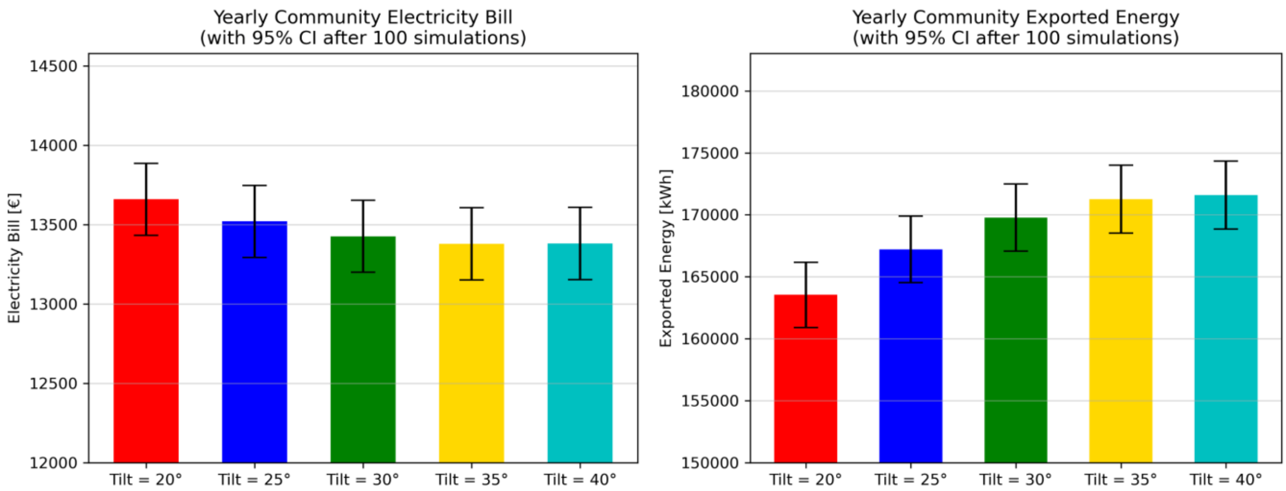

Figure 4.9: Yearly electricity bill and energy exported by the energy community, comparing five different inclinations of PV systems.

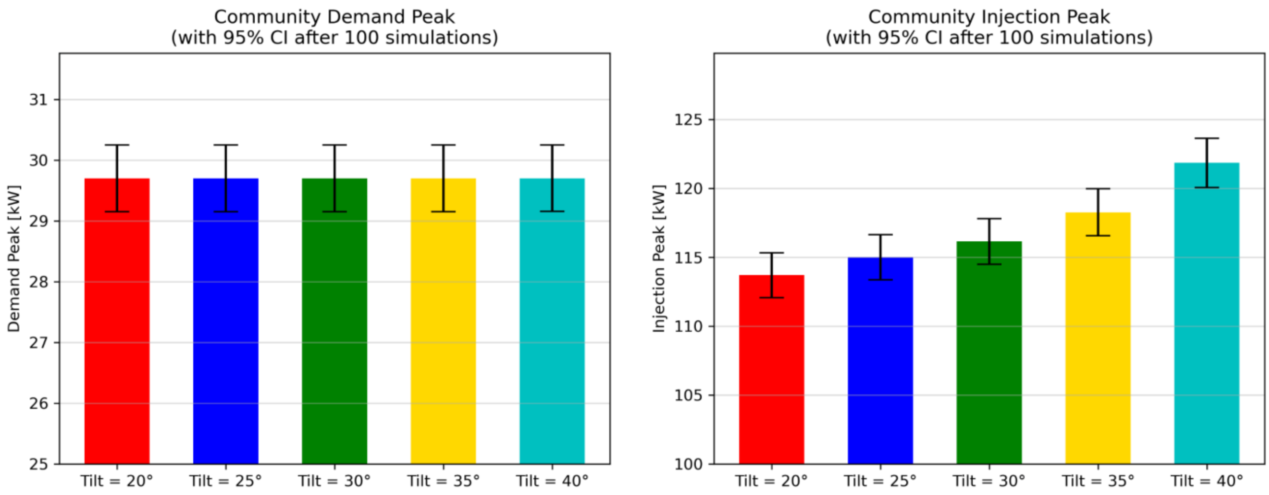

Figure 4.10: Demand peak and injection peak, comparing five different inclinations of PV systems.

Generally speaking, the KPIs reported in Figure 4.8, Figure 4.9, and Figure 4.10 vary only slightly considering different inclinations of PV systems, validating the prediction made by looking at the limited changes observed in the values of PCC and normalized demand. In particular, even comparing the two furthest inclinations considered, i.e. 20° and 40°, the KPIs relative to these two inclinations differ only by a few percentage points, with the highest variation observed for the injection peak (which is 5.6% higher in the case of a 40° tilt angle), while all the other KPIs vary by less than 3% when comparing 20° and 40°. Comparing inclinations that are closer between themselves the differences between KPIs are then even smaller.

Considering the small changes in KPIs, whose confidence intervals often overlap for close values of tilt angle, not all of the trends that emerge may be fully accurate and some may need further validation to be generalized; nevertheless, these trends are worth analyzing and discussing as preliminary results. The most evident trends are, as expected, observable in the KPIs that are closely related to PV generation, meaning the injection peak of the community (reported in Figure 4.10) and the energy exported in one year by the community (reported in Figure 4.9). The injection peak tends to increase with inclinations closer to 40°, this is logical since 40° is the optimal tilt angle that maximizes PV production and a higher PV power generation causes the injection peak to increase if the demand is fixed (as is the case in these simulations, in which the same demand profiles have been selected for all of the inclinations due to the use of the same seeds, as explained in section 2.1.3). A higher injection peak can be considered a negative factor, potentially increasing the needed size of the transformer receiving the power from the energy community, however, the difference in injection peak observable for the different inclinations is quite limited and thus the magnitude of the injection peak does not appear to be a particularly relevant KPI to evaluate different PV inclinations. Similarly to the injection peak, the yearly energy exported by the community tends to increase when getting closer to an inclination of 40°, since the latter is the tilt angle that maximizes the energy generated by the PV systems in one year.

The community self-consumption (SC), reported in Figure 4.8, slightly decreases for inclinations closer to 40°, but this should not necessarily be interpreted as a drawback of using tilt angles closer to 40°. Indeed, the reason for this trend is that the demand is the same for all five cases, while the yearly PV generation increases for inclinations closer to 40°. What the trend of the SC indicates is that, going towards an inclination of 40°, the yearly PV-generated energy (which is at the denominator of the SC) increases faster than the energy self-consumed by the community (which is at the numerator of the SC). However, self-consuming energy is not the only way of profiting from an increase in the amount of PV-generated energy, exporting it to the main electrical grid external to the community can also allow for an economic profit, as shown by the decrease (even if limited, due to the only slight change in yearly PV generated energy caused by the different inclinations) of the electricity bill for inclinations closer to 40°, reported in Figure 4.9.

A very slight decrease in community self-sufficiency (SS) for inclinations closer to 40° can be observed in Figure 4.8. It is hard to establish if this trend is significant or not, considering the very slight changes in SS between the different inclinations and the overlap of several confidence intervals. Considering the small changes, this trend may not be a reliable result, in particular considering its counter-intuitive nature: a generally higher PV generation should increase the energy self-consumed by the community and therefore the SS. These simulations, however, suggest the opposite: the self-consumed energy decreased for inclinations closer to 40°. In this case, this result may be the consequence of a particular combination of demand and supply, with the latter being oversized compared to the former (as shown by the low SC values). Users may then be already self-consuming close to the maximum of energy they can self-consume in the case of a 20° tilt angle and thus be unable to increase their self-consumed energy. As for the slight reduction of the latter going towards 40°, it is likely caused by the fact that, as previously mentioned, lower inclinations favor PV generation during Summer, while higher inclinations favor it during Winter. The users of the simulated community then are likely able to self-consume more PV-produced energy during Summer (for example due to more time with sunlight or more time spent at home) than during Winter, making an increase in PV generation during Summer more beneficial to the amount of self-consumed energy than an increase during Winter. In any case, it is unlikely that this trend of SS is general, but it highlights how, for the above-mentioned reasons, an increase in PV-generated energy due to a

different inclination of PV systems does not always cause an increase in SS, as one could have instead presumed.
Finally, the only KPI that is totally unaffected by different inclinations of the PV systems is the demand peak of the community, reported in Figure 4.10. The reason for this lack of change is more than likely due to the demand peak occurring in all the cases during times in which the PV systems did not generate any power (due to lack of sunlight), making the inclinations of the PV systems irrelevant to this KPI.

The main conclusions that can be drawn from the results of these simulations are two. The first is that limited changes in the distribution of demand profiles in the PCC-demand plane with normalized demand seem to predict limited changes in the KPIs of energy communities using these profiles. The second conclusion is that the inclination of PV systems, within the range of inclinations considered, seems to have very little effect on the KPIs of energy communities. This would favor choosing the inclination of each rooftop PV system based on factors not tied to the KPIs of the community. For example, the tilt angle of the PV system could be chosen considering the characteristics of the relative rooftop, in order to maximize the integration of the PV panel in the latter, to maximize the structural solidity of the system, and/or to minimize installation costs.

4.2 Orientation of PV systems

The goal of this section is to investigate the effects that the orientation of PV systems has on an energy community. All of the PV systems simulated have the general characteristics introduced in section 2.2 and are supposed to have a tilt angle of 25°. The only change considered in the PV parameters between the different cases analyzed in this section is the orientation, which, for sake of simplicity and to better analyze its effect, is supposed for each case to be equal for all of the PV panels present in the energy community.

The possible orientations of PV systems analyzed in this section are East, South-East, South, South-West, and West, which, according to the convention utilized in this work and introduced in section 2.2, correspond respectively to azimuth angles of 90°, 135°, 180°, 225° and 270°. The base case chosen out of these orientations is the South orientation, which is generally known to be the optimal orientation for maximizing the energy production of PV systems located in the Northern hemisphere [49]. The other orientations should generally cause a lower energy production over the whole year, but they should cause a shift in the trend of the PV power generation, moving its peak towards earlier or later in the day. This change in the trend of daily PV power generation should consequently cause a change in the values of PCC associated with the various demand profiles.

In sections 4.2.1 and 4.2.2, some considerations are made on the effects that the orientation of PV systems has on the synchronism between energy demand and PV generation and on the amount of yearly energy produced. These considerations do not depend on the simulation of an energy community, being based on methods, such as the PCC-demand plane with normalized demand, that allow to preliminarily analyze the demand and supply of an energy community without simulating it. On the other hand, in sections 4.2.3 and 4.2.4, energy communities with different orientations of PV systems are simulated, in order to analyze the values of KPIs in the different cases and to compare them. In section 4.2.3 these simulations are conducted using all of the demand profiles from the Italian dataset, while in section 4.2.4 the simulations are made utilizing only the Italian demand profiles whose PCC increased using an orientation different from South, in order to see if energy communities with these particular demand profiles could benefit, in terms of KPIs, from orientations different from South.

4.2.1 PV energy production and normalized demand

First of all, the impact of the orientations of PV systems on PV power production is analyzed. For each orientation, the power variations compared to the base case of a South orientation are reported in Table 4.4. In this table, each column considers differences between two hourly PV production profiles with peak power equal to 1 kW (obtained as illustrated in section 2.2), with one orientation being always the base case of South orientation (corresponding to an azimuth angle of 180°), whose power profile is subtracted from the power profile of the compared orientation. For example, in the column "90° - 180°" the differences between the PV production profile corresponding to an azimuth angle of 90° (i.e. East orientation) and the one corresponding to 180° are considered.

Table 4.4: Power differences between PV generation profiles (with peak power = 1 kW) corresponding to different orientations.

Azimuth	**90° - 180°**	**135° - 180°**	**225° - 180°**	**270° - 180°**
Max power positive difference [W]	373.97	250.88	223.31	318.76
Max power negative difference [W]	-574.17	-286.82	-309.78	-548.46
Average power difference [W]	-28.45	-7.20	-10.63	-32.99

Analyzing the data reported in Table 4.4, it is noticeable that the maximum power variations (both negative and positive) are very significant, compared to the peak power. They are significantly higher than the maximum power variations caused by different inclinations, reported in Table 4.1, and this suggests that the values of PCC should vary significantly more due to different orientations of PV systems than how much they varied due to different inclinations. The high values of both positive and negative maximum differences suggest that there are both moments in which orientations different from South are very beneficial to PV power production and moments in which they are very detrimental. Therefore, both increases and decreases in PCCs are expected, depending on the demand profiles, whose synchronism with PV production may either benefit or be hindered by these significant changes in PV power production's profiles. The average power differences are also higher than the ones found for changes in inclination, suggesting greater changes in the yearly generated energy due to changes in orientation than due to changes in tilt angle. This is confirmed by looking at the energy that PV systems with a peak power of 1 kW produce in one year, reported in Table 4.5.

Table 4.5: Comparison of the yearly energy generation values corresponding to different orientations of PV systems (with peak power = 1 kW).

Azimuth	**90°**	**135°**	**180°**	**225°**	**270°**
Yearly generated energy [kWh]	1234.4	1420.6	1483.6	1390.5	1194.6
Decrease in energy compared to 180° [%]	16.80	4.25	0.00	6.28	19.48

The data reported in Table 4.5 confirm what was expected: the South orientation is the one that maximizes the yearly PV energy production. The orientations that partially face South, i.e. South-

East (azimuth = 135°) and South-West (azimuth = 225°) are the next best choice for maximizing PV energy production, causing a low but non-negligible decrease of the latter compared to the South orientation. Finally, the East (azimuth = 90°) and West (azimuth = 270°) orientations are the worst, among the ones considered, from the point of view of the energy generated by the PV systems in one year. The decreases in PV energy production produced by orientations different from South are significant, in particular for the East and West orientations, much more than the decreases caused by inclinations different from 40° (reported in Table 4.2). This means that the orientation of PV systems should not be chosen lightly, as the choices differ much more than in the case of different inclinations. The choice of a South orientation, however, is not always possible due to the necessity of installing the rooftop PV systems on one of the orientations toward which the rooftop faces. Moreover, the different PV generation profiles for different orientations could mean that some demand profiles could have an increased synchronism with the PV generation using orientations different from South. As explained in section 4.1.1, the effect that a different yearly PV production has on the PCC-demand plane with normalized demand is to change the PV energy allocated to one user, therefore changing the normalized demand. To quickly visualize the different distributions of normalized demand corresponding to the different orientations, a joyplot has been realized (using JoyPy [50]) and it is reported in Figure 4.11.

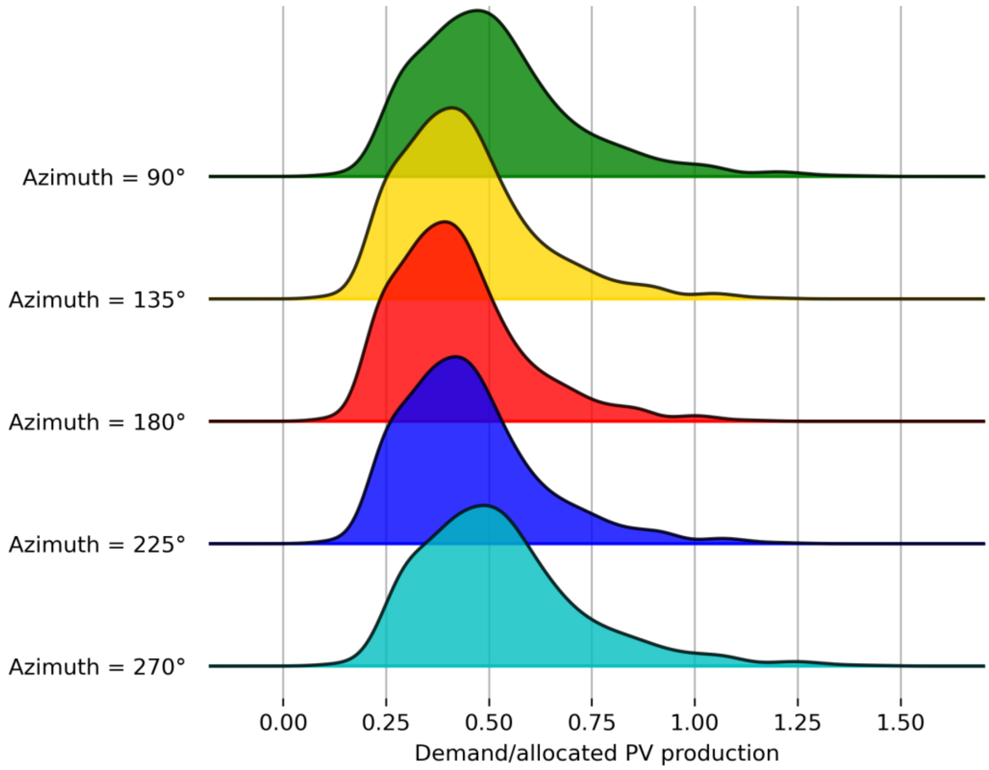

Figure 4.11: Joyplot representing the distributions of normalized demand corresponding to different orientations of PV systems.

Observing the distributions of normalized demand reported in Figure 4.11, it is clear how the differences between the distributions are more significant than the differences due to changes in inclinations (visible in Figure 4.1). This is logical since the yearly PV-generated energy varies much more due to different orientations than due to different inclinations of the PV systems. Compared to the distribution of the base case (which is the South orientation), the other distributions are shifted toward the right of the plot, indicating a predictable increase in normalized demand, due to a decrease in yearly PV generation. In particular, as it is logical, the more the yearly PV generation is reduced (compared to the base case) with a certain orientation and the more the distribution of normalized demand relative to such orientation is shifted toward the right of the plot.

Before analyzing the changes in PCC produced by different orientations, it can be useful to analyze the average daily profiles of PV generation with different orientations, reported in Figure 4.12, in order to have an idea of the different PV production daily trends, since the trend of the PV profiles is what determines the PCC, once the demand profile is fixed.

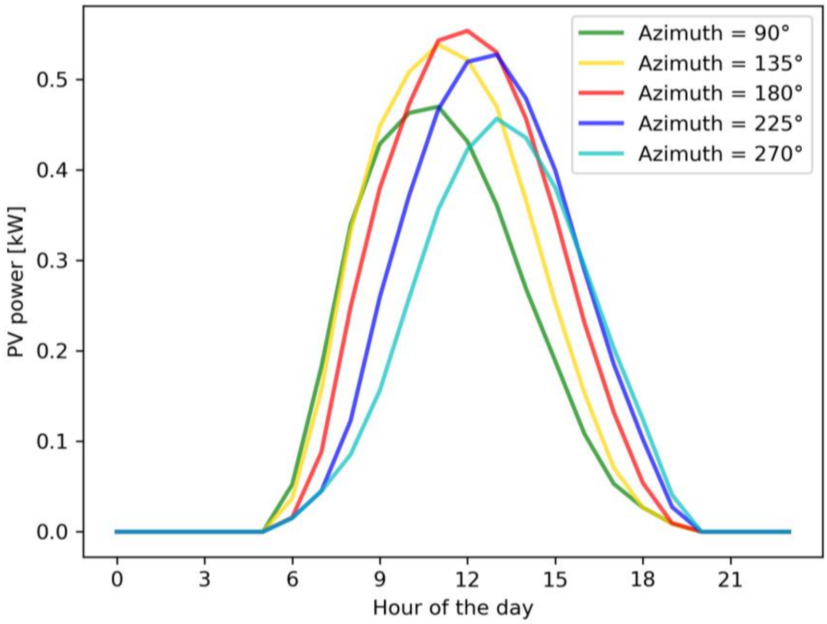

Figure 4.12: Average (over the whole year) daily profiles of PV generation with different orientations, considering a peak power of 1 kW.

Figure 4.12 was obtained performing averages of power over the whole year for each hour of the day, considering PV generation profiles with a peak power of 1 kW. For example, the value of power plotted for 9 a.m. is the average of all the values of power that the profiles had at 9 a.m. on each day of the year. Figure 4.12 shows how the average daily trends relative to the different PV orientations significantly differ from each other. Compared to the base case of the South orientation, the other orientations cause the peak of PV power production to be lower in magnitude and shifted, towards the morning in the cases of East and South-East orientations and towards the afternoon in the cases of West and South-West orientations. It is clear how the South-East and South-West orientations are intermediate cases between the South orientation and the East and West orientations respectively. Indeed, the South-East and South-West orientations present a lower peak reduction and peak shift compared to the East and West orientations. These trends suggest that an East or South-East PV orientation may be beneficial to the synchronism of demand profiles with a high energy demand in the early morning, while a West or South-West PV orientation may be beneficial to the synchronism of demand profiles with a high energy demand in the afternoon. Moreover, considering the trends shown in Figure 4.12, it appears that the South-East orientation will likely be generally better than the East orientation and the South-West orientation will likely be generally better than the West orientation. This is because the average PV generation profiles of the East and West orientations present only very slightly higher power than the South-East and South-West profiles in some moments of the day, while they present significantly lower power in other parts of the day. Considering this, it is unlikely that the East or West orientations will perform generally better than the South-East or South-West orientations, since the latter two, on average, perform very similarly to or better than the former two during the whole average day. In any case, considerations on the effects of the orientations on the KPIs of energy communities are made in more detail in sections 4.2.3 and 4.2.4.

Another thing to keep in mind before analyzing the PCC is that it does not consider the magnitude of the PV generation but only its trend. For example, this means that a profile could result to have a higher PCC in the case of an East PV orientation than in the case of a South-East PV orientation due to having its average peak daily demand corresponding to the generation peak of the East-oriented PV panel. However, in this example, the value of generated power in the moment of daily peak demand could actually be greater in the case of South-East orientation, even if in that case the PV generation has not yet reached its peak, as it is clear from Figure 4.12 that on average the generation of a PV with azimuth = 135° already exceeds that of a PV with azimuth = 90° some time before reaching the peak of the former. This example highlights how PCC should not be the only metric considered when comparing different PV orientations. Indeed, it is not the only one considered in this work, since the normalized demand allows to also take into account the value of energy produced, showing which orientations are better from this point of view.

4.2.2 PCC

In order to assess the effect of the described changes in the profiles of PV production, the variations in PCC considering different orientations of the PV systems are then analyzed. Five different values of PCC were calculated for each of the 992 demand profiles present in the Italian dataset, considering the synchronism with the five different PV generation profiles corresponding to the five different orientations.

Table 4.6 considers the differences between PCCs corresponding to the same demand profile, for the five different orientations of the PV systems, comparing each orientation to the base case of an azimuth angle of 180° (South orientation). For example, in the column "90° - 180°" the differences between the PCCs of demand profiles calculated with the PV production profile corresponding to an azimuth angle of 90° (East orientation) and the PCCs of demand profiles calculated with the PV production profile corresponding to 180° are considered. Each of the reported differences is a difference between PCCs relative to a same demand profile, whose PCC is calculated with different PV production profiles. For example, if one profile has a PCC of 0.1542 for an East orientation and a PCC of 0.1021 for a South orientation, the relative value of difference taken into account for the column "90° - 180°" is 0.0521.

Table 4.6: PCC differences considering different orientations of PV systems.

	90° - 180°	**135° - 180°**	**225° - 180°**	**270° - 180°**
Max PCC positive difference	0.0519	0.0346	0.0259	0.0401
Max PCC negative difference	-0.0423	-0.0245	-0.0497	-0.0820
Average PCC difference	0.0028	0.0035	-0.0057	-0.0090

Analyzing Table 4.6 it is clear that the variations in PCC, both maximum and average, due to changes in the orientation of PV systems are significantly higher than the variations of PCC due to changes in the inclination of PV (reported in Table 4.3). This was expected since different orientations change the trend of PV systems significantly more than different inclinations. This can be easily seen, for example, by confronting the average PV daily profiles for different inclinations, reported in Figure 4.2, and for different orientations, reported in Figure 4.12.

The average differences in PCC are not so high comparing the different orientations; however, it is noticeable that the East and South-East orientations slightly increase the PCCs on average while the West and South-West orientations slightly decrease them. In particular, the average change produced by the West orientation seems to be not negligible: considering that (as discussed in section 2.4.1) most of the demand profiles in the Italian dataset present a PCC between -0.1 and 0.1, an average

decrease of PCC of 0.009 is not as low as it may seem. This average decrease of PCC for the South-West and West orientations, combined with the significant decrease in PV generation that these orientations cause, makes these orientations appear not promising for what concerns the KPIs of energy communities with demand profiles taken from the Italian dataset. The East and South-East orientations seem more promising in this regard, due to the slight average increase in PCC that they cause. In particular, the South-East orientation appears to be the most promising (not considering the South orientation) from the point of view of energy communities' KPIs, since it causes the lowest energy production reduction and the highest average increase in PCC out of the four orientations compared with the South orientation.
Moreover, the maximum negative and positive variations of PCC reported in Table 4.6 highlight how a change in the orientation of PV systems can produce very significant (relatively to the original values) changes in the values of PCC relative to some demand profiles. This suggests that, even if the average variations of PCC do not appear to be so impactful, the variations of PCC for some particular demand profiles could potentially compensate for the reduction of PV generation due to orientations different from South. A possible example of this last case is investigated in section 4.2.4.

Once the relevance of the variations of PCC due to different orientations of the PV systems has been highlighted, such variations are further analyzed by studying the joyplot, reported in Figure 4.13, that represents the distributions of PCC in the cases of the five different orientations considered in this section.

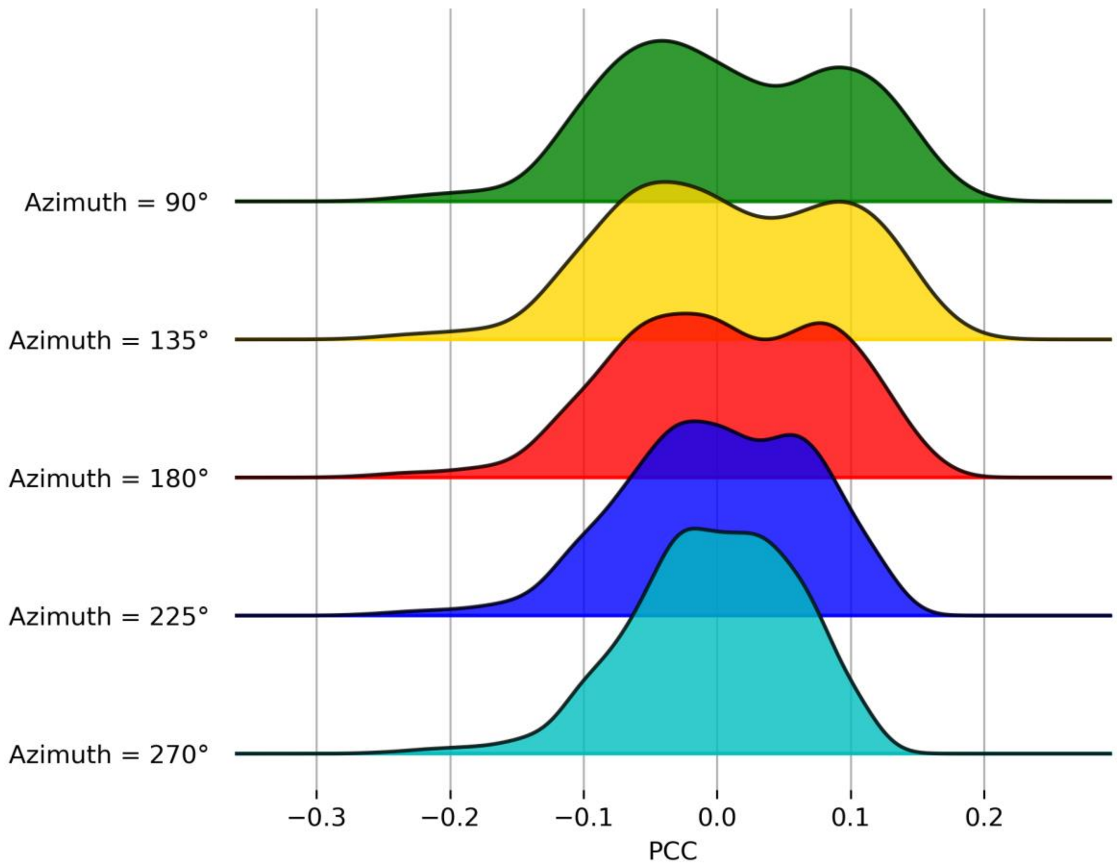

Figure 4.13: Joyplot representing the distributions of PCC corresponding to different orientations of PV systems.

Observing Figure 4.13 it is notable that, compared to the base case of South orientation (azimuth = 180°), the East orientation (azimuth = 90°), and the South-East orientation (azimuth = 135°), tend to produce very limited changes, while the West orientation (azimuth = 270°), and to a lesser degree the South-West distribution (azimuth = 225°) tend to significantly "narrow" the PCC distribution.

In order to analyze in more detail the reasons for these changes, it is also necessary to consider the arrow plots that compare, in the PCC-demand plane with normalized demand (in which an average PV power of 5 kW is considered in these cases), each orientation of the PV systems with the base case of South orientation. These arrow plots follow the same logic as those introduced in section 4.1.1, representing each demand profile as an arrow (which has a color that depends on the quadrant in which its starting point is) that starts from the coordinates (i.e. values of PCC and normalized demand) corresponding to the South orientation and ends in the coordinates corresponding to the compared orientation. The arrow plots for the four orientations different from South are reported in Figure 4.14, Figure 4.15, Figure 4.16, and Figure 4.17. In each of these figures, there are also two histograms that compare, between the South orientation and the other orientation, the frequency distributions of PCC (on the right of the arrow plot) and normalized demand (over the arrow plot). These histograms contain the same information reported in the joyplots of Figure 4.11 and Figure 4.13, but they focus on the comparison between the distributions relative to the two orientations reported in each arrow plot, for easier visualization.

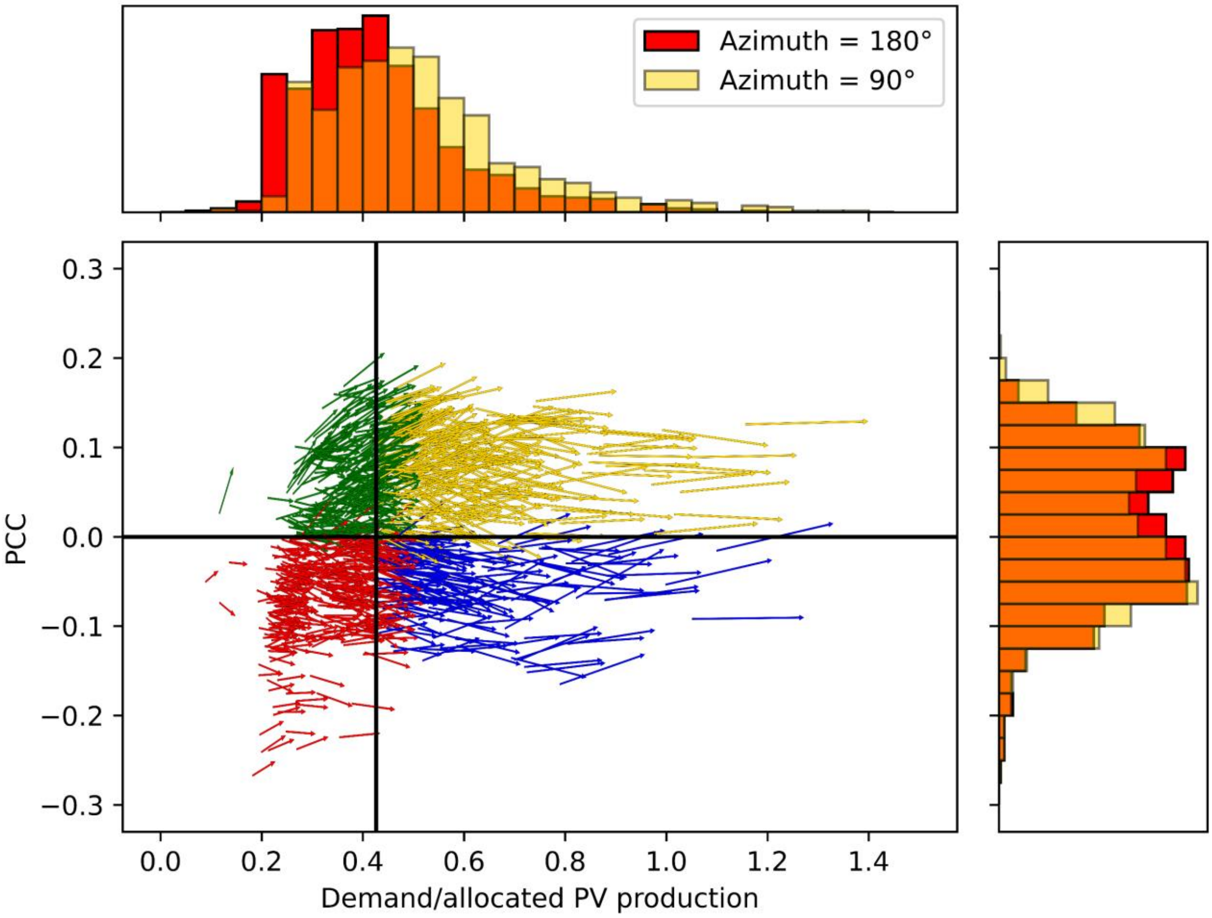

Figure 4.14: Arrow plot (in the PCC-demand plane with normalized demand) and frequency distributions of PCC and normalized demand, comparing South orientation and East orientation.

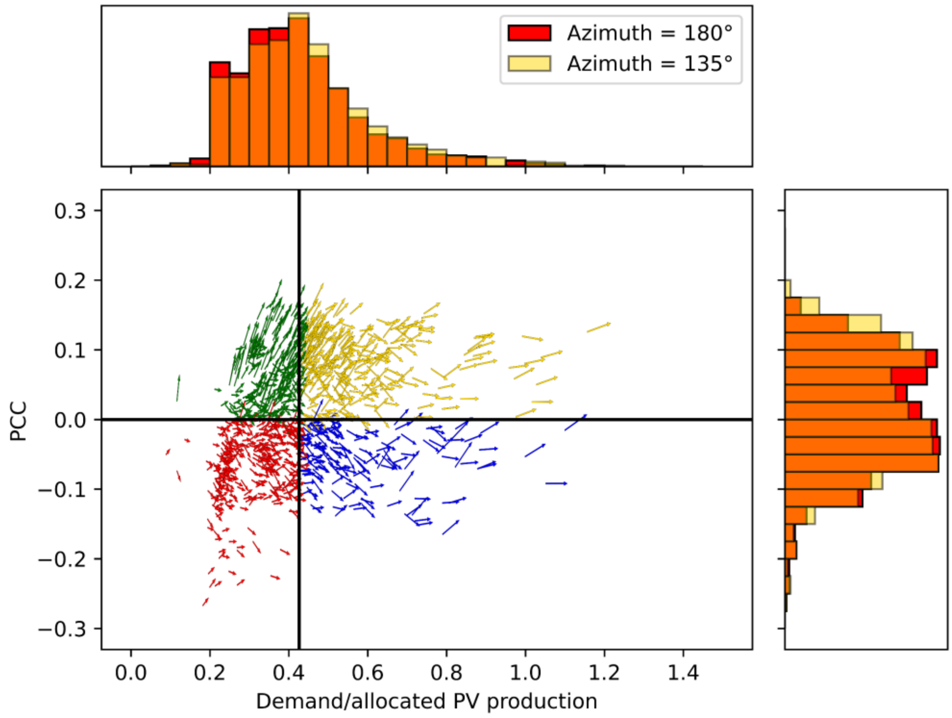

Figure 4.15: Arrow plot (in the PCC-demand plane with normalized demand) and frequency distributions of PCC and normalized demand, comparing South orientation and South-East orientation.

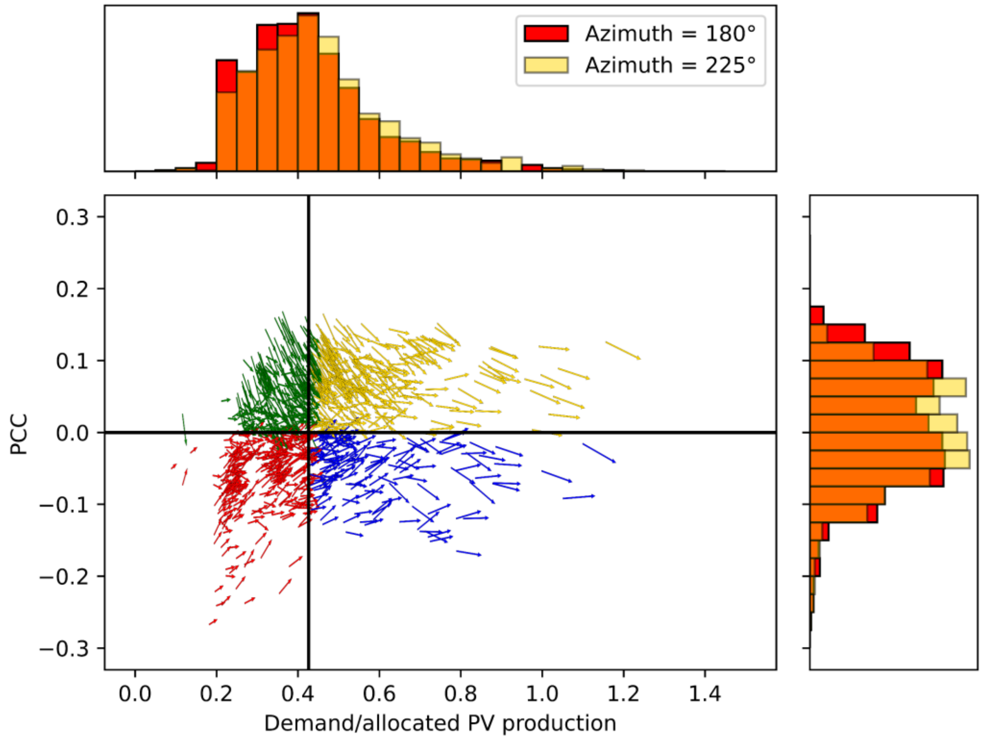

Figure 4.16: Arrow plot (in the PCC-demand plane with normalized demand) and frequency distributions of PCC and normalized demand, comparing South orientation and South-West orientation.

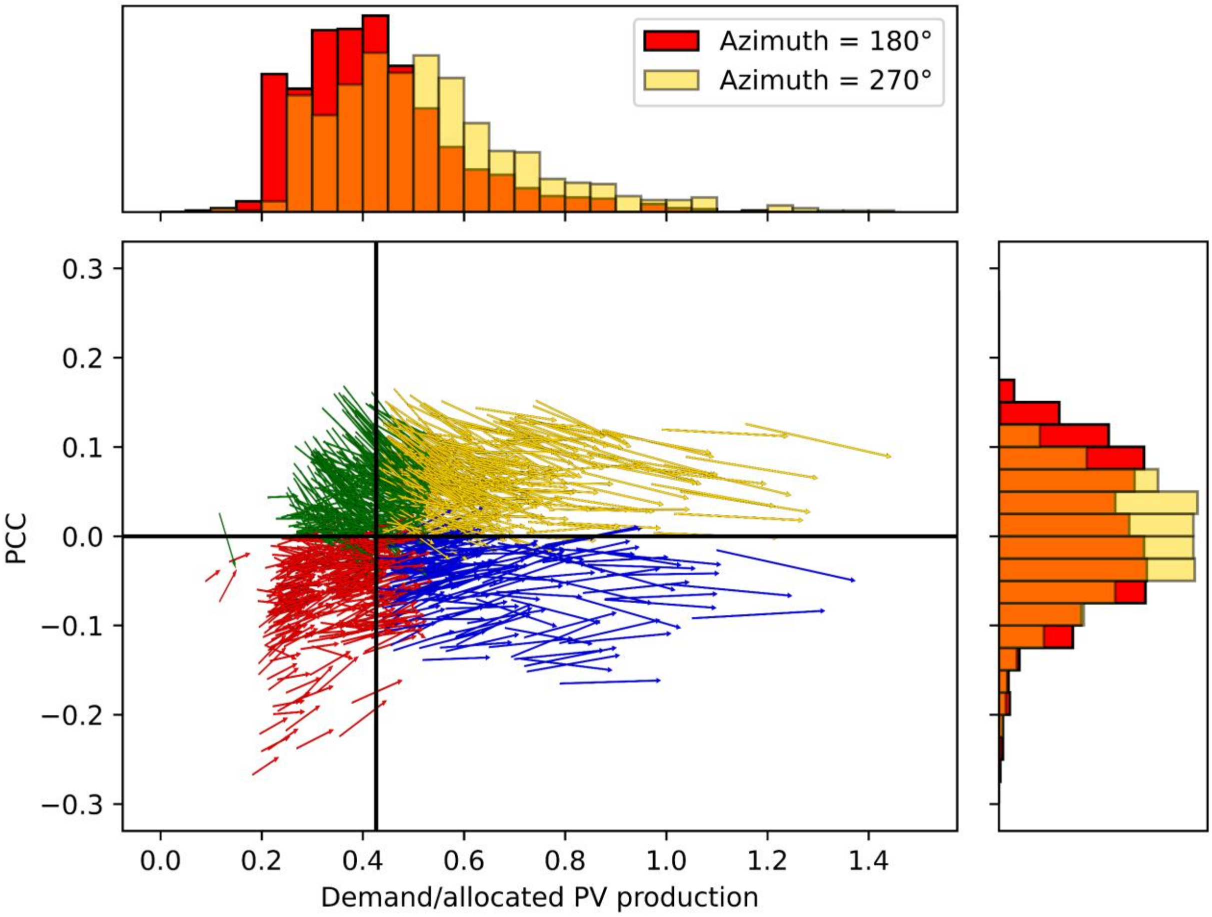

Figure 4.17: Arrow plot (in the PCC-demand plane with normalized demand) and frequency distributions of PCC and normalized demand, comparing South orientation and West orientation.

Before continuing the analysis of the PCC distributions, a quick observation regarding the normalized demand in Figure 4.14, Figure 4.15, Figure 4.16, and Figure 4.17 has to be made. It is clear that in each of these figures the arrows point toward the right, with the horizontal displacement being larger for the cases of East and West orientation. This is due to the previously explained reduction of yearly PV energy generation, compared to the South orientation, causing an increase in normalized demand that is higher in the cases in which the PV production decreases more (i.e. the East and West orientations).

Considering Figure 4.17, the reason why the West orientation, as shown in Figure 4.13, tends to have a narrower distribution of PCC can be explained.

The West orientation tends to uniform the PCCs of the demand profiles, in general by reducing the PCC of profiles that tended to be synchronous (i.e. with positive PCC) in the case of South orientation and by increasing the PCC of profiles that tended to be asynchronous (i.e. with negative PCC) in the case of South orientation. This trend can be seen in Figure 4.17, in which it is clear how the arrows starting from the quadrants that have negative PCC tend to go upwards, meaning that the relative PCCs tend to increase with the West orientation, while the arrows starting from the quadrants that have positive PCC tend to go downwards, meaning that the relative PCCs tend to decrease with the West orientation.

In order to give a possible explanation of this trend, some considerations are then made with the help of some images that represent the average daily trends of certain demand profiles together with the average daily profile of PV generation. The average daily profiles represented in these images are found in the same way previously explained for the average daily PV generation profiles, meaning that the average value for each hour of the day is found by performing the average between all the values relative to that hour that the profile assumes over the whole year.

Firstly, it is important to consider that the demand profiles that generally present a relatively high PCC, regardless of the orientation of the PV systems, are those with a high energy demand in the hours in which the PV generation is close to its maximum (meaning around 12 a.m.). One example of this kind of profiles is the profile that presents the maximum PCC (out of the profiles in the Italian dataset) for PV panels having an azimuth of 90°, 135°, or 180°. The daily average of this demand profile is represented in Figure 4.18, together with the average daily generation of a South-oriented PV system with a peak power of 2 kW.

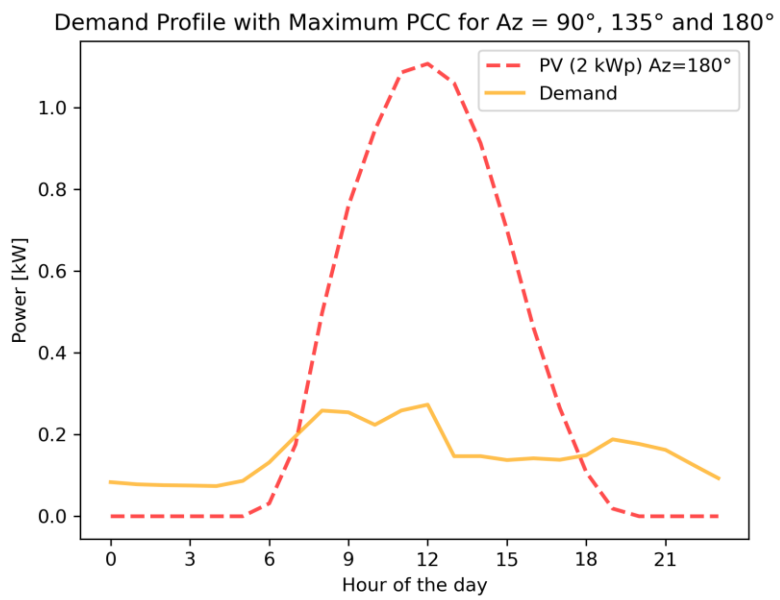

Figure 4.18: Average daily profile of the demand profile with maximum PCC for azimuth angles = 90°, 135°, and 180°, together with the average daily generation profile of a South-oriented PV system with peak power = 2 kW.

Profiles presenting significant demand in the middle of the day have high PCCs with South-oriented PV panels, but their PCCs decrease considering West-oriented PV panels since the latter tend to generate energy later in the day. On the other hand, the profiles whose PCCs increase considering a West orientation compared to a South orientation tend to have a peak of demand later in the afternoon. One example of this latter kind of profiles is the profile that presents the maximum PCC (out of the profiles in the Italian dataset) for PV panels having an azimuth of 270°. The daily average of such demand profile is represented in Figure 4.19, together with the average daily generations of a South-oriented PV system and a West-oriented PV system, both with a peak power of 2 kW.

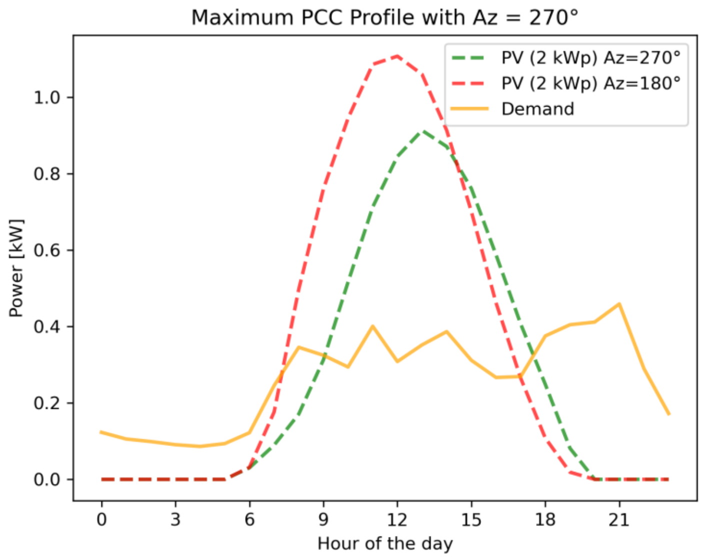

Figure 4.19: Average daily profile of the demand profile with maximum PCC for azimuth angle = 270°, together with the average daily generation profiles of South-oriented and West-oriented PV systems with peak power = 2 kW.

The synchronism of this latter kind of profiles can indeed benefit from the higher energy generation of West-oriented PV systems in the afternoon, but the PCC of these demand profiles can only increase up to a certain point since the peak of PV generation remains quite close to 12 a.m. even for an azimuth of 270°. Therefore, a demand profile that presents most of its energy demand in the afternoon can never be as synchronous with the PV generation as a profile whose energy demand is mostly in the middle of the day, whatever the PV orientation is.

Taking together these two effects (i.e. the PCC decrease of some profiles that presented a high PCC and the PCC increase of some profiles that presented a low PCC), the PCC distribution in the case of a West orientation is “narrowed” and profiles tend to have PCCs more similar to each other and closer to zero. This is confirmed by the numerical data reported in Table 4.7, which highlights a significant increase in the number of profiles that have a PCC close to zero in the case of a West PV orientation compared to the case of a South PV orientation.

Table 4.7: Comparison of the number of demand profiles (belonging to the Italian dataset) whose PCC is in certain ranges, for different orientations of the PV systems.

Azimuth	**90°**	**135°**	**180°**	**225°**	**270°**
Number of profiles with -0.1 < PCC < 0.1	715	715	766	851	899
Number of profiles with -0.05 < PCC < 0.05	354	368	394	476	572
Number of profiles with PCC > 0.1	182	184	135	65	31
Number of profiles with PCC < -0.1	95	93	91	76	62

These reasonings on the effect of the West orientation appear to be confirmed when analyzing two particular demand profiles: the one whose PCC had the maximum increase (out of the demand profiles in the Italian dataset), compared to the South orientation, considering a West PV orientation and the one whose PCC had the maximum decrease due to the same change. The average daily trend of the former is represented in Figure 4.20, while the average daily trend of the latter is represented in Figure 4.21. In both images, the average daily trends of the demand profiles are represented together with the average daily generations of a South-oriented PV system and a West-oriented PV system, both with a peak power of 2 kW.

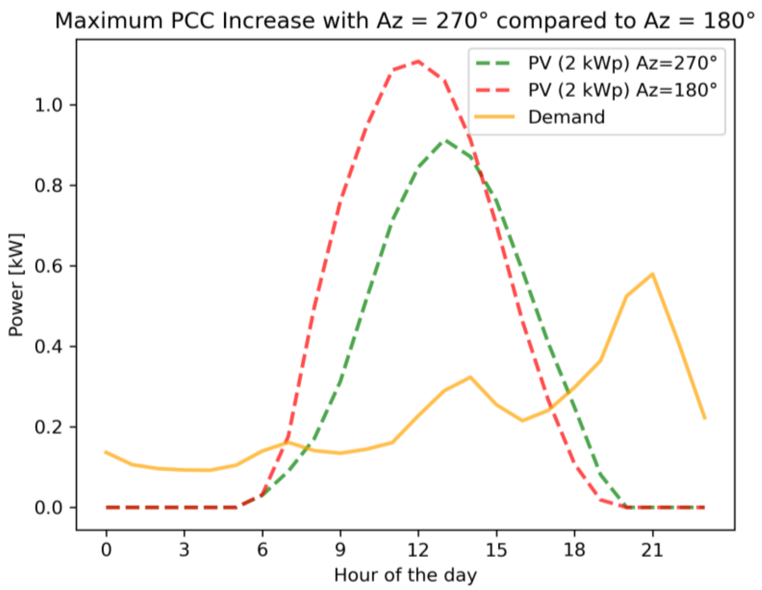

Figure 4.20: Average daily profile of the demand profile whose PCC had the maximum increase for azimuth angle = 270°, together with the average daily generation profiles of South-oriented and West-oriented PV systems with peak power = 2 kW.

The profile with the maximum PCC increase with the West orientation, represented in Figure 4.20, is indeed one of those profiles with significant energy demand in the afternoon. It is also clear how the low energy demand in the morning is what enables the PCC of this profile to increase so significantly when considering a West-oriented PV system since it causes the lower energy generation of the latter in the morning to have a lower negative impact on synchronism. At the same time, the relatively low energy demand in the morning and in the middle of the day prevents the PCC of this profile from being relatively high, even with the West orientation. Indeed, the PCC of this demand profile is -0.002 with West-oriented PV systems and it is an example of a profile that cannot achieve a high synchronism with any PV orientation due to its concentration of demand in the evening and late afternoon.

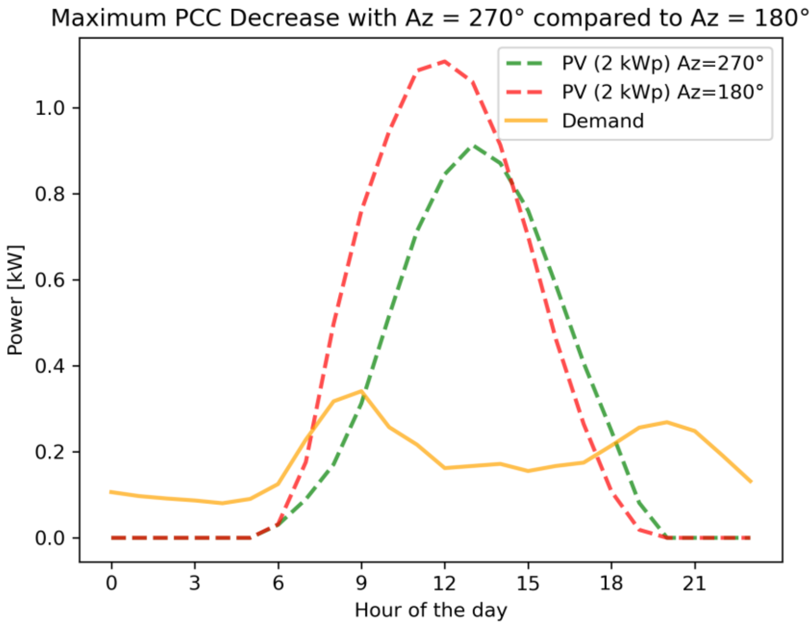

Figure 4.21: Average daily profile of the demand profile whose PCC had the maximum decrease for azimuth angle = 270°, together with the average daily generation profiles of South-oriented and West-oriented PV systems with peak power = 2 kW.

The profile with the maximum PCC decrease with the West orientation, represented in Figure 4.21, presents a demand peak in the morning, when the generation of South-oriented PV systems is significantly higher than that of West-oriented PV systems. This is also an example of a profile that has a relatively high PCC (roughly 0.1) when considering a South orientation, but a PCC quite close to zero (roughly 0.02) when considering a West orientation, showing how the West orientation tends to decrease the PCC of profiles whose PCC was relatively high with a South PV orientation.

When considering a South-West orientation, represented in the PCC-demand plane with normalized demand in Figure 4.16, similar considerations to the ones made for the West orientation can be made: the distribution of PCC tends to become narrower, due to the same reasons presented for the West orientation. The only difference is that the changes in PCC (compared to the South orientation) are generally smaller than those produced by the West orientation, which is logical since the South-West orientation is an intermediate case between the South and West orientation.

Considering the East orientation of PV systems, the first noticeable difference with the West orientation is that the former produces a change in the PCC distribution that is significantly lower than that produced by the latter. This can be observed not only graphically in the joyplot of Figure 4.13, but also considering the absolute values of the average PCC variation (compared to the base-case of South orientation), reported in Table 4.6, which for the West orientation is 0.0090, more than three times that of the East orientation, equal to 0.0028.
The reason for the lower change of PCC produced by the East orientation is that demand profiles that are synchronous with South-oriented PV generation tend to be similarly synchronous with East-oriented PV generation. For example, the demand profile, already represented in Figure 4.18, with the maximum PCC for azimuth = 180° is also the one with the maximum PCC for azimuth = 90° (and azimuth = 135°).
This trend of PCCs being more similar between azimuths 90° and 180° than between 270° and 180° is due to the average daily trends of the demand profiles of the Italian dataset. In order to have an idea of these average daily trends, the aggregate average daily trends of more profiles can be considered. These trends are found performing for each hour of the day the average of the values of power assumed at that hour of the day, over the whole year, by all of the demand profiles whose aggregate average daily profile wants to be found. Considering the aggregate average daily profile of demand profiles that tend to be more synchronous and of demand profiles that tend to be more asynchronous some insights on the reasons for the similarity of PCCs between the East and South orientation can then be found. The aggregate demand profiles analyzed in this section are those with negative PCC, confronted with those with positive PCC in Figure 4.22, and those with PCC greater than 0.1, confronted with those with PCC smaller than -0.1 in Figure 4.23. These figures consider PCCs relative to a South orientation of PV systems.

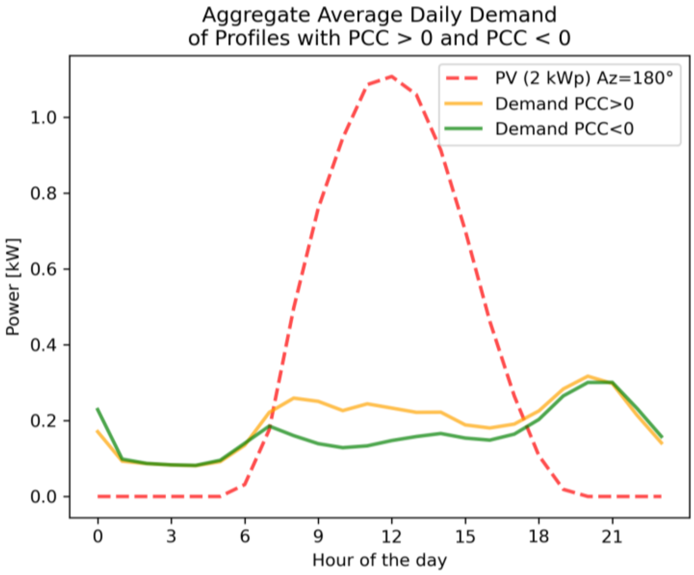

Figure 4.22: Aggregate average daily profile of demand profiles with PCC > 0 and of demand profiles with PCC < 0, together with the average daily generation profile of a South-oriented PV system with peak power = 2 kW.

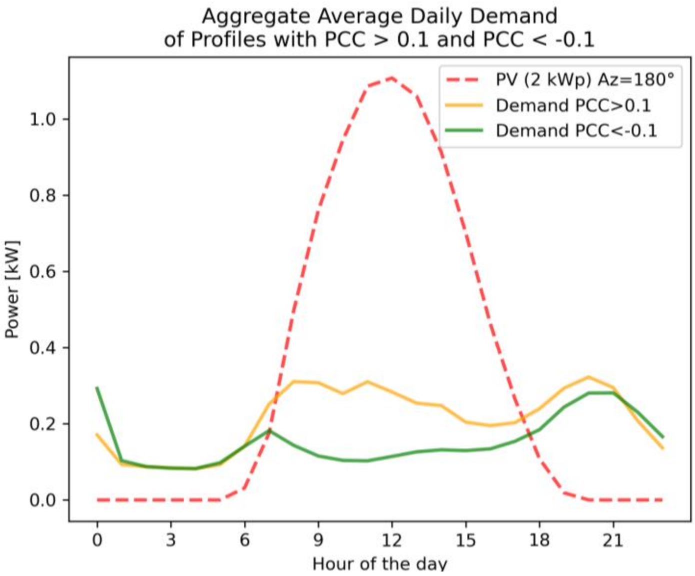

Figure 4.23: Aggregate average daily profile of demand profiles with PCC > 0.1 and of demand profiles with PCC < -0.1, together with the average daily generation profile of a South-oriented PV system with peak power = 2 kW.

Figure 4.22 and Figure 4.23 show how profiles that are more synchronous with the South-oriented PV generation have, on average, higher demand in the morning than in the afternoon. This means that these profiles will generally be less synchronous with a West-oriented PV generation than with an East-oriented one, since the latter generates more in the morning, when the demand of these profiles is generally higher.

On the other hand, as shown in Figure 4.22 and Figure 4.23, profiles that have negative PCCs in the case of South-oriented PV panels tend to have quite a low demand in the morning and a growing demand in the late afternoon, causing them to have higher PCCs in case of West orientation than in case of East orientation.

In summary, the reason for the significant change in the PCC distribution produced by the West orientation and the limited change caused by the East orientation is that the demand profiles of the utilized Italian dataset tend to belong to one of two categories:

- Profiles with higher demand in the morning, which are more synchronous with South and East-oriented PV systems,
- Profiles with higher demand in the afternoon, which are more synchronous with West-oriented PV systems.

The reason for this is likely that households that have a high demand around 12 a.m. (thus favoring synchronism with South-oriented PV systems) generally have some inhabitants at home in the morning, thus making the demand relevant also before 12 a.m.

On the other hand, households that present low demand around 12 a.m. (thus having low synchronism with South-oriented PV systems) are likely to not have any inhabitants at home in the morning and the demand tends to increase in the afternoon when the inhabitants return to their households.

Of course, these are general trends and there are single profiles that present different characteristics. For example, two profiles that present a significant change in PCC comparing azimuth = 180° and azimuth = 90° are reported in Figure 4.24 and Figure 4.25.

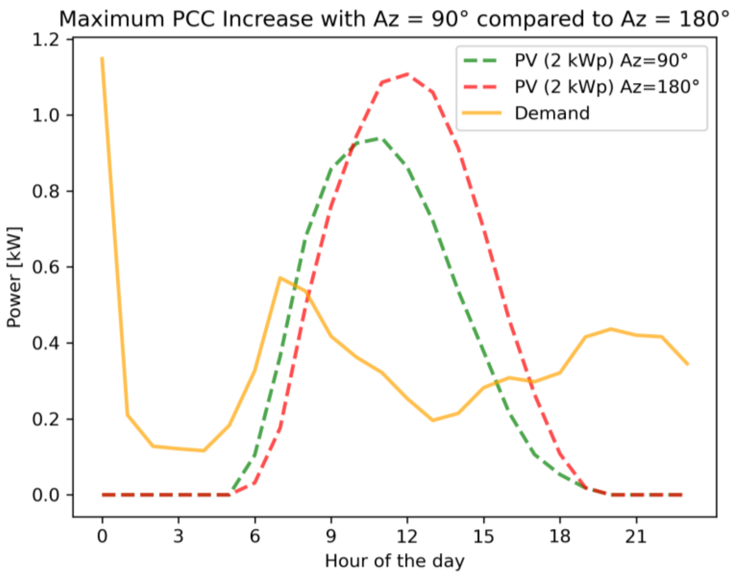

Figure 4.24: Average daily profile of the demand profile whose PCC had the maximum increase for azimuth angle = 90°, together with the average daily generation profiles of South-oriented and East-oriented PV systems with peak power = 2 kW.

The profile represented in Figure 4.24 shows a particular case of a profile having a high demand peak early in the morning and a decreasing demand in the rest of the morning, causing the PCC to have the maximum increase out of all the profiles when considering an East PV orientation rather than a South orientation.

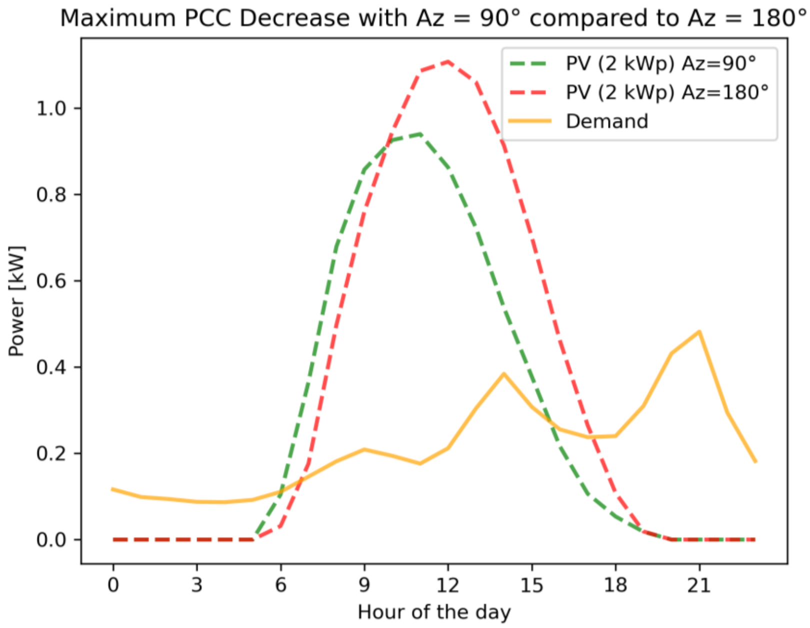

Figure 4.25: Average daily profile of the demand profile whose PCC had the maximum decrease for azimuth angle = 90°, together with the average daily generation profiles of South-oriented and East-oriented PV systems with peak power = 2 kW.

The profile represented in Figure 4.25 shows a particular case of a profile having quite a high demand close to 12 a.m. but a low demand earlier in the morning, causing the PCC to have the maximum decrease out of all the profiles when considering an East PV orientation rather than a South orientation.

In any case, those just shown are particular cases, and the East and South-East orientations generally tend to alter only slightly the distribution of PCC compared to the South orientation. The slight modifications that they produce appear to be generally positive, causing a slight increase in the average PCC (as shown in Table 4.6). The reason for this slight increase is likely that the power generation of East or South-East oriented PV panels is generally higher (compared to the South orientation) in the morning and, as shown in Figure 4.22 and Figure 4.23, demand profiles that are relatively synchronous with South-oriented PV generation generally present a higher demand in the earlier hours of PV generation than in the later hours.

4.2.3 KPIs of energy communities with the whole Italian dataset

The changes in the distributions of demand profiles in the PCC-demand plane with normalized demand due to different orientations of PV systems are expected to produce some differences between the KPIs of simulated energy communities whose PV systems have different orientations. Since the changes in distributions due to different orientations are significantly greater than the changes due to different inclinations, the changes in KPIs of energy communities are also expected to be significantly higher than those reported in section 4.1.2.

The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops, while no users have batteries installed in their houses. The choice of not considering batteries in these simulations is made to "isolate" the impact of the variations of the parameters of PV systems, without including the influence of batteries that could potentially alter the impact that changes in the PV systems by themselves cause.

The PV parameters utilized in these simulations are an inclination of 25° and an orientation different for each case, in order to investigate its impact. Moreover, the PV sizes of the community members are randomly selected in each simulation according to a normal distribution with average PV power of 5 kW, symmetrically truncated at 1 kW and 9 kW. Additional simulations are also performed with an average PV power of 2.06 kW, for the reasons explained further below.

100 simulations were conducted for five energy communities, each with all PV systems having one of the five orientations analyzed in this section. The means of the KPIs found from these simulations, along with their 95% confidence intervals, are reported in Figure 4.26, Figure 4.27, and Figure 4.28.

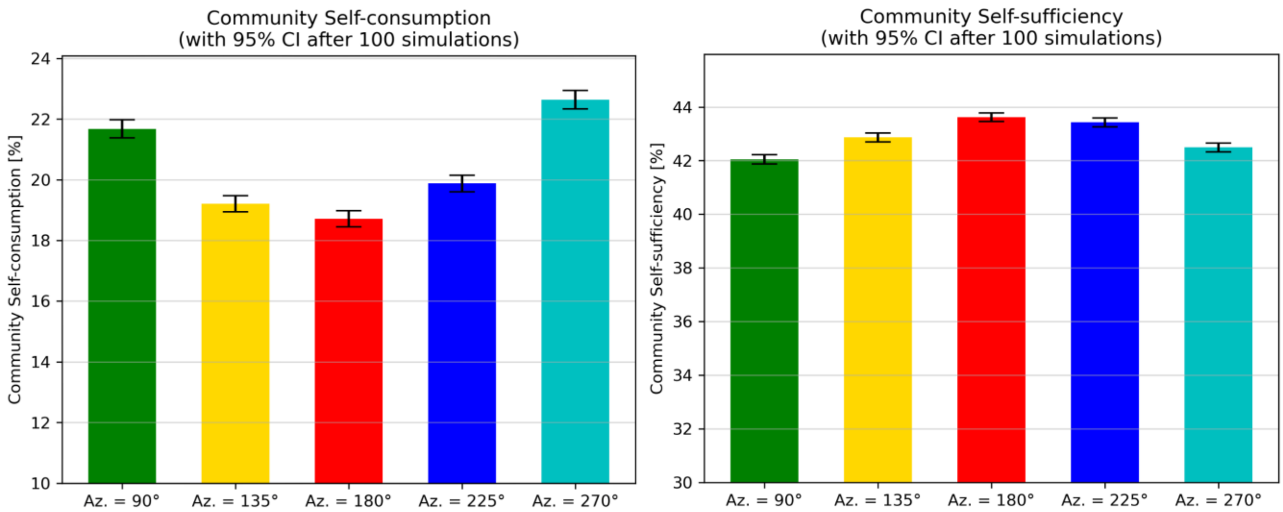

Figure 4.26: Self-sufficiency and self-consumption of the energy community, comparing five different orientations of PV systems.

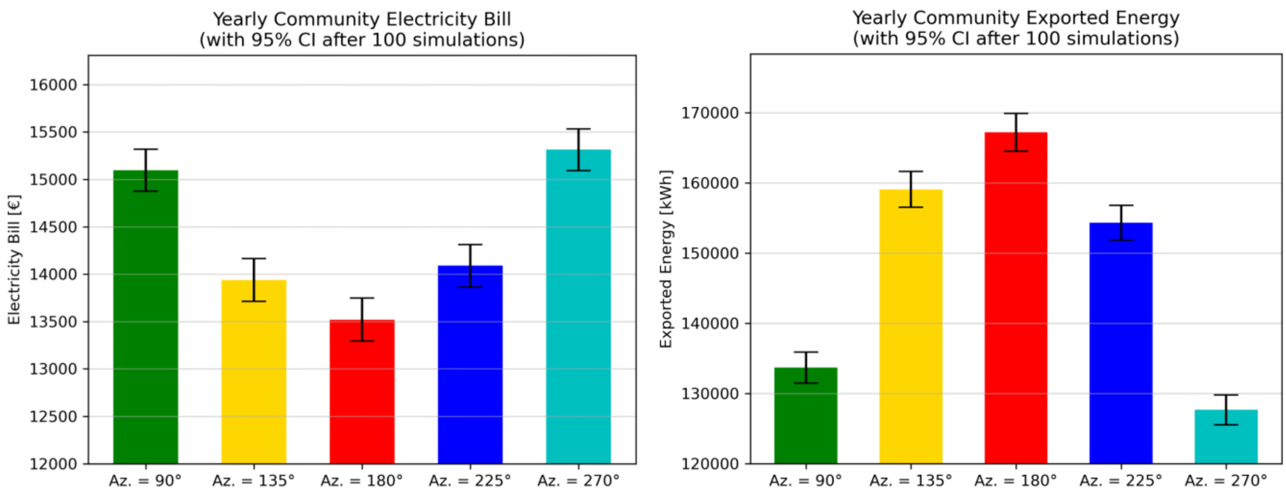

Figure 4.27: Yearly electricity bill and energy exported by the energy community, comparing five different orientations of PV systems.

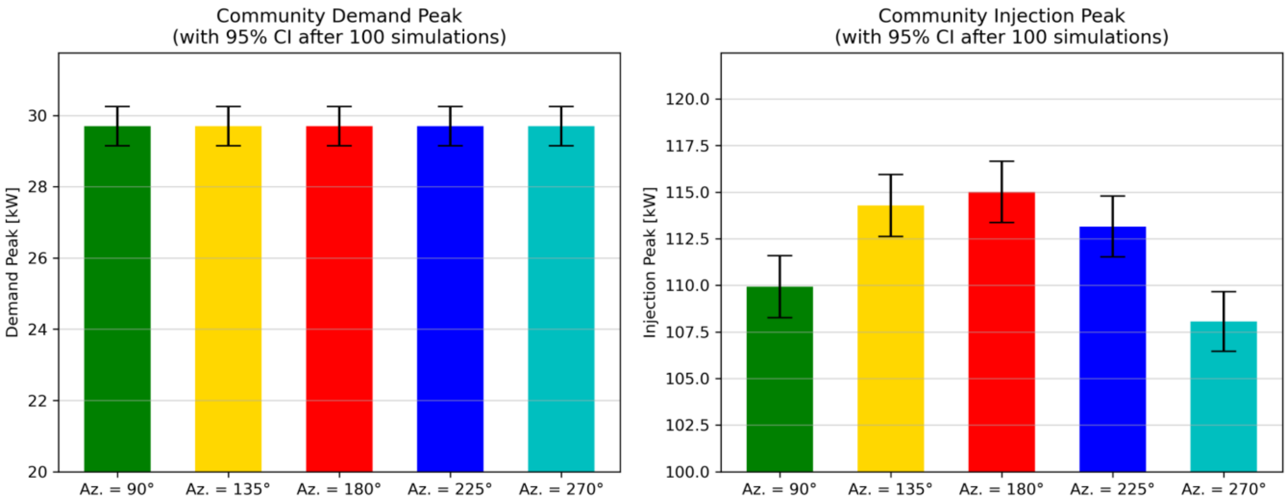

Figure 4.28: Demand peak and injection peak, comparing five different orientations of PV systems.

Observing Figure 4.26, Figure 4.27, and Figure 4.28, it is quite clear how the KPIs vary significantly more due to different orientations of PV systems, compared to the variations observed due to different inclinations shown in section 4.1.2. Indeed, the KPI that varies the most between the South orientation and the others, which is the yearly exported energy, varies by a maximum of 23.7% (for the case of the West orientation), a much greater variation compared to the maximum KPI variation of 5.6% observed for different inclinations in section 4.1.2. This is in line with the greater variations in the distributions of demand profiles in the PCC-demand plane with normalized demand that are observed for changes in PV orientation.

The only exception to the significant variations of KPIs is the demand peak (reported in Figure 4.28), which is constant regardless of the PV orientation. The most likely reason for this is the same one explained in section 4.1.2: the demand peak occurs when there is no PV power generation, making the PV parameters irrelevant to the value of the demand peak.

The KPIs that are the most directly tied to PV generation, meaning the injection peak of the community (reported in Figure 4.28) and the energy exported in one year by the community (reported in Figure 4.27), show trends that are coherent with the values of yearly PV generation for the different orientations, reported in Table 4.5. Indeed, the orientations producing more yearly energy also cause a higher injection peak and a higher yearly exported energy, as it was predictable. A higher injection peak can be considered a negative factor, potentially increasing the needed size of the transformer receiving the power from the energy community, however, the difference in injection peak observable for the different orientations is quite limited (with a maximum percentage difference of 6%) and thus

the magnitude of the injection peak does not appear to be a particularly relevant KPI to evaluate different PV orientations.
The community self-consumption (SC), reported in Figure 4.26, is slightly lower for PV orientations that produce more energy in a year. What the trend of the SC indicates is that, choosing orientations that increase the yearly PV-generated energy (which is at the denominator of the SC), the latter increases faster than the energy self-consumed by the community (which is at the numerator of the SC), due to the energy demand being constant in all of the cases. However, self-consuming energy is not the only way of profiting from an increase in the amount of PV-generated energy, exporting it to the main electrical grid external to the community can also allow for an economic profit, as shown by the lower electricity bill (reported in Figure 4.27) for orientations that cause a higher yearly PV production.
Finally, the KPI that requires the most detailed discussion is the community self-sufficiency (SS), reported in Figure 4.26. The SS being the highest for the South orientation was expected, due to the highest energy production caused by this orientation. In the same way, higher SS for South-East compared to East and for South-West compared to West were expected, due to both the better changes in PCC (shown in Table 4.6) and the higher yearly energy production caused by South-East and South-West compared to East and West respectively. The unexpected results are that the SS of the South-West orientation is higher than the one of the South-East orientation and that the SS of the West orientation is higher than the one of the East orientation. This was not expected since the South-East and East orientations caused both a slightly higher average PCC (shown in Table 4.6) and a slightly higher PV yearly energy production (shown in Table 4.5) compared to the South-West and West orientations respectively.
The reason for these unexpected results is that the energy self-consumed by the energy community tends to increase more thanks to a higher PV generation in the afternoon (caused by the South-West and West orientations) than to a higher PV generation in the morning (caused by the South-East and East orientations). The likely reason for this occurring even if the PCC suggests, on average, a higher synchronism due to PV generation in the morning is that the PCC does not consider the magnitude of energy demand and PV generation. The simulated energy communities have high PV energy generation compared to the energy demand and are thus likely close to a sort of plateau of the self-consumed energy since the energy demand of the community during the hours with sunlight is already mostly satisfied by the PV generation. In particular, the results of SS seem to indicate that there is a larger unsatisfied energy demand in the hours of the afternoon that the South-West and West orientations can better cover than in the hours of the morning that the South-East and East orientations

can better cover. This reasoning seems to be supported also by the aggregated average daily demand profiles reported in Figure 4.22, in which a higher demand peak in the late afternoon is observed than in the early morning.

However, it is likely that the situation just described, in which the late afternoon offers “more opportunity” for self-consumption than the early morning, is due to the high PV generation compared to the energy demand. Indeed, the values of PCC highlight a better synchronism with the East and South-East PV orientations than with the West and South-West orientations, therefore the causes for these unexpected values have to be the magnitudes of PV generation and energy demand, which are not considered by the PCC.

To verify if this reasoning is correct, an additional set of simulations for the five different orientations is performed, using a lower average PV power to simulate energy communities that have a lower PV production. The input parameters are the same, except for the average PV power, which is reduced to 2.06 kW, which is the PV power that was found in section 2.4.2 to make the values of average normalized demand equal for the Italian and German datasets. These new simulations produce trends that are the same observed with average PV power of 5 kW for all of the KPIs, except for the trend of the SS (whose new values are reported in Figure 4.29), which is different for this new average PV power.

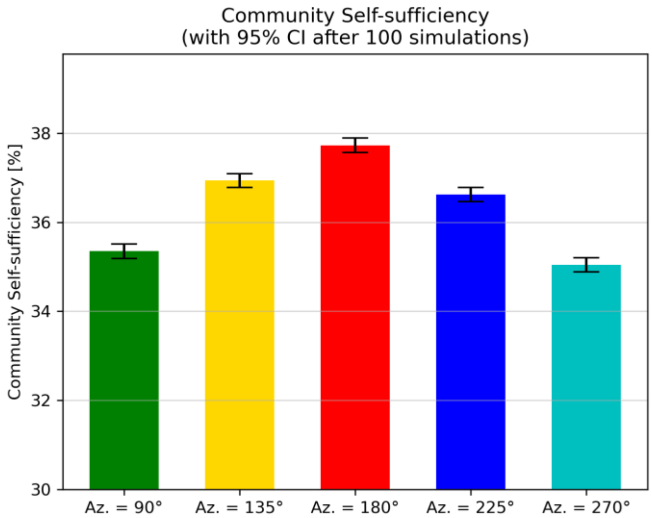

Figure 4.29: Self-sufficiency of an energy community with average PV power equal to 2.06 kW, comparing five different orientations of PV systems.

The values of SS reported in Figure 4.29, relative to an energy community with average PV power equal to 2.06 kW, are in line with the trends that were expected based on PCC and yearly PV generation: the SS relative to the South-East and East orientations are higher than those relative to the South-West and West orientations. These new results support the reasoning that has been made: the average PCC can be an effective predictor of the values of SS, but only up to a certain point, because it does not consider the magnitudes of PV generation and energy demand and thus cannot predict if some situations of “saturation” of the energy self-consumed by an energy community will occur, altering the trends of SS compared to the predictions made based on the PCC.

The main conclusions that can be drawn from the results of these simulations are three.
The first is that significant changes in the distribution of demand profiles in the PCC-demand plane with normalized demand seem to predict significant changes in the KPIs of energy communities using such demand profiles.
The second conclusion is that the orientation of PV systems appears to be a significant choice with regard to the impact produced on the KPIs of an energy community. The South orientation appears, as expected, to be generally the best PV orientation with regards to the KPIs of an energy community, maximizing the community's self-sufficiency and minimizing the community’s electricity bill. Moreover, the South-West and South-East orientations appear to be sensible choices, that do not cause too much of a worsening of KPIs compared to the South orientation and that appear to be generally better than the West and East orientations (as predicted in section 4.2.1, observing the average PV daily generation trends reported in Figure 4.12). However, the worsening of KPIs caused by PV systems with East and West orientations does not appear so drastic as to make installing PV systems with these orientations unreasonable, just non-optimal. Therefore, these orientations could be present in an energy community for PV systems located on rooftops that do not face South.
The third conclusion is that, considering demand profiles belonging to the whole Italian dataset, the PCC variations produced by orientations different from South seem to not compensate for the negative effects caused by the decrease in yearly energy production that these orientations cause. In the next section, it is investigated if these orientations could successfully compensate for the decrease in PV production in some particular cases for certain subsets of demand profiles.

4.2.4 KPIs of energy communities using only the demand profiles whose PCCs increased

The objective of this section is to establish if, for particular subsets of demand profiles, whose PCCs are increased by an orientation different from South, the PCC increase can compensate, in terms of energy communities’ KPIs, for the decrease of yearly PV generation. In other words, the goal is to verify if orientations different from South can be beneficial to the performances of energy communities whose households have particular demand profiles whose synchronism with PV production improves with PV orientations different from South. Of course, in a real setting, it would hardly be possible to know during the design phase which households will have demand profiles more synchronous with a certain orientation. The objective of this section is to perform a preliminary analysis to see if some demand profiles of the Italian dataset can cause an improvement of KPIs with orientations different from South.

A Python script was created to compare the PCCs of each demand profile belonging to the Italian dataset between the base case of South orientation (azimuth = 180°) and the other possible orientations and to extract for each orientation the profiles whose PCC increased when considering an azimuth different from 180°. In this way, four datasets of demand profiles were created, each containing the profiles with a PCC increase for a certain PV orientation different from South. Then, for each dataset two sets of 100 simulations were performed: one with the orientation producing the PCC increase and one with the South orientation. In this way, comparing the KPIs resulting from the couples of simulations it is possible to see if the performances of the energy communities with these datasets of profiles can improve with orientations different from South.

Table 4.8 shows the values of PCC of the profiles that belong to the four datasets of users created with the Python script just mentioned. The table shows how the profiles in each of these datasets present indeed a higher PCC with an orientation different from South. It is noticeable how the East orientation produces a higher increment of PCC compared to the South-East orientation and the West orientation produces a higher increment compared to the South-West orientation. This is logical since the East and West orientations' PV generation profiles differ more from the one of the South orientation and can thus produce greater changes in PCC. It is also noticeable how, as described in section 4.2.2, the West and South-West orientations tend to improve the PCC of profiles that presented a negative PCC with the South orientation.

Table 4.8: Average values of PCC, with different PV orientations, for the demand profiles belonging to the four created datasets.

Azimuth of comparison	**Average PCC with South orientation**	**Average PCC with compared orientation**
90°	0.020	0.035
135°	0.029	0.040
225°	-0.049	-0.041
270°	-0.054	-0.039

The characteristics of the energy communities simulated in this section are the same as those used in section 4.2.3 and an average PV power of 5 kW is considered (simulations with an average PV power of 2.06 kW were performed as well but without finding significantly different trends in the values of KPIs and are therefore not reported here).
The KPIs resulting from the 100 simulations conducted from each case are reported in Figure 4.30, Figure 4.31, and Figure 4.32. In each of these figures, there are couples of values of KPIs, each one relative to one of the four created datasets of demand profiles. The left value of KPI in each couple is relative to the PV orientation for which the demand profiles in the relative dataset had an increase of PCC, while the right value of KPI is the one found using the same demand profiles used for the left KPI but using a South orientation of PV. For example, the leftmost couple of each of these figures is made of the green bar (relative to the East orientation) and the red bar next to it (relative to the South orientation). These two bars represent the values of KPIs obtained using in both cases the dataset with demand profiles whose PCC increased with an East orientation, but using East-oriented PV systems in the case of the green bar and South-oriented PV systems in the case of the red bar.

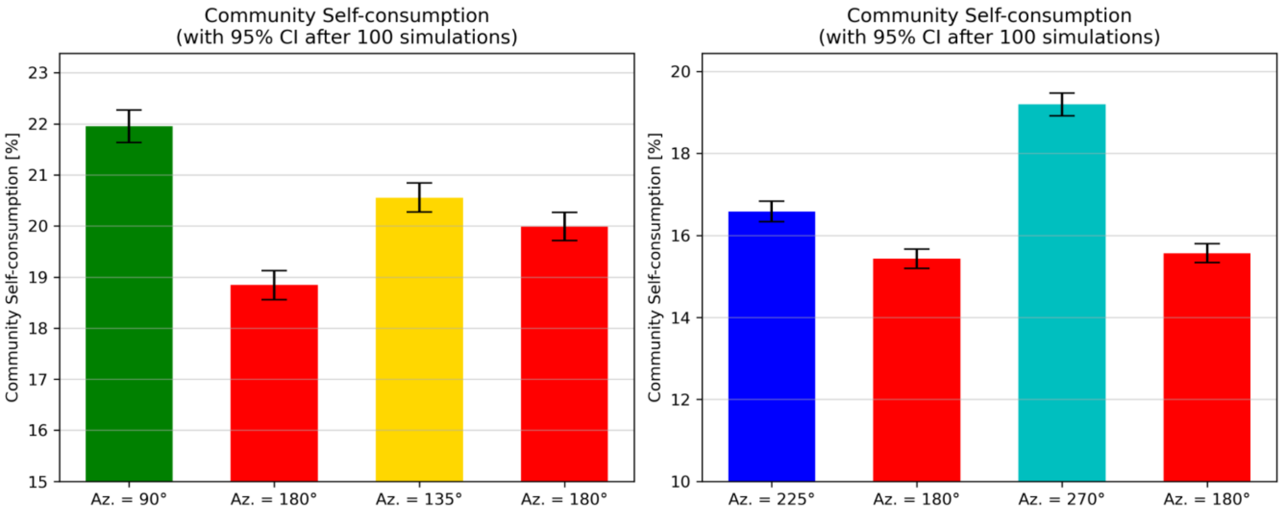

Figure 4.30: Comparisons of community self-consumption for different PV orientations for the four created datasets with demand profiles whose PCC increased with an orientation different from South.

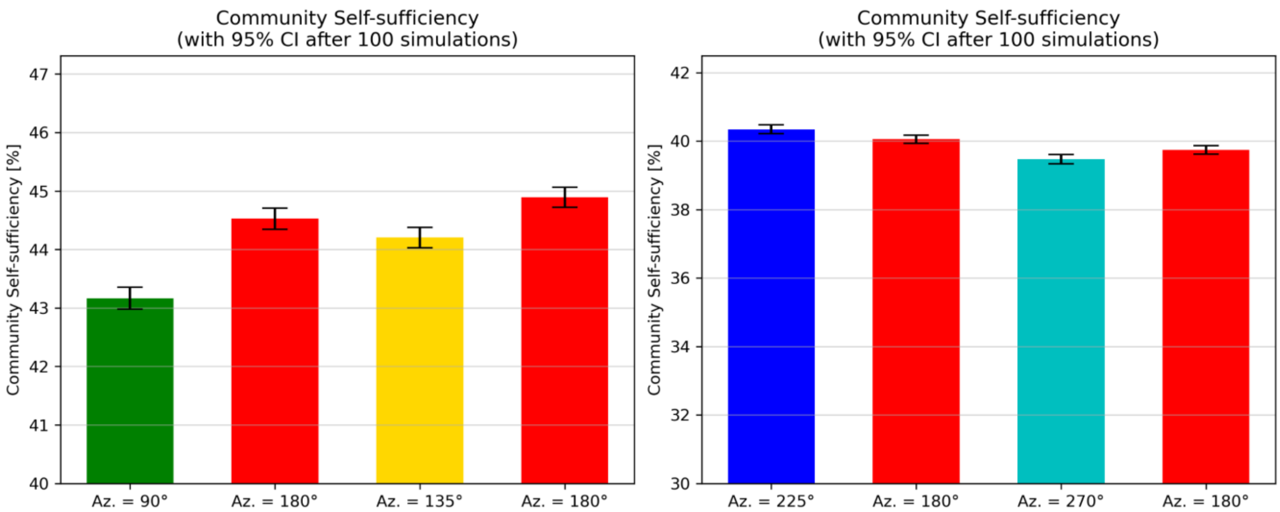

Figure 4.31: Comparisons of community self-sufficiency for different PV orientations for the four created datasets with demand profiles whose PCC increased with an orientation different from South.

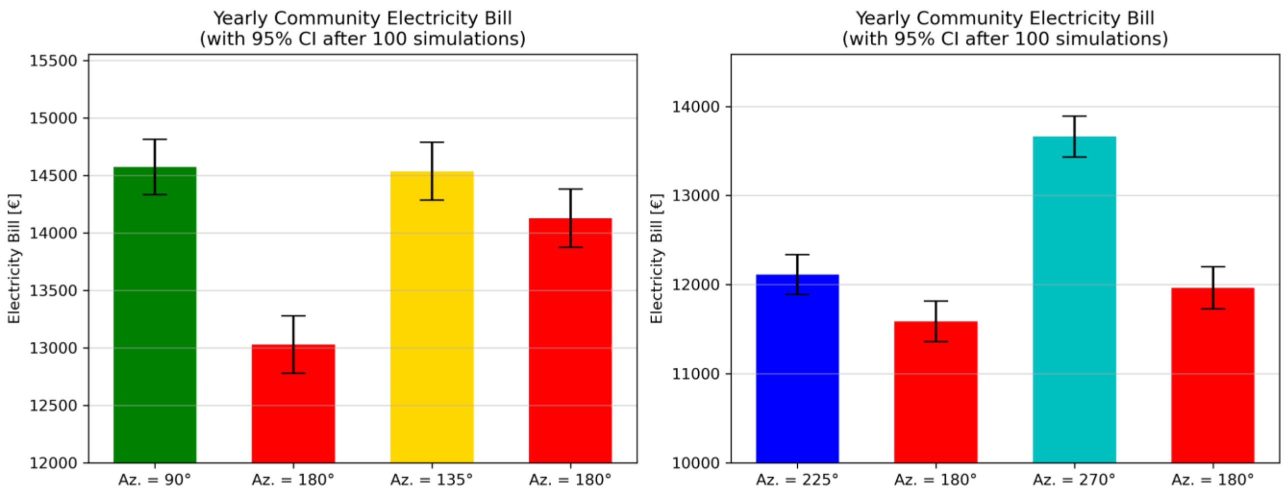

Figure 4.32: Comparisons of community yearly electricity bill for different PV orientations for the four created datasets with demand profiles whose PCC increased with an orientation different from South.

It is important to keep in mind that the only comparisons that can be made for the reported KPIs are between couples of KPIs for which the same demand profiles were used in the simulations. It is not possible, for example, to compare the KPIs represented by the green bars with the ones represented by the blue bars, because they are found using different datasets of demand profiles, with different average demand and average PCC.

Not all of the KPIs considered in section 4.2.3 have been reported in the figures above, but only those that are more relevant to the objective of this section; the graphical representations of the other results are reported in the appendix, in section 8.1. In summary, what is found for the KPIs that are reported in section 8.1 is that the demand peak is once again unaffected by PV parameters, while the injection peak and exported energy were both always greater for the South orientation, due to their strong dependence on the magnitude of yearly PV generation.

Figure 4.30 shows how the self-consumption of the energy communities simulated is always lower in the cases with South orientation, likely mainly due to higher yearly energy production in those cases.

Figure 4.31 shows how the self-sufficiency of the energy communities simulated is generally slightly lower in the cases with orientations different from South. This suggests that, when considering orientations different from South, the slight increases in PCC of the demand profiles of the created datasets are not generally enough to counterbalance the decrease in PV production for what concerns the energy self-consumed by the community (which is at the numerator of the self-sufficiency). The only exception to this is the South-West orientation, which causes self-sufficiency comparable to the South orientation.

However, even the better result, in terms of self-sufficiency, achieved by the South-West orientation does not translate to a lower yearly electricity bill, which, as shown in Figure 4.32, is lower for the South orientation in all of the four comparisons.

In conclusion, even considering particular demand profiles whose PCCs increase due to orientations different from South, these orientations do not appear to produce KPIs that are generally better than or comparable to those produced by a South orientation of PV systems. The reason for this is likely that the improvements in PCC caused are too low to compensate for the significant reductions in the yearly PV production. It would be possible to realize analogous comparisons for particular demand profiles whose PCCs do not simply increase but increase significantly, but this analysis would concern a much lower number of profiles of the Italian dataset and would likely be too specific. The goal of this section was to see if the “average improvement” of PCC produced by orientations different from South could be enough to cause better performances of energy communities with such orientations; the obtained results suggest that the average improvement of PCC, with the utilized Italian dataset, is not enough to achieve this.

5 Results: effects of demand profiles on energy communities

In sections 2.4 and 4 of this work, the PCC-demand plane has been shown to be a potentially effective method to represent the demand profiles of an energy community, showing examples in which changes in the distribution of demand profiles in the plane predict changes in the KPIs of an energy community.

The goal of this section is to better characterize these changes in KPIs, trying to relate them to changes in the characteristics of the dataset of demand profiles used as input in the simulations.

The parameters that were chosen to characterize the datasets of demand profiles are the average of PCC, the standard deviation of PCC, the average of yearly demand, and the standard deviation of yearly demand. In order to explore the effects of these four parameters, a Python script, illustrated in section 5.1, has been developed to create custom datasets of demand profiles with the desired values of the four parameters.

Then, in section 5.2, two datasets of demand profiles with different origins but similar values of the parameters chosen to characterize the datasets were used in different simulations, to test if similar values of such parameters could cause similar values of the KPIs of simulated energy communities.

Finally, in section 5.3, the effects of varying the parameters chosen to characterize the datasets of demand profiles were investigated in terms of KPIs of simulated energy communities.

5.1 Development of a script to create custom datasets of demand profiles

In order to study the effects that the average of PCC, the standard deviation of PCC, the average of yearly demand and the standard deviation of yearly demand of datasets of demand profiles can have, it is necessary to be able to create custom datasets that have the desired values of these four parameters.

Therefore, a Python script was developed to create new custom datasets of demand profiles with given characteristics with regard to yearly demand and PCC. This script uses the demand profiles of the Italian dataset, which in the following are called “initial profiles” for the sake of brevity, as a starting point to create the wanted custom datasets of demand profiles.

The input parameters required by the script (besides the .csv file containing the demand profiles of the Italian dataset) are the following:

- The number of demand profiles to include in the created dataset,
- The desired mean of PCC of the demand profiles of the created dataset,
- The desired mean of yearly demand of the demand profiles of the created dataset,
- The desired standard deviation of PCC of the demand profiles of the created dataset,
- The desired standard deviation of yearly demand of the demand profiles of the created dataset.

The script utilizes the input values of means and standard deviations to generate two normal distributions, one for the yearly demand and one for the PCC. These distributions are then truncated in such a way that they remain symmetric, otherwise, the mean of the values extracted based on these distributions would significantly differ from the mean of the distributions.

For the yearly demand distribution, symmetry is accomplished by setting the minimum allowed value of the distribution equal to the minimum yearly demand ($E_{\text{min demand}}$) of the initial profiles (equal to 328.8 kWh for the Italian dataset), while the maximum value ($E_{\text{max demand}}$) is chosen to maintain symmetry (thus choosing the maximum demand in a way that it and the minimum demand are equidistant from the mean, $E_{\text{mean demand}}$), through equation (5.1).

$$E_{max\ demand} = 2 * E_{mean\ demand} - E_{min\ demand} \tag{5.1}$$

For the PCC distribution, symmetry is enforced by considering two different cases: one in which the input value of the mean of PCC (PCC_{mean}) is closer to the maximum PCC of the initial profiles (0.168 for the Italian dataset) and one in which the input value of the mean of PCC is closer to the minimum PCC of the initial profiles (-0.267 for the Italian dataset).

In the first case, the maximum PCC (PCC_{max}) of the truncated normal distribution is set equal to the maximum PCC of the initial profiles, while the minimum PCC (PCC_{min}) of the distribution is found through equation (5.2).

$$PCC_{min} = 2 * PCC_{mean} - PCC_{max} \tag{5.2}$$

In the second case, the minimum PCC of the truncated normal distribution is set equal to the minimum PCC of the initial profiles, while the maximum PCC of the distribution is found through equation (5.3).

$$PCC_{max} = 2 * PCC_{mean} - PCC_{min} \tag{5.3}$$

Once the nature of the truncated normal distributions used is clear, the steps executed by the script can be described as follows:

1) The PCC and yearly demand of each initial profile are calculated.
2) A number of random values (equal to the wanted number of users in the custom dataset of demand profiles to create) of PCC and yearly demand are extracted, considering the probabilities given by the truncated normal distributions previously described, using the Python function scipy.stats.truncnorm.rvs [51].
3) For each value of PCC extracted, the initial profile whose PCC is closest to the extracted value is found and selected to be part of the created custom dataset.
4) For each of the profiles selected in step 3, the original demand is rescaled, making it equal to each value of yearly demand extracted in point 2 and saving the multiplier needed for this rescaling.
5) A .csv file is created containing the values of PCC and yearly demand of the demand profiles of the created dataset, along with the multipliers used for the rescaling of the yearly demand.
6) The created custom dataset of demand profiles is plotted on the PCC-demand plane, keeping the axes relative to the initial profiles for easier comparison.
7) The complete rescaled demand profiles (with an hourly resolution of the power demand) belonging to the custom dataset of demand profiles are created by extracting the corresponding initial profiles and multiplying them for the multiplier found in step 4. The profiles are then saved to a .csv file in a format ready to be used in the simulations of energy communities and keeping the information of which initial profiles were used (and with which multipliers) to form the new profiles.

Due to the rescaling described, the created custom dataset of demand profiles contains profiles with demands that differ from those of the initial profiles. However, this is deemed acceptable because the modifications are done only with regard to the magnitude of the demand (which is multiplied in every timestep for the same multiplier) and not with regard to its trend. Modifying the latter would change the PCC and would be a more arbitrary choice, significantly altering the initial demand profiles. If the rescaling of the demand was not performed then the script would have to “compromise” more in looking for profiles with characteristics similar to those extracted because it would need to look for the profile with the closest PCC and demand to the extracted PCC-demand couple. Doing this would cause the selected profiles’ PCC and demand to differ significantly more from the extracted values, thus decreasing the fidelity of the created dataset of demand profiles to the input parameters chosen. For this reason, the rescaling of demand profiles has been deemed a better way to proceed, allowing

the creation of custom datasets of demand profiles with proprieties that are generally close to respecting the input parameters.
The described script has been used in sections 5.2 and 5.3 to generate the custom datasets of demand profiles used in such sections. These datasets have been created with 1000 demand profiles each, verifying for each dataset that its characteristics did not significantly differ from the parameters used as input to the script.

5.2 Comparison of the German dataset and a custom dataset with the parameters of the German dataset

The goal of this section is to compare the German dataset of demand profiles (introduced in section 2.3.1) with a similar custom dataset, in terms of KPIs of energy communities using these datasets. This is done to verify if demand datasets with similar values of average of PCC, standard deviation of PCC, average of yearly demand, and standard deviation of yearly demand could cause similar KPIs of energy communities that use such datasets.
The custom dataset (or custom Italian dataset, since it is derived from the original Italian dataset) is composed of 1000 demand profiles and created with the script explained in section 5.1 (starting from the profiles of the Italian dataset), using as values of input parameters those that characterize the German dataset:

- $PCC_{mean} = 0.0238$,
- $PCC_{standard\ deviation} = 0.0952$,
- Yearly demand $_{mean}$ = 4685.1 kWh,
- Yearly demand $_{standard\ deviation}$ = 1424.0 kWh.

In this way, the German dataset and the custom Italian dataset will have similar values of these four parameters. These values are close but not exactly equal due to the randomness of the extractions of values of PCC and yearly demand performed by the script and due to the necessity of approximating the extracted values of PCC with the closest available among the original demand profiles of the Italian dataset. Using different seeds (with each corresponding to a certain random extraction of the values of yearly demand and PCC) for the generation of the custom dataset slightly different custom datasets are produced. Using these different custom datasets produces slightly different KPIs in the relative simulations of energy communities, but these variations were found to be generally below 2-3% for the custom datasets tested. Due to the impossibility (due to lack of computational power) of effectuating simulations for a large number of custom datasets and taking the average values of KPIs,

simulations were conducted for a low number of custom datasets, finding the above-mentioned low difference in KPIs. The results reported in this section are then those relative to one custom dataset which resulted in KPIs close to the average of the KPIs relative to the custom datasets for which simulations were made.
The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops.
Three subcases (distinguishable by the labels used for them in the figures reporting the KPIs) regarding batteries have been considered: one without any batteries (labeled as “No batt.”) and two with batteries of 10 kWh each installed in 15 households of the energy communities. The two cases with batteries are differentiated based on the strategy of the utilization of the batteries, considering the two strategies introduced in section 2.1.1: the self-consumption strategy (labeled as “SC”) and the peer-to-peer strategy (labeled as “P2P”). The reason for considering three subcases regarding batteries is to compare the KPIs of the German dataset and of the custom Italian dataset in all of the three subcases, to see if the presence of batteries alters the differences in KPIs or not. Therefore, both of these demand datasets have been simulated for each of the subcases, labeling the German dataset as “DE” and the custom Italian dataset “IT” (since it is created starting from profiles belonging to the Italian dataset) when presenting the results.
The generation profiles and distributions of sizes of PV systems used are different for the simulations using the German dataset and the custom Italian dataset. For simulations using the German dataset, the PV profile and the distribution of PV sizes used by Pena-Bello et al. in [26] are utilized. For simulations using the custom Italian dataset, the PV profile is generated with the method introduced in section 2.2, an inclination of 25° and a South orientation, while the distribution of PV sizes is a normal symmetrical distribution with an average PV power of 6.1 kW (and a minimum power of 1 kW, resulting in a maximum power of 11.2 kW). The rationale for the choice of this average power is to have an equal product of average PV power and yearly energy generated by a PV system with 1 kW of peak power between the cases of the two datasets. Indeed, 6.1 kW is the result of this equivalence, considering that the yearly energy generated by a PV system with 1 kW of peak power is 1535.83 kWh for the German case and 1483.63 kWh for the Italian case, while the average PV power in the German case is 5.9 kW.
100 simulations were conducted for six energy communities, corresponding to the use of the two different datasets of demand profiles for the three subcases of batteries. The means of the KPIs found from these simulations, along with their 95% confidence intervals, are reported in Figure 5.1, Figure 5.2, and Figure 5.3.

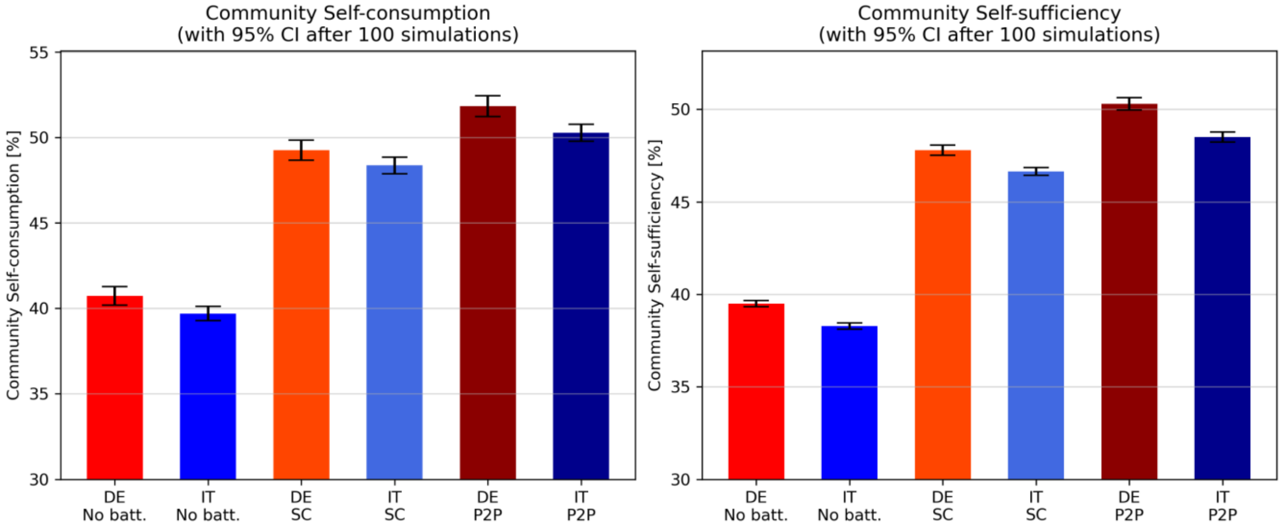

Figure 5.1: Self-sufficiency and self-consumption of the energy community, comparing the German and Italian custom datasets for three subcases relative to batteries.

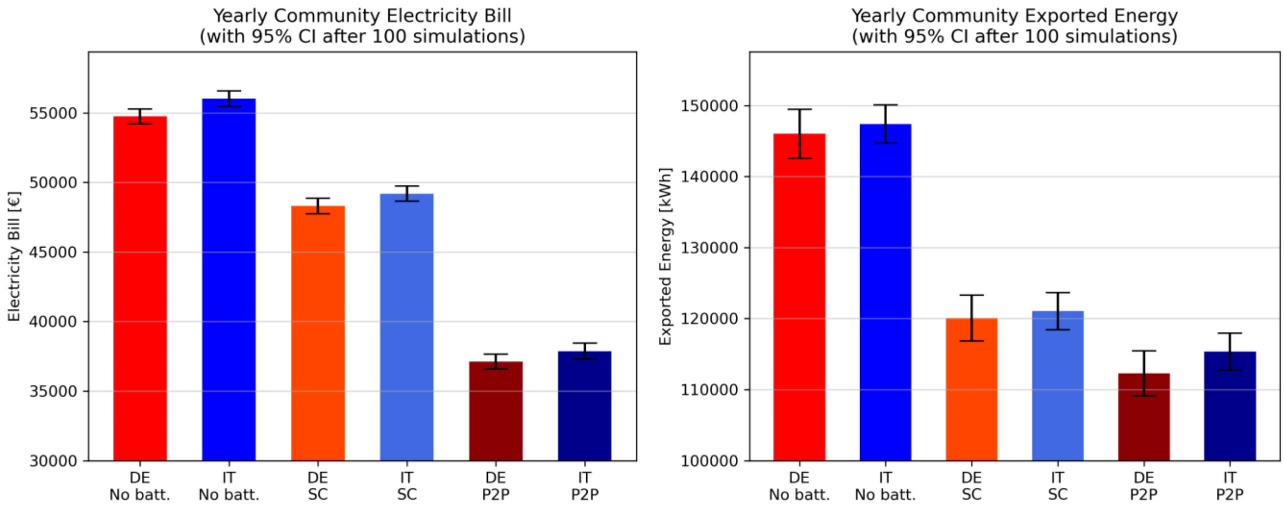

Figure 5.2: Yearly electricity bill and energy exported by the energy community, comparing the German and Italian custom datasets for three subcases relative to batteries.

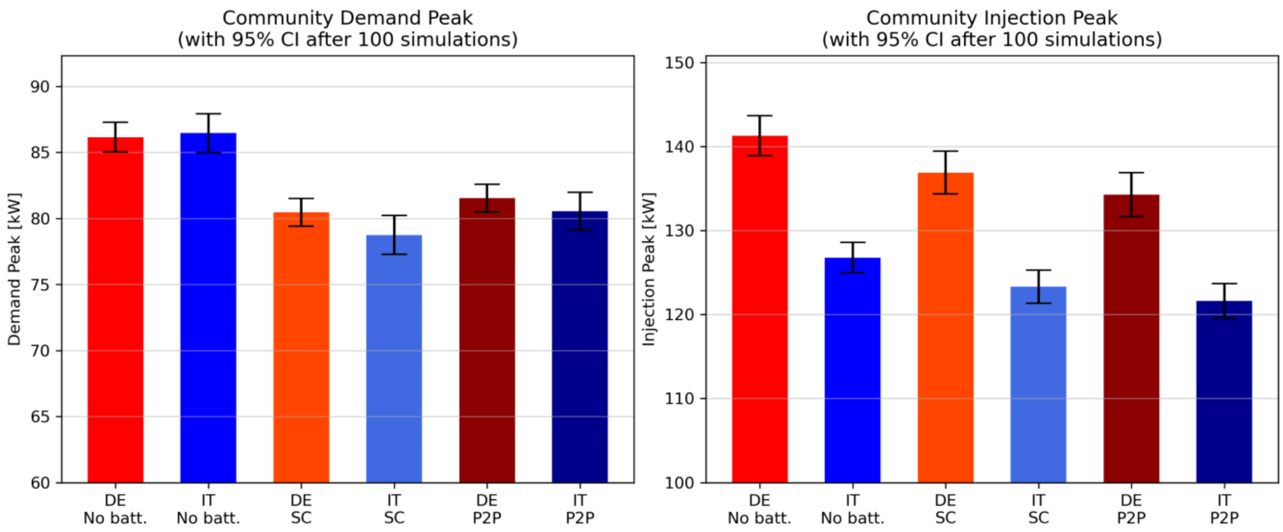

Figure 5.3: Demand peak and injection peak, comparing the German and Italian custom datasets for three subcases relative to batteries.

Observing Figure 5.1, Figure 5.2, and Figure 5.3, it is noticeable that the values of KPIs relative to the two compared demand datasets are quite close to each other, comparing the values relative to the same subcases relative to batteries. To better quantify this similarity, the percentage differences (in absolute values) between the corresponding KPIs relative to the two datasets of demand profiles, for the three batteries subcases, are reported in Table 5.1.

Table 5.1: Percentage differences of KPIs relative to the two compared datasets of demand profiles, for three subcases relative to batteries.

	Self-consumption	**Self-sufficiency**	**Demand Peak**	**Injection Peak**	**Electricity Bill**	**Exported Energy**
No batteries	2.53	3.07	0.36	10.26	2.32	0.93
Batteries, SC strategy	1.81	2.40	2.13	9.93	1.83	0.81
Batteries, P2P strategy	3.01	3.59	1.22	9.43	2.02	2.72

The percentage differences reported in Table 5.1 are found through equation (5.4).

$$Percentage\ difference = \left|\frac{KPI_{DE} - KPI_{IT}}{KPI_{DE}} * 100\right| \tag{5.4}$$

The contents of Table 5.1 show how the percentage differences between the KPIs relative to the two compared datasets of demand profiles are relatively low, generally being below 3% or just slightly above it. The relevant exception to this is constituted by the injection peak, which is significantly higher in the case of the German dataset than in the case of the custom Italian dataset, being roughly 10% higher in all the battery subcases. The reason for this higher difference is that the profiles of PV generation used in the two cases are different, as their daily averages, reported in Figure 5.4 (which considers PV peak powers of 1 kW), show.

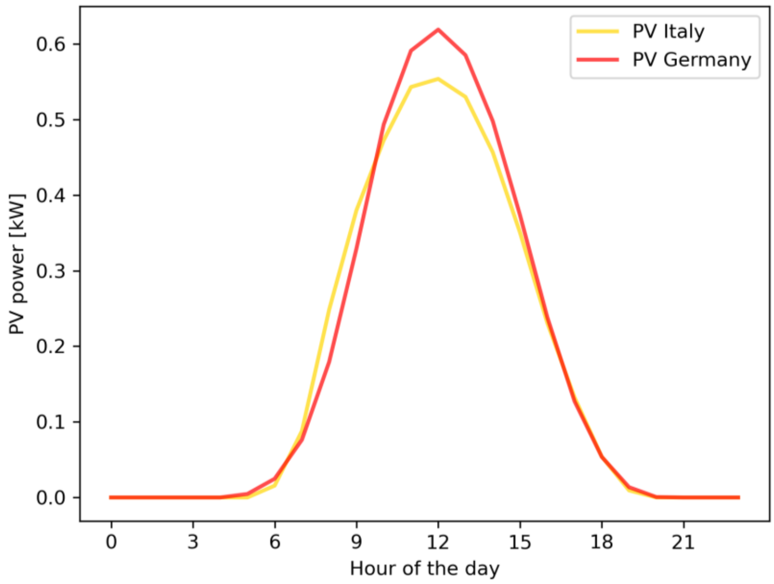

Figure 5.4: Average daily trends of the PV profiles used in the case of the German dataset and of the custom Italian dataset, considering a peak power of 1 kW.

Figure 5.4 shows how the daily peak of the PV profile used with the German dataset is, on average, higher than the peak of the profile used with the custom Italian dataset. This is what causes higher power production peaks to be reached by the PV systems considered in the simulations relative to the German dataset, causing in turn higher injection peaks.

Finally, an additional observation that can be made on the data reported in Table 5.1 is that the subcase in which the differences seem to be slightly higher is the one in which batteries are present and managed with the peer-to-peer strategy. The cause for this is likely that this strategy, relying on the individual choices made by the users that have batteries installed in their households, introduces more variables, which can in turn increase the differences in KPIs.

In conclusion, the results of this section show that two datasets of demand profiles that have different origins but similar values of four characterizing parameters (their averages and standard deviations of yearly demand and PCC) can produce similar values of KPIs in energy communities that have demand profiles taken from such datasets. This suggests that the four characterizing parameters could be a possibly effective way to identify demand datasets that could produce similar performances in energy communities using them as inputs. Further trials, with a larger number of datasets with different origins and equal characterizing parameters, would be necessary to definitively prove this concept, but the results reported in this section highlight that it could be interesting to investigate this method further.

5.3 Effects of varying the parameters of custom demand datasets

The goal of this section is to analyze the impact that the characteristics of the datasets of demand profiles have on the KPIs of energy communities using such datasets. This is done by simulating energy communities with different custom datasets (created with the script described in section 5.1) that have different values of the four input parameters considered by the script, which are the average of PCC, the standard deviation of PCC, the average of yearly demand and the standard deviation of yearly demand. The effect of these input parameters is investigated by changing the values of one parameter at a time, while keeping the others constant, and seeing the impact that this change produces on the various KPIs of energy communities. The input parameters that are not varied are kept equal to the values relative to the German dataset (reported in section 5.2), except for the average of the yearly demand, for which different values have been considered while investigating the effects of varying the average of PCC and the standard deviation of yearly demand.

The effects of varying the standard deviation of PCC have not been investigated, since the relatively narrow range of values of PCC of the demand profiles belonging to the Italian dataset (which is used as the starting point of the script described in section 5.1) did not allow to create custom datasets of demand profiles with widely different values of the standard deviation of PCC.

The energy communities simulated in this section are each composed of 60 residential users, 30 of which have a PV system installed on their rooftops. The average PV power is considered to be equal to 6.1 kW, like for the simulations performed with the custom Italian dataset in section 5.2, while the PV systems are considered to be South-oriented and with an inclination of 25°.

Three subcases regarding batteries have been considered: one without any batteries and two with batteries of 10 kWh each installed in 15 households (that also have PV systems) of the energy communities. The two cases with batteries are differentiated based on the strategy of the utilization of the batteries, considering the two strategies introduced in section 2.1.1: the self-consumption strategy (labeled as “SC”) and the peer-to-peer strategy (labeled as “P2P”).

100 simulations were conducted for each combination of custom dataset of demand profiles and subcase regarding batteries, and the results reported are the means of the KPIs found from these simulations, along with their 95% confidence intervals.

The graphs with the results of the simulations without batteries are reported in the appendix (in section 8.2), while the results of the simulations with batteries are reported in sections 5.3.1, 5.3.2, and 5.3.3; moreover, in these sections, the results both with and without batteries are commented.

5.3.1 Mean of yearly demand

The first parameter of the custom demand datasets which is varied to investigate its effects is the mean of the yearly demand. The values of average yearly demand considered in this section range from 1000 kWh to 8000 kWh, with steps of 1000 kWh. To consider also the yearly PV energy production when presenting the results, the average of the normalized demand is reported in the graphs that present the variations of the KPIs of the energy communities. The average normalized demand is found by dividing the mean of the yearly demand for the PV-produced energy allocated to one user. The latter is found by applying equation (2.7) and is equal to 4525.08 kWh.

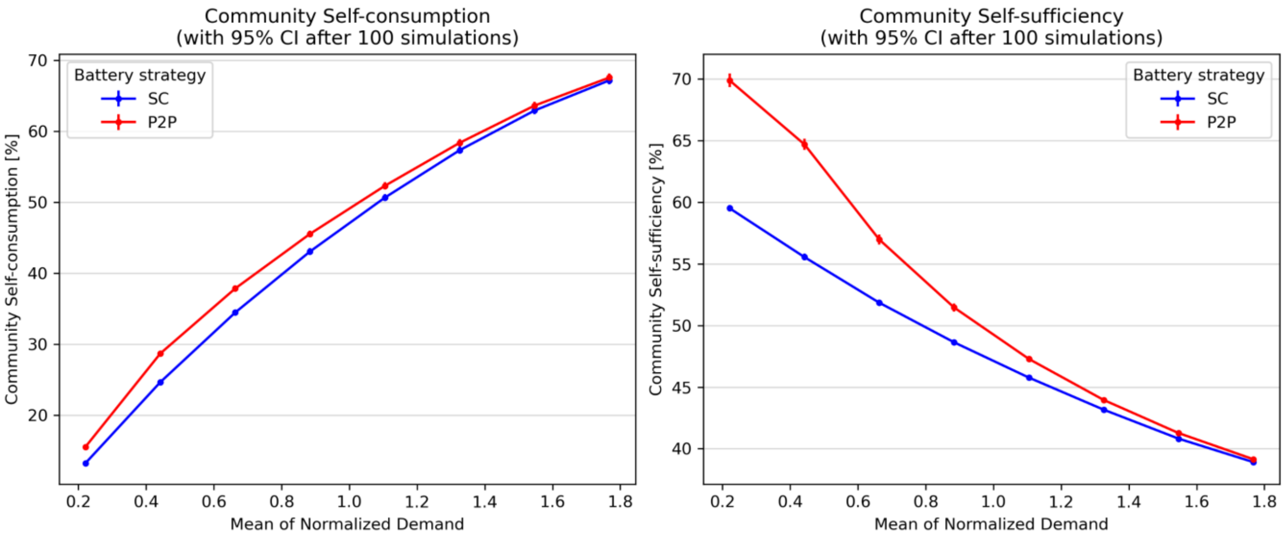

Figure 5.5: Effects of varying the mean of the yearly demand on the community self-consumption and self-sufficiency, in the case of energy communities with batteries.

The first two KPIs analyzed are the community self-consumption and self-sufficiency, whose variations are shown in Figure 5.5 for the case of communities with batteries and in Figure 8.4 for the case of communities without batteries.

In both the cases of energy communities with and without batteries, it is clear that the SC tends to increase with an increasing average of yearly demand, while the SS tends to decrease. This is logical since a higher demand with fixed PV production allows to increase the amount of energy self-consumed within the energy community, thus making the SC increase. However, considering SS, the increase of self-consumed energy (at the numerator of SS) is not enough to offset the increase of energy demand (at the denominator or SS), with the latter increasing more quickly, thus making the SS decrease with increasing average demand.

Comparing the different strategies for managing batteries, it is clear that the P2P strategy produces significantly higher values of SS and SC compared to the SC strategy when considering low values of average yearly demand. For example, the SS and the SC for a normalized average demand of 0.22 increase by 17.4% when considering a P2P strategy rather than a SC strategy. The increase in SS and in SC is exactly the same in this case because they both have the self-consumed energy at the numerator, which is what varies between the two different strategies, and equal values at their denominators. For higher values of average yearly demand, the difference between the values of SS and SC between the two different battery strategies becomes significantly lower. For example, the SS and the SC for a normalized average demand of 1.77 increase by only 0.6% when considering a P2P strategy rather than a SC strategy.
The reason for the P2P strategy being more advantageous for low values of average normalized demand is that a low normalized demand makes it so that there is a higher quantity of PV surplus energy that can be stored in batteries. Due to the nature of the P2P strategy allowing trading of battery-stored energy, the batteries are "used" more in the case of this strategy, increasing the number of charge/discharge cycles and allowing the batteries to store more surplus PV energy over the year, increasing the amount of self-consumed energy. This increase is significant when the normalized demand is low, since a lot of PV surplus energy is available, but for high values of normalized demand the PV surplus becomes lower and its storage is nearly as effective managing batteries with the SC strategy as with the P2P strategy. Therefore, the P2P strategy appears to be more convenient the more the PV systems and the batteries are oversized compared to the demand of the households.

Other observations can be made by analyzing the differences between the two most distant cases of average normalized demand considered, i.e. 0.22 and 1.77. The percentage SC increases and SS decreases from an average normalized demand of 0.22 to an average normalized demand of 1.77, for the three cases regarding batteries, are reported in Table 5.2.

Table 5.2: Percentage SC increases and SS decreases from an average normalized demand of 0.22 to an average normalized demand of 1.77, for the three cases regarding batteries.

	No batteries	**Batteries, SC**	**Batteries, P2P**
Increase of SC [%]	453.7	408.52	335.6
Decrease of SS [%]	28.9	34.6	44.0

The results in Table 5.2 show that the P2P strategy is the case in which the percentage increase in SC is the lowest and the decrease in SS is the highest, this is due to the fact that SC and SS tend to be better for the P2P strategy at lower values of normalized demand, while the advantage of the P2P strategy tends to fade for higher values of normalized demand.

The case without batteries has the highest percentage increase of SC and the lowest percentage decrease of SS. This shows that this case tends to be, relatively speaking, the one whose SC and SS have the most benefits or least drawbacks when comparing a higher and a lower normalized demand. The reason for this is that the size of the batteries is the same for all of the cases of average normalized demand considered, therefore batteries produce higher increases in SC and SS, compared to the absence of batteries, in cases of lower normalized demand, when more PV surplus is available for them to store. In cases of high normalized demand, less PV surplus is available for the batteries, therefore the performances with and without batteries tend to become closer. For example, in the case of an average normalized demand of 0.22 the community SC and SS due to the presence of batteries increase by 26.4% for a SC strategy and 48.4% for a P2P strategy. However, in the case of an average normalized demand of 1.77 the community SC and SS due to the presence of batteries increase by only 16.1% for a SC strategy and 16.8% for a P2P strategy.

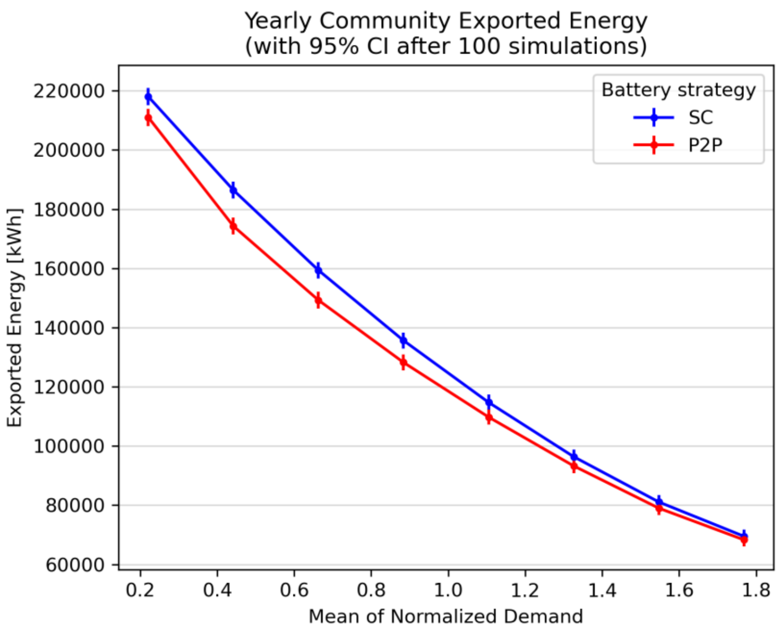

Figure 5.6: Effects of varying the mean of the yearly demand on the yearly energy exported by the community, in the case of energy communities with batteries.

The energy exported in one year by the simulated energy communities is reported in Figure 5.6 for the communities with batteries and in Figure 8.5 for the communities without batteries.

As expected, in both the cases of energy communities with and without batteries, the exported energy tends to decrease with the increase of average normalized demand, since more of the PV-produced energy is self-consumed and thus less of it is exported.
The P2P strategy tends to reduce the exported energy compared to the SC strategy for lower values of average normalized demand, while for higher values of average normalized demand the difference between the two strategies tends to become negligible. This is in line with what was observed analyzing the SC and SS: the P2P strategy tends to better increase the self-consumed energy, therefore decreasing the exported energy, when the average normalized demand is lower.
Analyzing the differences between the two most distant cases of average normalized demand considered, it can be noted that the percentage decrease of exported energy from an average normalized demand of 0.22 to an average normalized demand of 1.77 is 56.6% in the case of no batteries, 68.1% in the case of batteries with the SC strategy and 67.6% in the case of batteries with the P2P strategy.

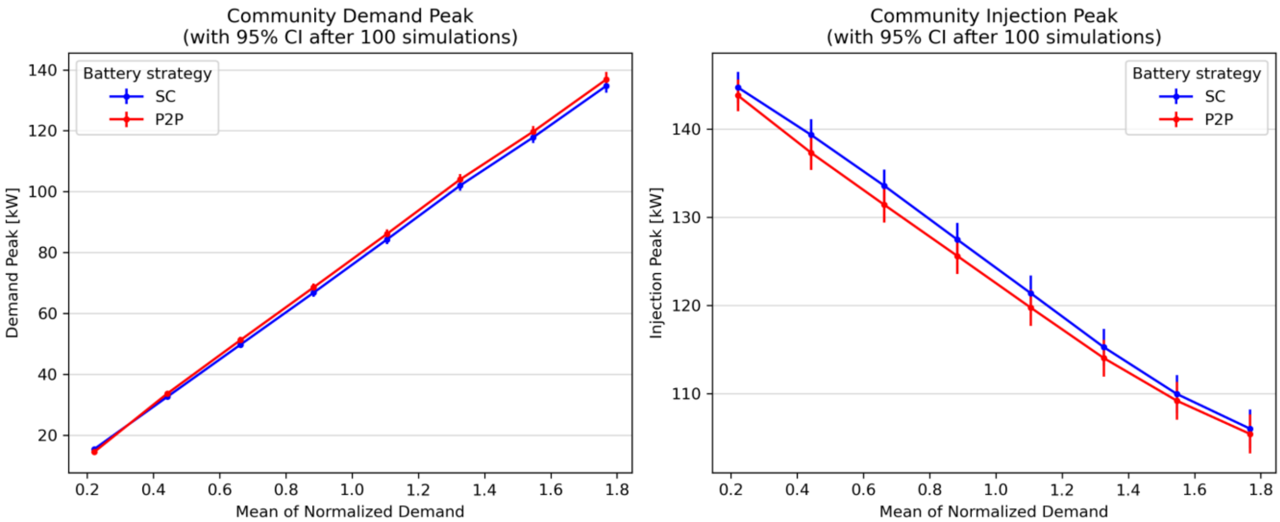

Figure 5.7: Effects of varying the mean of the yearly demand on the community demand peak and injection peak, in the case of energy communities with batteries.

Finally, the results relative to the demand peak and the injection peaks are reported in Figure 5.7 for the energy communities with batteries and in Figure 8.6 for the energy communities without batteries. Analyzing these figures, it can be noted that, predictably, a higher value of average normalized demand tends to increase the demand peak and to decrease the injection peak. The decrease in the injection peak is due to the higher demand reducing the PV power surplus during the moments in which it is maximum.

It can be noted that the values of the demand peak and the injection peak relative to the SC and P2P strategies do not generally differ in a significant way, with most of the confidence intervals overlapping, even if a slight decrease in the average values of the injection peak in the case of the P2P strategy is observed.

The percentage demand peak increases and injection peak decreases from an average normalized demand of 0.22 to an average normalized demand of 1.77, for the three cases regarding batteries, are reported in Table 5.3, highlighting how the variation of the demand peak is much more significant than that of the injection peak.

Table 5.3: Percentage demand peak increases and injection peak decreases from an average normalized demand of 0.22 to an average normalized demand of 1.77, for the three cases regarding batteries.

	No batteries	**Batteries, SC**	**Batteries, P2P**
Increase of demand peak [%]	660.7	773.2	844.8
Decrease of injection peak [%]	22.0	26.8	26.7

Considering the effects of batteries, it is worth noting that batteries are more effective in decreasing the injection peak in the case of high average normalized demand, while they are more effective in decreasing the demand peak in the case of low average normalized demand. For example, the injection peak is lowered by 0.67% by the presence of batteries (P2P strategy) for an average normalized demand of 0.22 and by 6.63% for an average normalized demand of 1.77. On the other hand, the demand peak is lowered by 22.58% by the presence of batteries (P2P strategy) for an average normalized demand of 0.22 and by 3.85% for an average normalized demand of 1.77.

The reason for the trend of the injection peak is that batteries can better mitigate the injection peak when they tend to have, on average, a lower state of charge, so that when the injection peak occurs a larger part of it can be absorbed by batteries. This occurs for higher values of average normalized demand, for which there is less PV energy surplus.

The reason for the trend of the demand peak is that batteries can better mitigate the demand peak when they tend to have, on average, a higher state of charge, so that when the demand peak occurs a larger part of it can be covered by batteries. This occurs for lower values of average normalized demand, for which there is more PV energy surplus.

5.3.2 Standard deviation of yearly demand

The second parameter of the custom demand datasets which is varied to investigate its effects is the standard deviation of the yearly demand. Four different values of average yearly demand have been considered in this section: 1500 kWh, 3000 kWh, 4685.1 kWh (equal to the average demand of the German dataset, labeled "DE" in the graphs), and 6000 kWh.
The values of the standard deviation of the yearly demand considered in this section for each value of average demand range from 10% to 50% of the average demand, with steps of 10%. However, creating a custom dataset with a standard deviation equal to 50% of the average demand was not possible for the case of average demand equal to 1500 kWh, due to not allowing the creation of profiles with yearly demand lower than the minimum yearly demand of the original Italian dataset. Therefore, the maximum standard deviation considered in this section for this case is 40% of the average demand.
Moreover, the results regarding the average demand of 6000 kWh for the standard deviation percentages of 40% and 50% had to be excluded. The reason for this is shown in Figure 5.8, which shows how the average demand of the demand profiles selected and utilized in the performed simulations was different from the desired value of 6000 kWh for the two excluded cases, causing the other results relative to those cases to be inadmissible. A possible explanation for this is that, even if the custom datasets relative to the excluded cases contain demand profiles whose average is roughly 6000 kWh, the standard deviation being so high caused the average demand of the utilized profiles to not converge towards the average value of the dataset within the 100 simulations performed. It can be seen in Figure 5.8 that this problem did not occur in other cases, except for the case of the 30% standard deviation in the case of 6000 kWh, in this case, the average demand is not so far from 6000 kWh, but it is 1% lower. Due to this low discrepancy, the results relative to the 30% case of 6000 kWh are reported, but they have to be analyzed with attention since they could be influenced by this discrepancy. Indeed, in the results presented in this section, there are some variations in some KPIs comparing the 20% and the 30% standard deviations for the average demand of 6000 kWh. These variations are generally not commented on since they are quite small in percentage and are likely due to the slight difference in average demand of the utilized demand profiles.

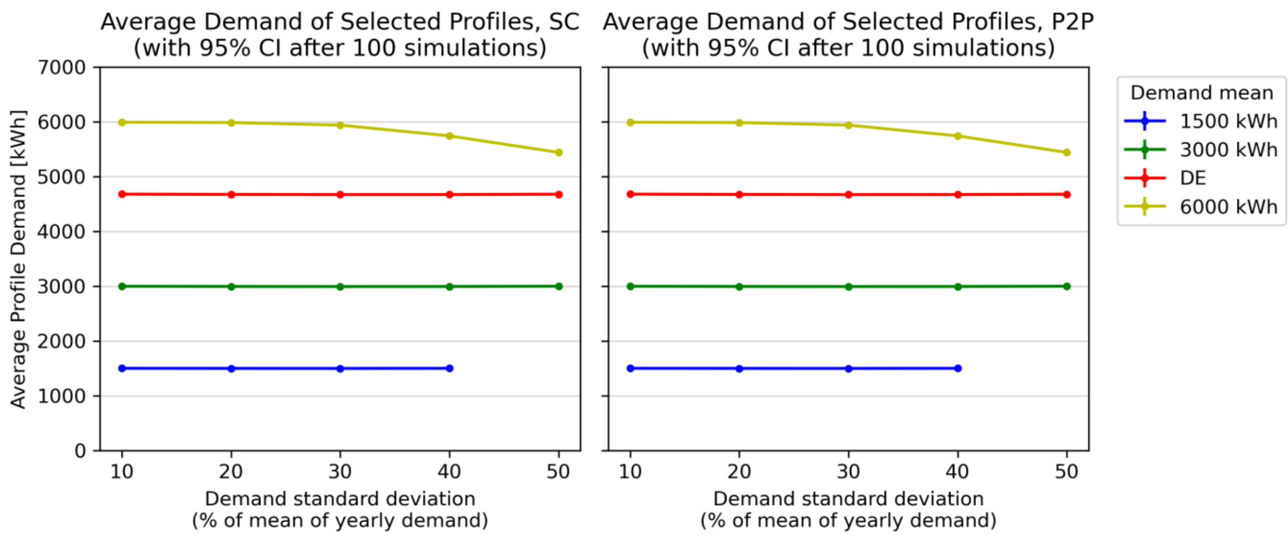

Figure 5.8: Average demand of the demand profiles used in the simulations performed to investigate the effect of varying the standard deviation of the yearly demand.

The results relative to energy communities without batteries are reported in Figure 8.7, Figure 8.8, and Figure 8.9. It can be noted how the variations of KPIs due to changes in the standard deviation of the yearly demand are generally very low, with the only exception of the demand peak. The slight variations emerging for the 30% standard deviation for the average demand of 6000 kWh are likely influenced by the previously mentioned slight difference in average demand and are therefore not considered to be a relevant result.

The percentage differences between the means of KPIs relative to the lowest and the highest values of the standard deviation of yearly demand considered for each value of average demand are all below 1%, except for the previously mentioned demand peak.

The trend of the demand peak in the case without batteries is reported in Figure 8.8 and shows a small but non-negligible increase of the demand peak with the increase of the standard deviation. For both of the values of average demand for which the widest range of standard deviation of demand has been considered (i.e. average demand of 3000 kWh and 4685.1 kWh), the percentage increase of the demand peak is around 4.4% when the standard deviation increases from 10% to 50% of the average demand.

The cause for this slight increase in the demand peak could be that when considering a higher standard deviation of demand there are more demand profiles with significantly higher yearly demand than the average. These profiles with higher demand could then have a moment, during the simulated year, in which they all present high demand, thus increasing the demand peak.

Therefore, it can be concluded that, for the investigated values of the standard deviation of yearly demand and average of yearly demand, the variation of the standard deviation of yearly demand has a very limited effect on the KPIs of energy communities without batteries, with the exception of the demand peak, which has a small but non-negligible increase with the increase of the standard deviation.

The results relative to energy communities with batteries are reported in Figure 5.9, Figure 5.10, Figure 5.11, Figure 5.12, Figure 5.13, and Figure 5.14, with the results relative to the SC strategy for batteries on the left and those relative to the P2P strategy on the right.

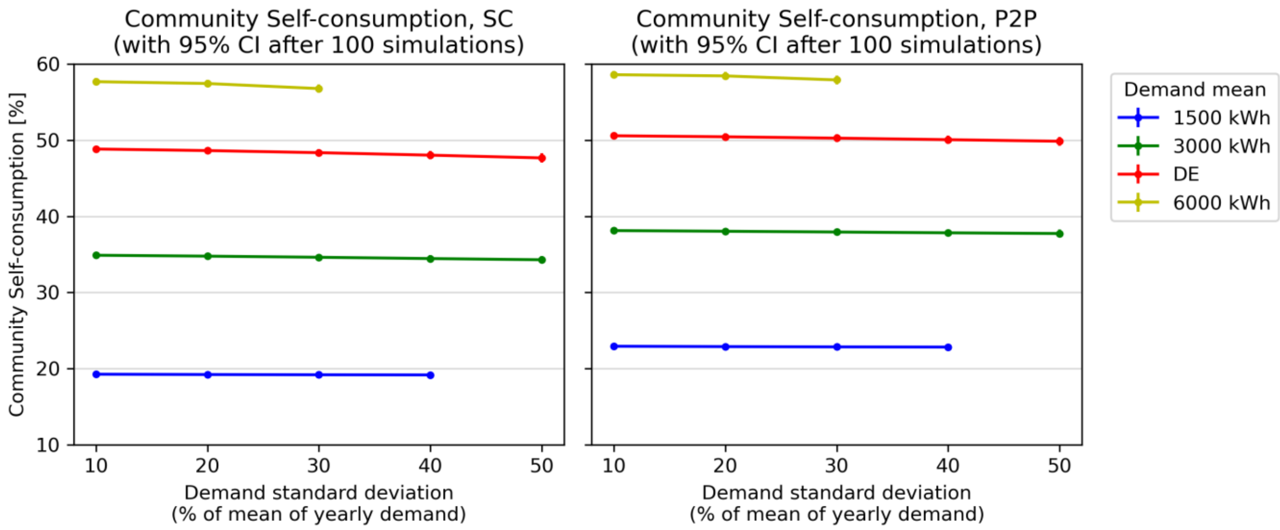

Figure 5.9: Effects of varying the standard deviation of the yearly demand on the community self-consumption, in the case of energy communities with batteries.

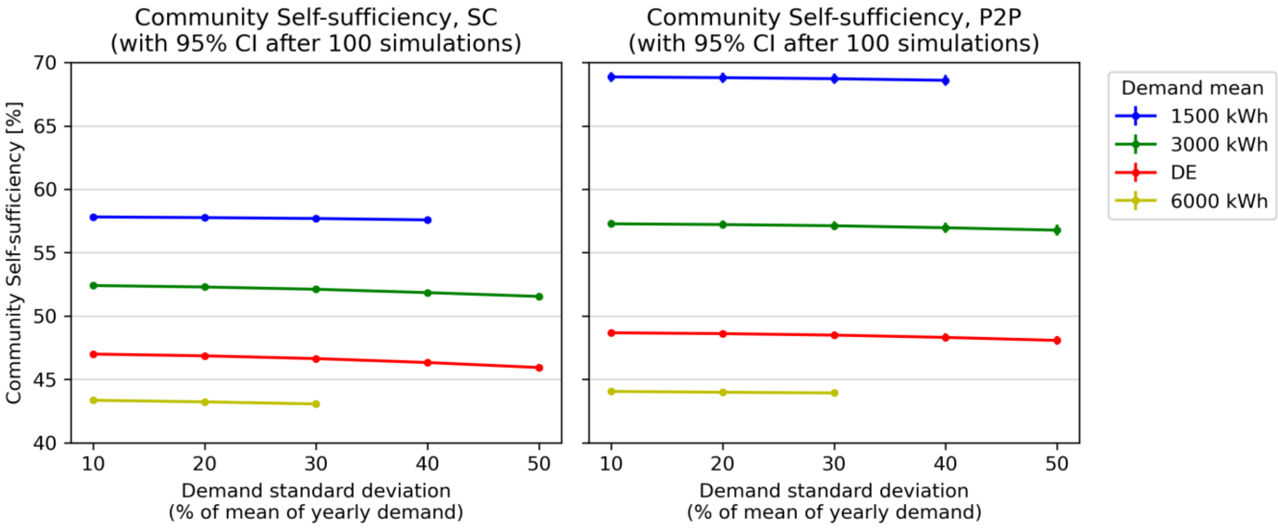

Figure 5.10: Effects of varying the standard deviation of the yearly demand on the community self-sufficiency, in the case of energy communities with batteries.

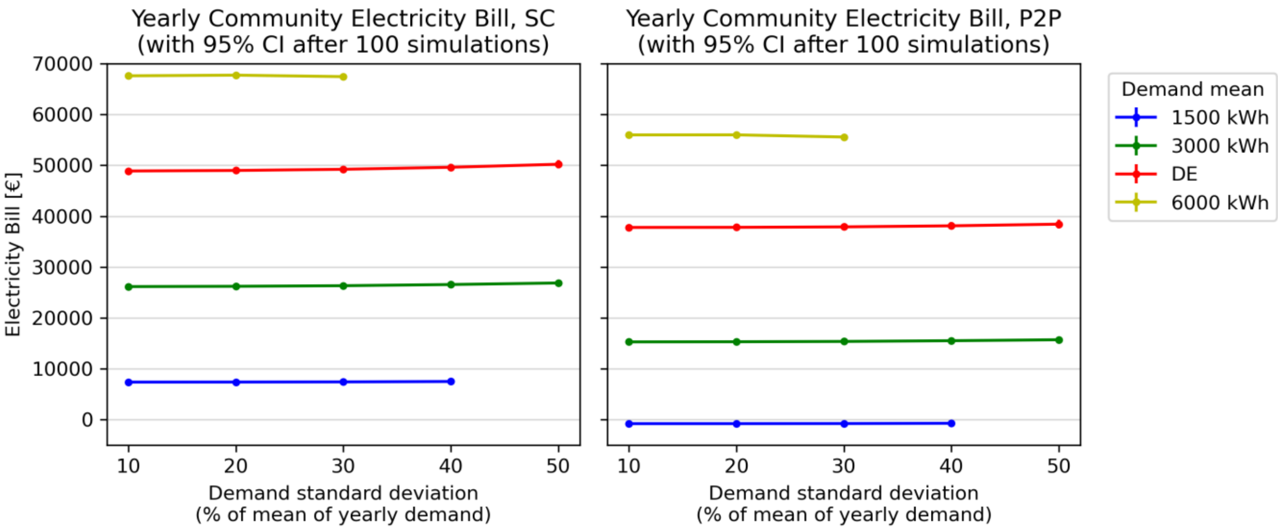

Figure 5.11: Effects of varying the standard deviation of the yearly demand on the community yearly electricity bill, in the case of energy communities with batteries.

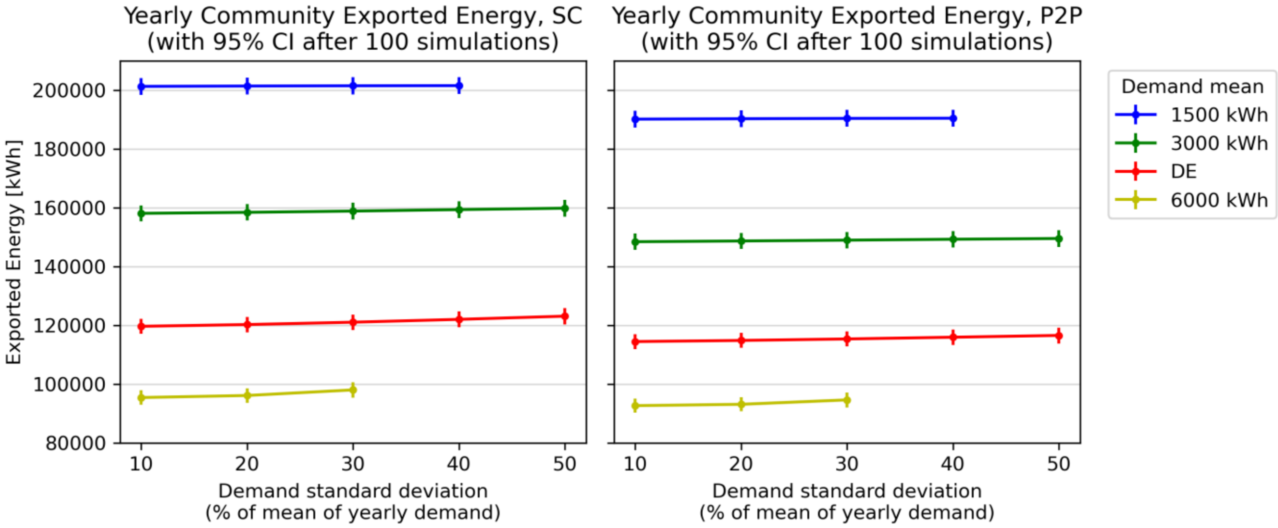

Figure 5.12: Effects of varying the standard deviation of the yearly demand on the energy exported in a year by the community, in the case of energy communities with batteries.

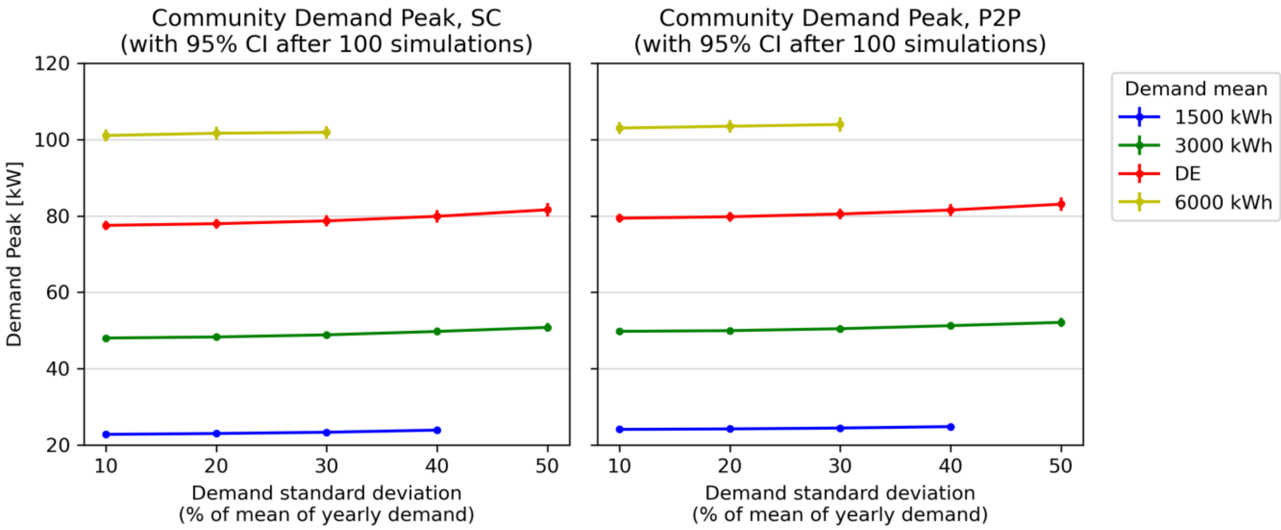

Figure 5.13: Effects of varying the standard deviation of the yearly demand on the community demand peak, in the case of energy communities with batteries.

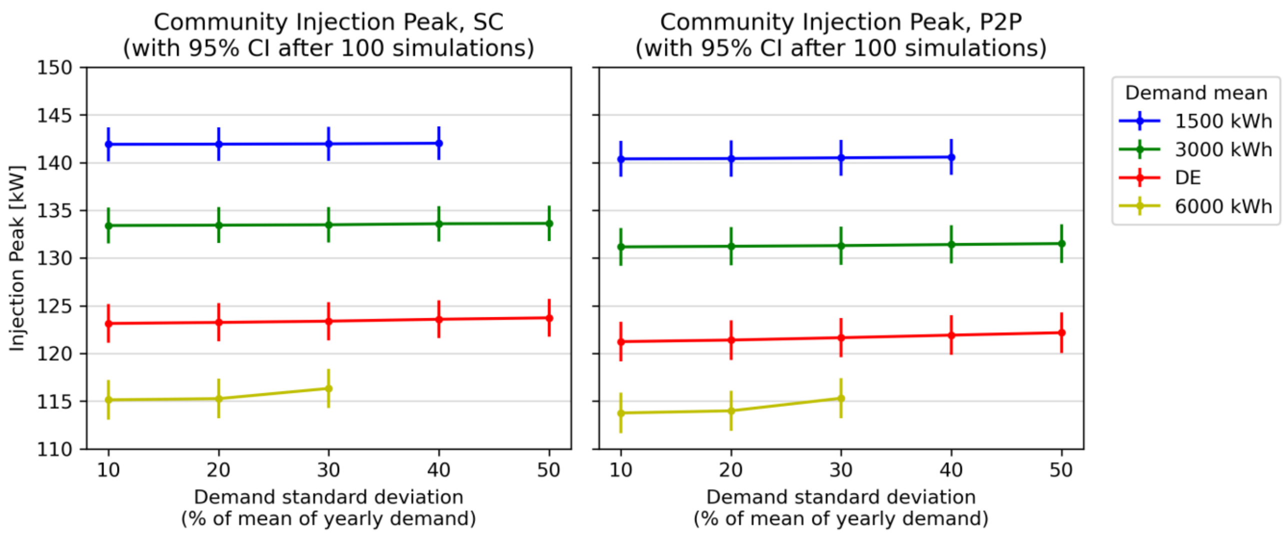

Figure 5.14: Effects of varying the standard deviation of the yearly demand on the community injection peak, in the case of energy communities with batteries.

It can be noted how the variations of KPIs of energy communities with batteries due to changes in the standard deviation of the yearly demand are generally very low, with the only exception of the demand peak. The slight variations emerging for the 30% standard deviation for the average demand of 6000 kWh are likely influenced by the previously mentioned slight difference in average demand and are therefore not considered to be a relevant result.

The variations of the mean values of KPIs due to variations in the standard deviation of yearly demand are slightly higher in presence of batteries than without batteries. However, excluding the demand peak, the percentage differences between the means of KPIs relative to the lowest and the highest values of the standard deviation of yearly demand considered for each value of average demand are all below 3% and below 2% in the great majority of cases. In this consideration, the variation of the bill in the case of P2P strategy and average demand of 1500 kWh is not included, since its mean values are very low and the confidence intervals relative to different values of standard deviation overlap.

The slightly higher variation of KPIs in presence of batteries than in their absence is more than likely due to the variability introduced by the selection of which users are assigned batteries. In case of a higher standard deviation of yearly demand, the demand profiles in the energy community differ more among them, therefore the difference between one battery being assigned to a household with high demand or to one with low demand is greater.

The percentage variations in KPIs are slightly greater in the case of the SC strategy than in the case of the P2P strategy. This is likely due to the fact that in the SC strategy batteries are utilized only by their owners, therefore the demand profiles of the households to which batteries are assigned matter more than in the P2P strategy, in which the energy stored in batteries can also be traded within the community, allowing for a use of batteries that is in part "shared" within the community.

The case of a SC strategy and an average demand of 4685.1 kWh is then analyzed in more detail because it is the case in which the variations of the mean values of KPIs due to variations in the standard deviation of yearly demand are the highest. In this case, considering the mean values of KPIs and going from a standard deviation of 10% to one of 50%, the self-consumption decreases by 2.4%, the self-sufficiency decreases by 2.3%, the demand peak increases by 5.3%, the bill increases by 2.7% and the exported energy increases by 2.9%, while the injection peak does not vary significantly considering its overlapping confidence intervals. The same trends, even if with lower percentage variations, are also observed for the other values of average demand and for both of the cases of battery strategies.

Besides the case of the demand peak, which presents the same trend and the same likely explanation previously presented for communities without batteries, the trends of the other KPIs seem to indicate a slight average decrease of the energy self-consumed by the community for higher values of the standard deviation of yearly demand. To explain this it is important to consider that, as previously mentioned, when there is a higher standard deviation of yearly demand, the random extraction of which households to assign the batteries to has a higher impact on the community KPIs. Therefore, in some simulations, the KPIs of the community will benefit from batteries being assigned to households with very high demand, which use the batteries a lot increasing the self-consumed energy, while in other simulations the KPIs will be worsened by the batteries being assigned to households with very low demand. A possible reason why the average of the self-consumed energy tends to decrease, worsening the KPIs of energy communities with batteries in cases of higher standard deviations, could then be that cases with low values of self-consumed energy are obtained slightly more frequently than cases with high values of self-consumed energy. However, it has to be considered that the variations of KPIs remain quite low and that the significance of this trend is in doubt and would need further analyses, considering other values of average demand and performing more than 100 simulations for each case.

In conclusion, the results obtained show that the KPIs of energy communities are generally affected only very slightly by changes in the standard deviation of the yearly demand of the demand dataset, suggesting a limited relevance of this parameter in determining the performances of energy communities. The most affected KPI is the demand peak, which tends to slightly increase for higher values of the standard deviation of the yearly demand. The KPIs of energy communities with batteries (in particular in the case of the SC strategy) appear to be slightly more affected by variations in the standard deviation of the yearly demand, compared to the KPIs of energy communities without batteries. A very slight decrease in self-consumed energy for an increasing standard deviation of the yearly demand emerges for energy communities with batteries, but this trend should be investigated further through more simulations to understand if it is significant or not.

5.3.3 Mean of PCC

The third and final parameter of the custom demand datasets which is varied to investigate its effects is the mean of the PCC. Four different values of average yearly demand have been considered in this section: 1500 kWh, 3000 kWh, 4685.1 kWh (equal to the average demand of the German dataset, labeled “DE” in the graphs), and 6000 kWh. The values of the mean of PCC considered in this section for each value of average demand range from -0.15 to 0.1, with steps of 0.05.

The results relative to energy communities without batteries are reported in section 8.2.3, while the results relative to energy communities with batteries are reported in the images of this section, with the results relative to the SC strategy for batteries on the left and those relative to the P2P strategy on the right.

In this section, when referring to percentage differences of KPIs between the two furthermost values of mean PCC, the differences are considered in absolute value and normalized dividing for the greater of the two compared values of the KPIs.

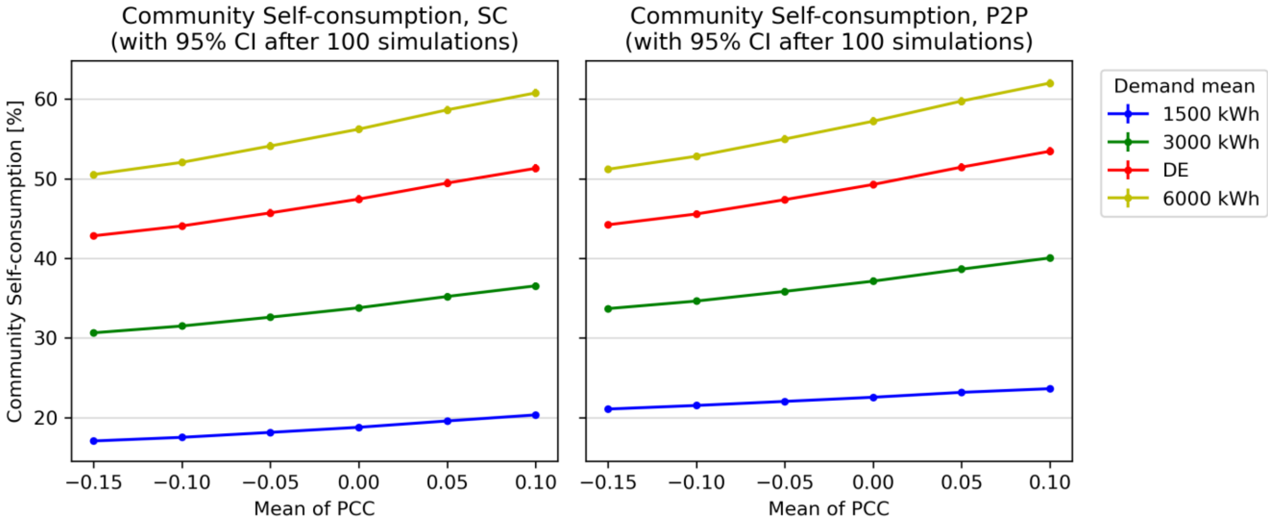

Figure 5.15: Effects of varying the mean of the PCC on the community self-consumption, in the case of energy communities with batteries.

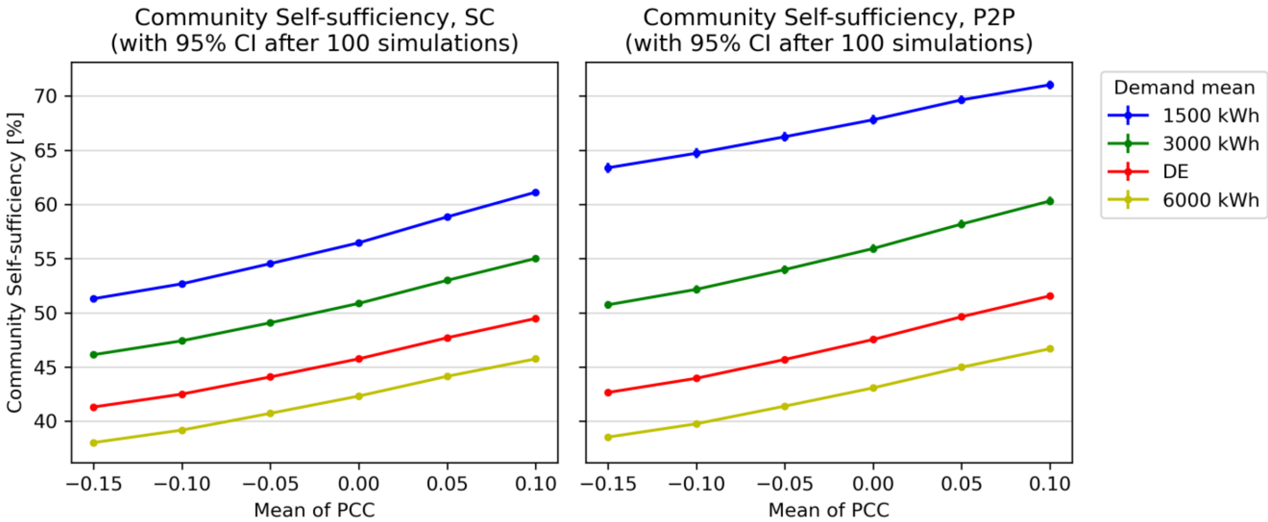

Figure 5.16: Effects of varying the mean of the PCC on the community self-sufficiency, in the case of energy communities with batteries.

The first two KPIs analyzed are the community SC and SS, which are reported in Figure 5.15 and Figure 5.16 for energy communities with batteries and in Figure 8.10 for energy communities without batteries.

In both the cases of energy communities with and without batteries, it is clear that the SC and SS tend to significantly increase with the increase of the mean of PCC. This was expected, since a greater synchronism between demand and PV generation, represented by higher values of PCC, tends to

increase the energy self-consumed by the community, which in turn increases the SC and SS, being at their numerators.
Considering the percentage differences of the values of SC and SS relative to the two furthermost values of the mean of PCC, meaning -0.15 and 0.1, some observations can be made. First of all, the percentage difference of SC is equal to that of SS in each case, since they both vary of how much the self-consumed energy at their numerators varies.

Secondly, it can be observed that in the cases of communities without batteries and of communities with batteries managed with the SC strategy the percentage differences of SC and SS between the two furthest values of PCC are almost the same regardless of the value of average demand.
On the other hand, the percentage differences of SC and SS between the two furthest values of PCC in the case of communities with batteries managed with the P2P strategy vary slightly, going from 10.8% for 1500 kWh to 17.5% for 6000 kWh. The reason for this increase is likely that for the low average yearly demand of 1500 kWh in the P2P case the self-consumed energy can only increase up to a certain point thanks to higher PCC because the self-consumed energy is already a lot compared to the energy demand and it reaches a sort of "plateau" or "saturation". This can be seen by looking at the SS for a mean PCC of 0.1, which is equal to 71.0% for the average demand of 1500 kWh in the P2P case, suggesting that the lower increase of SS (and SC) is due to the difficulty of going above such high values. When considering higher average demands, this effect does not seem to appear and the percentage differences of SC and SS are close in the other three considered cases of average demand for the case of batteries managed with the P2P strategy.
These observations suggest that, for the values of average demand and average PCC investigated, the effect of the PCC on SC and SS is similar in percentage considering different values of average demand, unless very high values of SS are considered, in which case a "saturation" of the energy that can be self-consumed can be reached, making the percentage variation in SC and SS change. The similarity of the percentage increases of SC and SS for different values of average demand appears to be a significant result, that should be investigated further, because if this trend could be generalized it could allow predicting how a change in the mean of PCC changes the SC and SS, without performing any simulations. To confirm this possibility, more simulations with more datasets and more values of average demand would be needed.

The average (across the different average demands) percentage differences of SC and SS between the two furthest values of PCC are 26.3% for energy communities without batteries, 16.4% for energy communities with batteries managed with the SC strategy and 15.4% for energy communities with batteries managed with the P2P strategy. These averages indicate that the effect of the mean of the PCC on SC and SS is stronger in the case of communities without batteries. This is logical since self-consumed energy in these communities only depends on the synchronism between demand profiles and PV generation, while communities with batteries have the latter to increase their self-consumed energy, thus reducing the impact of the PCC of the demand profiles. Moreover, the effect of the PCC on SC and SS of energy communities with batteries does not appear to significantly differ considering the SC and the P2P strategies.

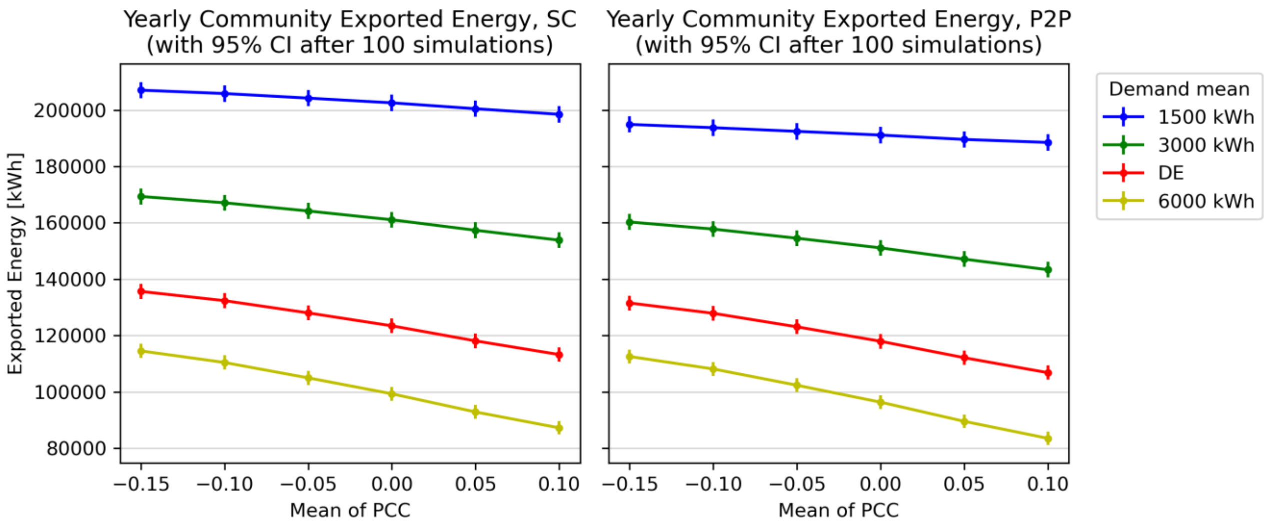

Figure 5.17: Effects of varying the mean of the PCC on the energy exported in a year by the community, in the case of energy communities with batteries.

The exported energy from the energy community is reported in Figure 8.11 for energy communities without batteries and in Figure 5.17 for energy communities with batteries. It is clear that the exported energy decreases with increasing mean of PCC, as expected since the values of SC and SS showed how the self-consumed energy increases with increasing mean of PCC. The percentage decreases of the exported energy are not commented on in detail here, since they are simply the consequences of the previously presented percentage increases of self-consumed energy (equal to the percentage increases of SC and SC). The only observation is that while the percentage increases of self-consumed energy were shown to be generally constant for different values of average demand, the percentage decreases of exported energy vary for different values of average demand, becoming higher the higher the average demand is. The reason for this is that, neglecting the battery losses, the self-consumed energy is roughly equal to the PV-generated energy (after considering the inverter losses) minus the exported energy. Therefore, a same percentual variation in self-consumed energy is not a same percentual variation in exported energy if the initial values of exported energy differ and the PV-generated energy stays constant (as is the case for all of the simulations conducted in this section).

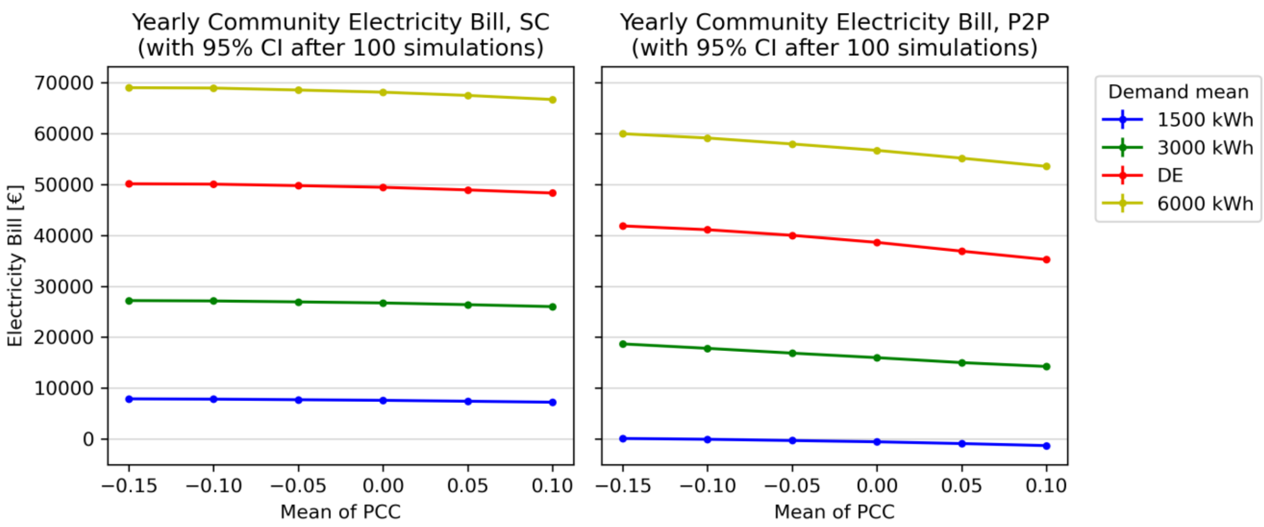

Figure 5.18: Effects of varying the mean of the PCC on the community yearly electricity bill, in the case of energy communities with batteries.

The yearly electricity bill of the energy community is reported in Figure 8.11 for energy communities without batteries and in Figure 5.18 for energy communities with batteries. The obvious trend is a decrease in electricity bill for increasing mean of PCC, due to an increase in self-consumed energy. Considering the percentage differences of the values of yearly electricity bill relative to the two furthermost values of the mean of PCC, meaning -0.15 and 0.1, some observations can be made. It is necessary to specify that the percentage difference in the bill for the average demand of 1500 kWh in the case of batteries managed with the P2P strategy is not considered in the following evaluations, since in this case the bill is very low (being actually a profit and not a cost) and its values corresponding to different means of PCC have confidence intervals that overlap.

The first consideration that can be made regarding the percentage differences of the bill is that they are lower for higher values of average energy demand. For example, passing from a PCC mean of -0.15 to one of 0.1 in the case of an average demand of 1500 kWh produces a decrease in the bill of 12.0% for energy communities without batteries and of 8.4% for energy communities with batteries managed with the SC strategy. On the other hand, considering the same values of PCC but an average demand of 6000 kWh, the decreases in the bill are only 4.4% for energy communities without batteries and 3.4% for energy communities with batteries managed with the SC strategy. The reason for the decreased effectiveness of the mean of PCC in affecting the electricity bill when considering high average demands is tied to the amount of energy imported by the community. This is because the imported energy is the energy with the highest associated price and therefore the higher it is and the higher is the bill. The sum of the imported energy and the self-consumed energy is constant and equal to the total energy demand of the community. The values of SC and SS showed that the percentage increases of self-consumed energy are generally constant for different values of average demand. However, how much these changes affect the imported energy depends on the share of energy demand that is satisfied by the self-consumed energy, which is the SS. If the SS is lower, which occurs for higher average demands, the same percentage increase in self-consumed energy causes a lower reduction of imported energy than if the SS is higher (which occurs for lower average demands). The higher the reduction of the imported energy is and the higher is the reduction of the electricity bill, therefore lower values of average demand are more significantly impacted, with regards to values of the bill, by a change in the mean of PCC.

The average (across the different average demands) percentage difference of the values of yearly electricity bill relative to the two furthermost values of the mean of PCC is 7.1% for communities without batteries, 4.9% for communities with batteries managed with the SC strategy, and 16.8% for communities with batteries managed with the P2P strategy. The significantly greater decrease in the bill in the case of the P2P strategy is due to the difference in pricing mechanisms applied in the different cases, described in section 2.1.2. Indeed, the pricing mechanism applied to the communities without batteries and the communities with batteries managed with the SC strategy rewards only the self-consumption of PV-generated energy directly done by the owner of each PV system, since importing energy from other members of the community or from outside of the community is considered to have the same cost in these cases. On the other hand, the pricing mechanism applied to the communities with batteries managed with the P2P strategy rewards all of the energy self-consumed by the whole energy community, since energy traded within the community has no impact on the total bill (since the profits made by users selling energy and the costs incurred by those buying it cancel each other out).
Therefore, the trend of the bill relative to the P2P strategy can be more representative of the trend of a bill that rewards the self-consumption of the whole community, while the trends of the bills relative to the SC strategy and to the case without batteries are representative of the trend of a bill that rewards only the self-consumption directly made by the owners of the PV systems.

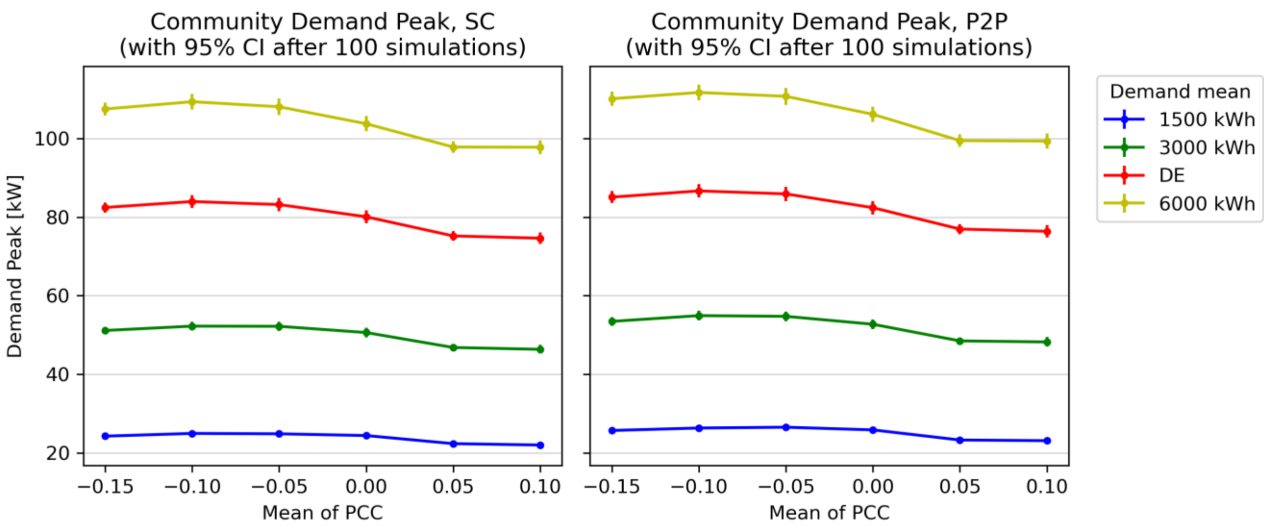

Figure 5.19: Effects of varying the mean of the PCC on the community demand peak, in the case of energy communities with batteries.

The demand peak of the energy community is reported in Figure 8.12 for energy communities without batteries and in Figure 5.19 for energy communities with batteries. The general trend is a decrease of the demand peak with increasing values of the mean of PCC, which was expected since a higher synchronism between PV generation and energy demand generally decreases the energy demand from outside of the community, thus reducing the demand peak.

The percentage differences of the values of demand peak relative to the two furthermost values of the mean of PCC, meaning -0.15 and 0.1, are similar among the different values of average demand considered, suggesting that the decrease in demand peak due to a certain increase in mean of PCC could be the same in percentage regardless of the average yearly demand. However, to confirm this last possibility, more simulations with more datasets and more values of average demand would be needed.

The average (across the different average demands) percentage difference of demand peak relative to the two furthermost values of the mean of PCC is 12.5% for communities without batteries, 9.3% for communities with batteries managed with the SC strategy, and 10.0% for communities with batteries managed with the P2P strategy. These average differences are lower than the average differences observed for other KPIs, but they are significant, nevertheless. The mean of PCC seems to have a slightly higher impact on the demand peak of communities without batteries. This is likely caused by the fact that the demand peaks of energy communities with batteries can be mitigated by the discharge of the batteries, while demand peaks of energy communities without batteries can only change due to a difference in the trends of the demand profiles (or the PV generation profiles, which are however fixed in this section).

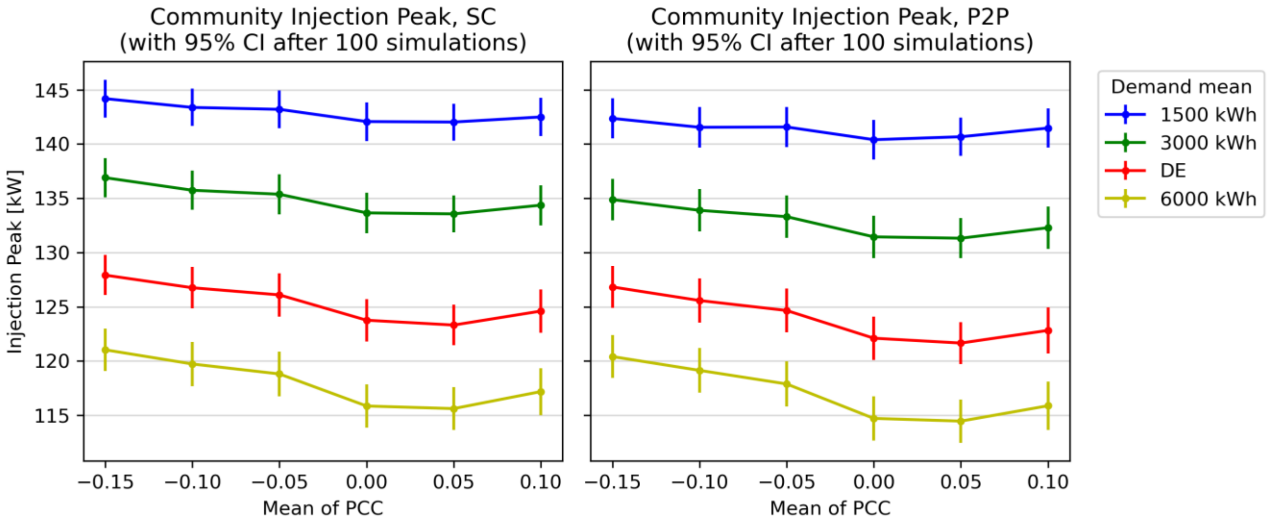

Figure 5.20: Effects of varying the mean of the PCC on the community injection peak, in the case of energy communities with batteries.

Finally, the injection peak of the energy community is reported in Figure 8.12 for energy communities without batteries and in Figure 5.20 for energy communities with batteries. The obtained values of the injection peak present very close means and confidence intervals that often overlap, therefore no particular trends can be drawn from these results, except for the fact that the injection peak does not appear to be strongly influenced by variations of the mean of the PCC.

This is shown by the low average (across the different average demands) percentage differences of the values of injection peak relative to the two furthermost values of the mean of PCC, which are equal to 3% for communities without batteries, 2.2% for communities with batteries managed with the SC strategy and 2.4% for communities with batteries managed with the P2P strategy. The injection peak appears to be slightly more affected by the mean of PCC in case of higher values of average yearly demand but verifying this trend would require performing more simulations to avoid the overlaps of some confidence intervals that are present in these results.

6 Results: effects of batteries on energy communities

Batteries can be installed in energy communities to allow the storage of part of the energy produced by intermittent renewable energy sources, allowing to increase the energy self-consumed by the community [12].

The goal of this section is to investigate how the presence of batteries can affect the performance of energy communities, comparing the KPIs relative to three cases of one energy community with the same demand profiles and PV generation parameters but that either has no batteries, has multiple distributed batteries, or has a single centralized battery.

In section 6.1, the effects of batteries on the whole energy community are analyzed, through its KPIs and the PCC relative to the global demand profile of the whole energy community.

In section 6.2, the effects of distributed batteries on single users are analyzed in more detail, seeing how the PCCs of the single users are affected and how the distribution of the energy community in the PCC-demand plane with normalized demand changes.

6.1 Effects of batteries on the whole community

In this section, the objective is to compare the same energy community in three different cases: without it having batteries, with it having multiple distributed batteries, and with it having a single centralized battery. This is done through the comparison of the KPIs obtained from simulating the three cases in section 6.1.1 and through the study of the effect that batteries have on the global PCC of the energy community in section 6.1.2.

6.1.1 Simulations of an energy community with and without batteries

In this section, the KPIs relative to three cases of the same energy community, meaning the absence of batteries, the presence of distributed batteries, and the presence of a centralized battery, are confronted. In order to do this, 100 simulations are performed for each case, keeping the input data of the different cases equal except for the presence of batteries.

Each energy community simulated in this section is composed of 60 residential users, 30 of which have a PV system installed on their rooftops. The demand profiles utilized in all of the simulations performed in this section are always the same 60, which are the entirety of the demand profiles that form a custom dataset created with the script presented in section 5.1, using as values of the input parameters those relative to the German dataset (which are reported at the beginning of section 5.2). The PV systems considered in these simulations have the same characteristics as those that were simulated in section 5.2 for simulations relative to the custom Italian dataset. This means that the PV generation profile is generated with the method introduced in section 2.2, an inclination of 25° and a South orientation, while the distribution of PV sizes is a normal symmetrical distribution with an average PV power of 6.1 kW (and a minimum power of 1 kW, resulting in a maximum power of 11.2 kW).

Three different cases regarding batteries are then considered and simulated.

In the first case, no batteries are present in the energy community.

In the second case, 15 distributed batteries are present in the energy community, each installed in a different household that also has a PV system. Each battery has a capacity of 10 kWh and is managed according to the “self-consumption” (SC) strategy (explained in section 2.1.1), meaning that the energy stored in each battery is only used by the members of the household in which the battery is installed.

In the third case, a single centralized battery is present, which can be used by the whole energy community. This battery has a capacity of 150 kWh, which is equal to the sum of the capacities of the distributed batteries considered in the second case. In this third case, the PV system installed in the energy community is also only one and centralized, available for the use of the whole energy community. The size of this PV system differs for each simulation and is always equal to the sum of the sizes of PV systems present in the corresponding simulation of the first and second cases. In this way, each simulation (and consequently the sets of 100 simulations considered) has the exact same amount of PV power installed in the energy community for the three compared cases.

Due to the demand profiles and the total size of PV systems being the same for each of the three cases, the overall demand and PV generation of the energy community are the same in all of the timesteps of the simulations of all of the three cases, making the only difference between them the presence of batteries.

100 simulations were then conducted for each of the three cases. The means of the KPIs found from these simulations, along with their 95% confidence intervals, are reported in Figure 6.1, Figure 6.2, and Figure 6.3.

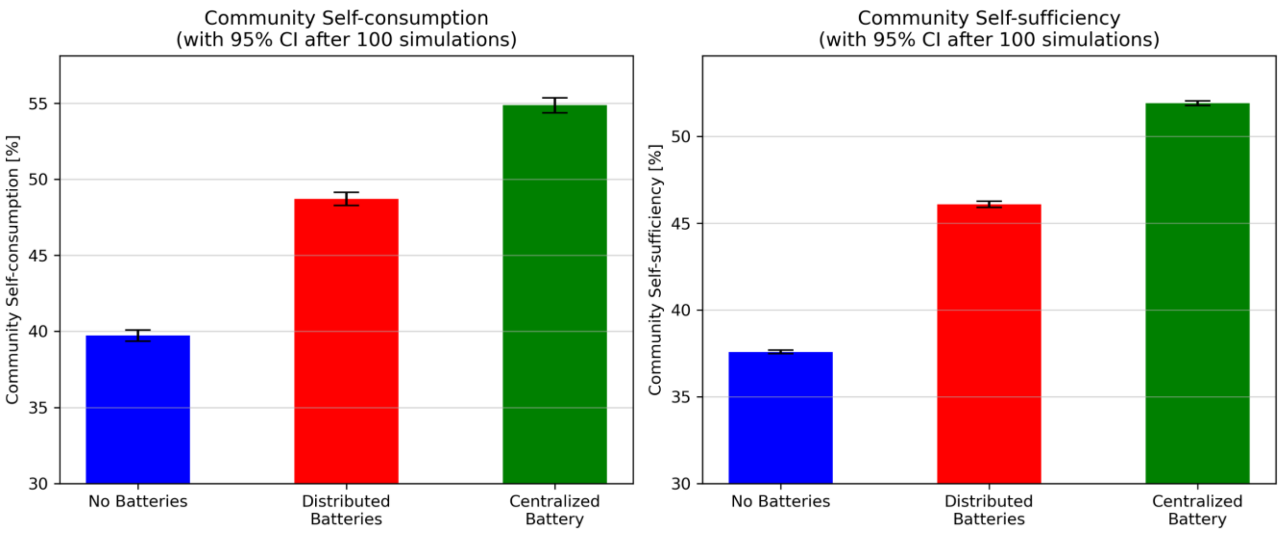

Figure 6.1: Self-sufficiency and self-consumption of the energy community, comparing three cases relative to batteries.

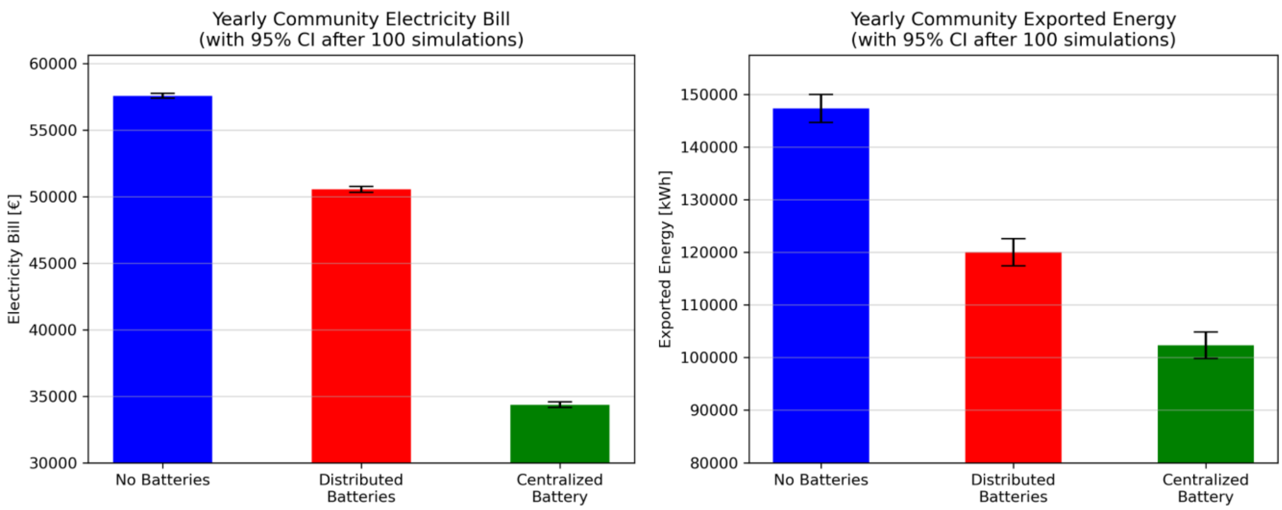

Figure 6.2: Yearly electricity bill and energy exported by the energy community, comparing three cases relative to batteries.

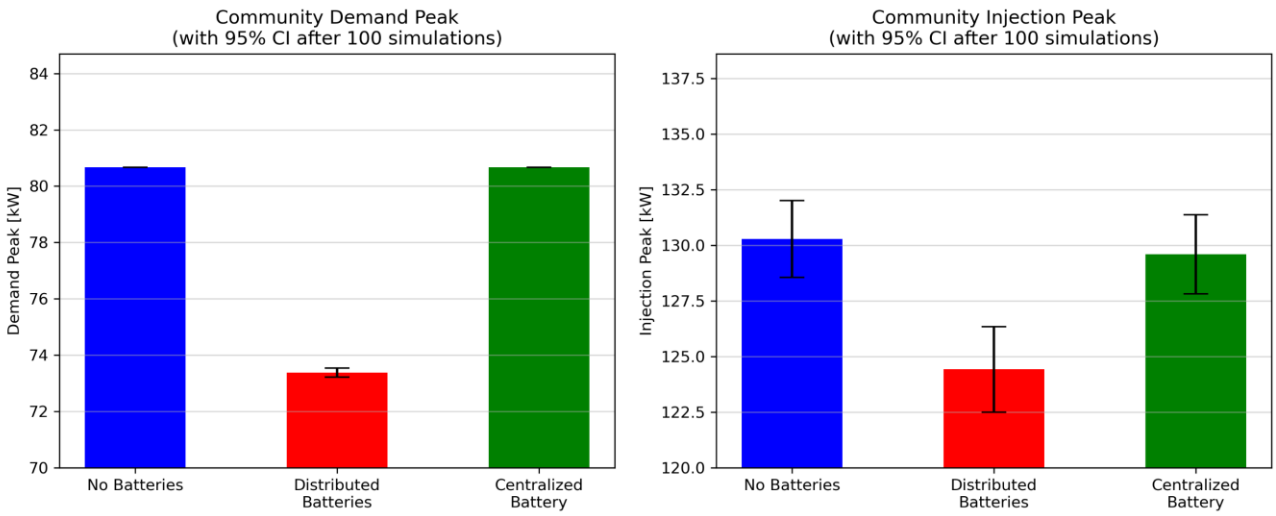

Figure 6.3: Demand peak and injection peak, comparing three cases relative to batteries.

Analyzing the results reported in Figure 6.1, Figure 6.2, and Figure 6.3, it is noticeable how the presence of batteries generally has a good effect on the performance of the simulated energy communities, significantly improving the KPIs both in the case of distributed batteries and of a centralized battery. Moreover, the centralized battery proves to be generally more effective in improving the KPIs of the energy community, producing better values of self-consumption, self-sufficiency, and electricity bill.

Analyzing the results more in detail, it is clear how both the community self-consumption and self-sufficiency (reported in Figure 6.1) increase significantly in the cases of the presence of batteries and in particular increase more in the case of the centralized battery. The cause of these increases is that batteries store part of the surplus energy produced from PV systems, allowing the members of the energy community to self-consume energy that would otherwise be exported to the main grid, thus increasing the amount of energy self-consumed by the energy community (which is at the numerator of both SS and SC).
The centralized battery causes a greater increase in self-consumed energy because it can be used by the whole energy community, while the distributed batteries can only be used by the users on whose premises they are installed. This means that the centralized battery is charged by the energy of the single centralized PV system, storing all of its surplus energy production as long as the battery is not fully charged, while the distributed batteries can only be charged by the PV system of the corresponding households, not allowing the storage of the 15 PV systems belonging to users that have no batteries. Therefore, in the energy community with distributed batteries, it is possible that in certain

moments some batteries are not fully charged, but power produced by PV systems belonging to users without batteries or to users whose batteries are fully charged is still exported from the energy community.
An analogous reasoning can be made regarding the discharge of batteries: the discharge of the centralized battery can serve all of the users of the energy community, while the energy stored in distributed batteries (considering the “SC strategy”, which is what was simulated in this section) can only be used by the users that own those batteries. This means that in the case of distributed batteries, in certain moments it is possible that some batteries have some energy stored which is not used to satisfy the demand of other users in the community that do not own batteries or own fully discharged batteries. On the other hand, the centralized battery is always discharged as long as it has some energy stored and there is energy demand in the community. These different ways of utilizing the same total installed storage capacity make it so that the capacity of the centralized battery is utilized more, performing more charge/discharge cycles and thus allowing for a greater energy self-consumption, which in turn increases SC and SS.

The fact that the increases in SC and SS are due to an increase in self-consumed energy is confirmed by the values of yearly exported energy, reported in Figure 6.2, which are lower for the cases in which the self-consumed energy is higher.

The increase in self-consumed energy also proves to be effective in reducing the yearly electricity bill of the energy community, reported in Figure 6.2, since self-consuming electricity is more economically convenient than exporting it, under the pricing mechanisms defined in section 2.1.2. The yearly electricity bill is then the lowest in the case with the highest self-consumed energy, meaning the energy community with the centralized battery.
Notably, the electricity bill decreases more using a centralized battery compared to distributed batteries (32.0% decrease) than using distributed batteries compared to not using batteries (12.2% decrease). The reason for this significantly lower bill in the case of the centralized battery is that it allows the self-consumption of energy within the community to occur at no cost for all of the members of the community. On the other hand, in the case of the energy community with distributed batteries (managed with the SC strategy) and of the energy community without batteries, there is a net cost (considering the total community bill) for energy that is self-consumed by members of the energy community that do not own the PV system that produced that energy. This is because the profit made by the community members that sell PV energy is lower than the cost incurred by the members that

buy this energy, under the first pricing mechanism illustrated in section 2.1.2, and used for the energy community with distributed batteries and the energy community without batteries.

Finally, Figure 6.3 shows the only two KPIs in which distributed batteries produce better values than the centralized battery: the demand peak and the injection peak. The reason why the distributed batteries are able to decrease these peaks, while the centralized battery has little to no effect, is that, as previously explained, the distributed batteries tend to perform fewer cycles of charge and discharge. This likely causes the distributed batteries to have some remaining charge to mitigate the demand peak when it occurs, discharging to cover part of the energy demand of the users who own them, while the centralized battery is fully discharged in the moment of the demand peak (as confirmed by the fact that the demand peak is equal in the case of the centralized battery and in the case of no batteries). In an analogous way, the distributed batteries have more free capacity than the centralized battery at the moment in which the injection peak occurs, thus reducing the peak more.

In conclusion, the presence of batteries significantly affected the KPIs of the simulated energy community. A single centralized battery appeared to be a better choice compared to multiple distributed batteries, from the point of view of the simulated energy community' KPIs. Indeed, the latter have better values in the case of the centralized battery, with the exception of the injection and demand peaks, whose variation is, though, limited and unlikely to be particularly impactful.

6.1.2 Study of the effect of batteries on the PCC of an energy community

The results of section 6.1.1 show how the presence of batteries improves the KPIs of an energy community thanks to an increase in self-consumed energy. This increase can, intuitively, be tied to an increase in synchronism between energy demand and PV production. The goal of this section is to quantify this increase, analyzing the PCC between the overall demand and the overall PV generation of the energy community simulated in section 6.1.1, in the three cases previously described.

To calculate the overall PCC of the energy community in the first case, the one without batteries, it is sufficient to sum up all the 60 demand profiles of the community to obtain the overall demand profile and then calculate the PCC of the latter with the PV production profile.

To calculate the overall PCC of the energy community in the second and third cases, those with batteries, it is necessary to quantify how batteries alter the overall demand profile of the community. The demand profiles used as input of the simulated energy communities represent the demand of the loads of the various households. However, when considering the presence of batteries, a "new demand" can be defined as the energy demand of the "black box" constituted by the ensemble of a battery and the loads to which it is connected. To better explain this concept, it is necessary to analyze the power flows considered in the simulations for each household that are illustrated in Figure 6.4 (which is taken from [28] and was already shown and explained in section 2.1.1).

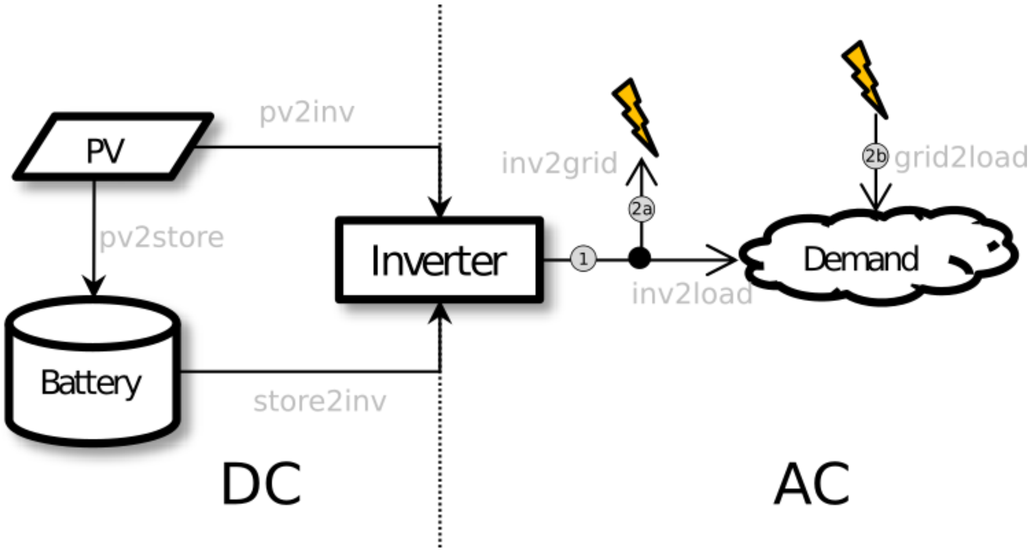

Figure 6.4: Technologies and power flows present in a household with a battery and a PV system [28].

If the battery and the loads (labeled as "Demand" in Figure 6.4) are seen as a black box, the power flows from the battery to the loads are not part of the demand of the black box, which is the so-called "new demand" to define. Only the power flows that enter or exit this black box have to be considered in defining its new demand. The latter can then be defined through equation (6.1), in which the power flows have the names reported in Figure 6.4, $P_{new\ demand}$ is the new demand, η_{inv} is the inverter efficiency (considered equal to 0.94 in this work, as explained in section 2.1.1) and $P_{PV\ system}$ is the PV power generation.

$$P_{new\ demand} = P_{PV\ system} * \eta_{inv} + grid2load - inv2grid \tag{6.1}$$

The rationale behind equation (6.1) is simply an energy balance applied to the control volume constituted by the battery and the loads. The new demand is then defined as the difference between the power flows entering this control volume (i.e. $P_{PV\ system}$, for which the inverter losses are considered through η_{inv}, and grid2load) and the power flow exiting the control volume (i.e. inv2grid). It is important to clarify that the new demand defined through equation (6.1) also includes the battery losses. The choice to include the latter is done to highlight how the presence of batteries slightly increases the energy demand due to part of the energy being lost in batteries. This means that the yearly sum of the profile of a household's new demand will be slightly higher than the yearly sum of the demand profile of the household's loads.

Applying equation (6.1) to the time series of the power flows obtained by the simulation, it is then possible to obtain yearly profiles of the new demands, with an hourly resolution. To find the overall PCC relative to the whole energy community, it is necessary to find the overall new demand of the community, meaning the global demand with its modifications due to the presence of batteries.

In the case of a centralized battery, the simulations allow to directly obtain the power flows inv2grid and grid2load relative to the whole energy community, while $P_{PV\ system}$ can be simply obtained by multiplying the PV production profile relative to 1 kW of peak power for the size of the PV system of the energy community. It is then possible to obtain the overall new demand of the energy community by simply applying equation (6.1) to the overall power flows of the energy community.

In the case of distributed batteries, equation (6.1) is instead applied to each of the households in which a battery is installed, finding the new demand relative to each of those households. The overall new demand of the energy community is then found as the sum of the profiles of new demand relative to the households with batteries and of the profiles of demand relative to the households without batteries. The latter are unchanged and equal to the input demand profiles since the presence of batteries in other households does not affect them.

Once the overall new demand of the energy community is found, the overall PCC relative to the whole community can be found considering the overall new demand and the PV production profile. In this way, the PCC is found for each of the 100 simulations of the two cases with batteries.

The means of the values of PCC obtained for all of the simulations (which are those described in section 6.1.1) of the three cases, along with the relative 95% confidence intervals, are reported in Figure 6.5.

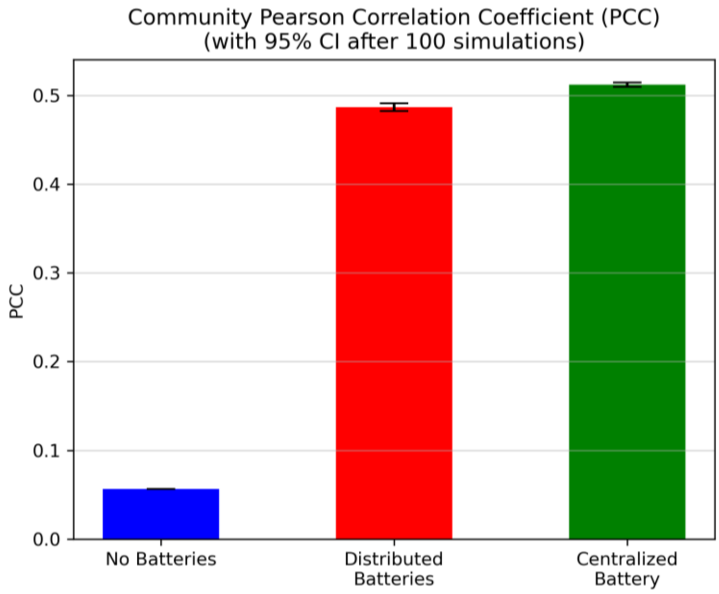

Figure 6.5: overall PCC of the energy community, comparing three cases relative to batteries.

Analyzing the results reported in Figure 6.5, it is clear that batteries do indeed significantly increase the overall PCC of the energy community, thanks to the increased synchronism that the overall new demand has with the PV production, compared to the original overall demand.

Another notable result is that the significative improvement in KPIs produced by the centralized batteries compared to the distributed batteries, shown in section 6.1.1, is not reflected by an equally significative increase in PCC. Indeed, the PCC in the case of a centralized battery is higher than in the case of distributed batteries, but only slightly. To understand the reason for this, it can be useful to consider the average daily profiles of the overall new demand in the cases of centralized and distributed batteries for one example of simulation, reported in Figure 6.6 along with the average daily trend of the total PV generation (with peak power equal to 185.2 kW, which is the one of the simulation whose profiles are reported).

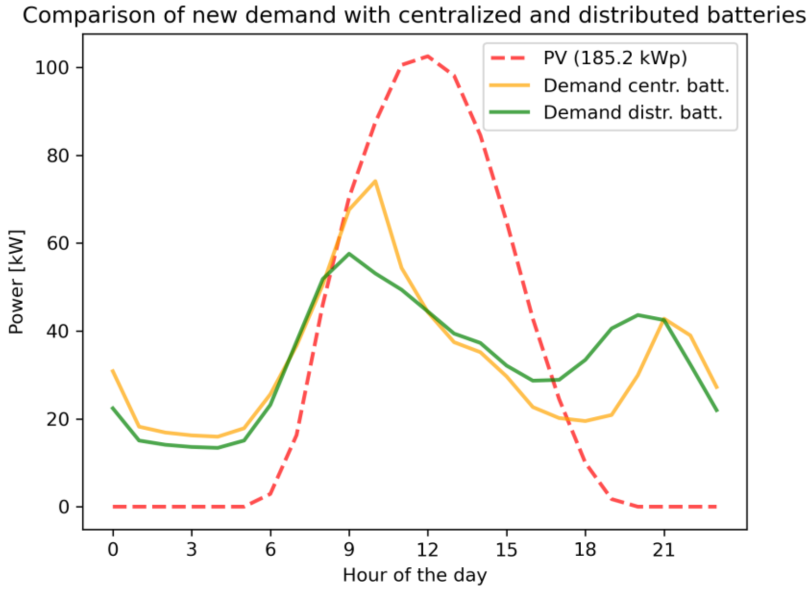

Figure 6.6: Average PV daily generation and average daily trends of the overall new demand for one simulation in the cases of centralized and distributed batteries.

Observing Figure 6.6 it is possible to see how on the average day, the new demand profile relative to a centralized battery causes a greater self-consumption of PV energy (this was also verified numerically considering the hourly values of the average trends reported in Figure 6.6), but the trend of this profile does not differ enough from the other (relative to distributed batteries) to have a much higher PCC. For example, neither of the profiles achieves, on average, a good synchronism with the PV generation during the hours without or with little PV generation. Therefore, a larger battery capacity would likely be needed to increase the PCC further, regardless of the type of configuration of the batteries.

In conclusion, the effect of batteries on the overall PCC of an energy community is to significantly increase it. However, the difference in PCC between the cases of centralized and distributed batteries does not fully reflect the differences in the KPIs of the energy community in these two cases.

6.2 Analysis of the effects of distributed batteries on single households

A further analysis can be conducted for the case of distributed batteries, investigating the effects that they have on the individual households on whose premises the batteries are installed. To do this, one of the simulations described in section 6.1.1, relative to the case of distributed batteries, is analyzed in more detail. The energy community simulated has all of the input data described in section 6.1.1, most notably all of the distributed batteries have the same size, 10 kWh each.

The 15 households in which batteries are present in this simulation are subject to a change in demand due to the presence of batteries. This change can be quantified through the definition of the new demand profiles for each of the users with batteries, using the method explained in section 6.1.2. Therefore, considering the new demand profiles for the households that have batteries, it is possible to represent the effects of batteries on the individual households on the PCC-demand plane. This is done in Figure 6.7, in which the 60 “original” demand profiles of the households’ loads are represented as points (of different colors based on the quadrant) and the effects of batteries are represented as arrows, which start from the coordinates relative to the PCC and yearly sum of the original demand and end in the coordinates relative to the PCC and yearly sum of the new demand.

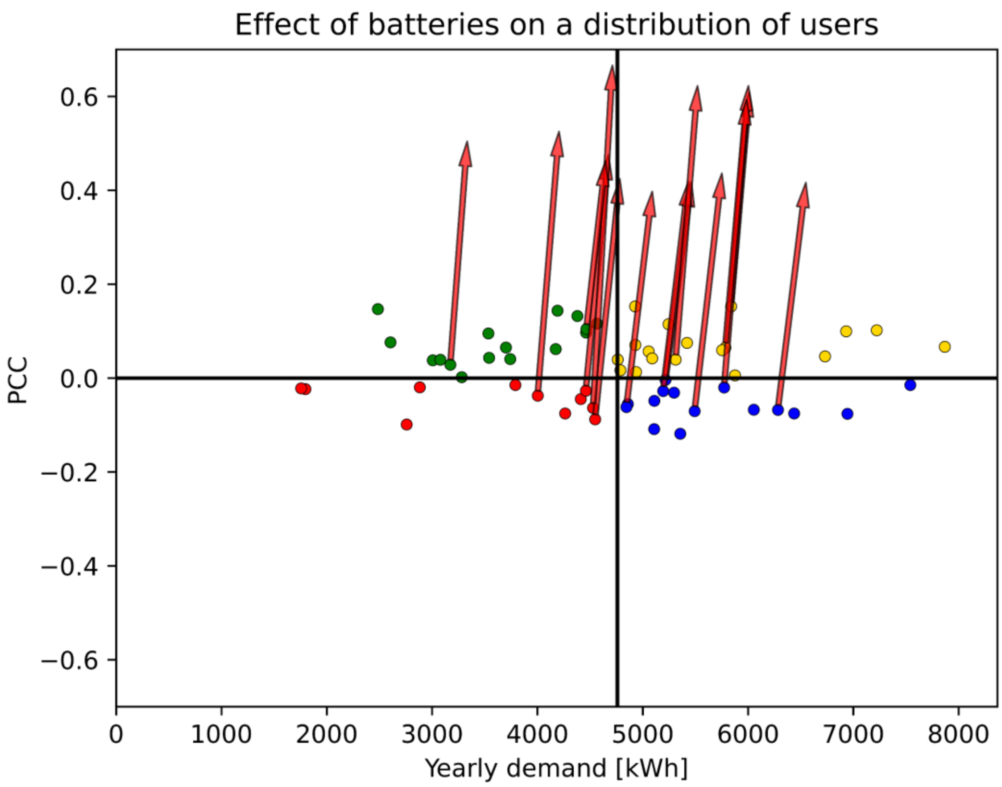

Figure 6.7: Representation of the effect of distributed batteries on users in the PCC-demand plane.

Analyzing Figure 6.7, it is clear how all the households that have installed batteries see a slight increase in yearly demand (due to the presence of battery losses) and a significant increase in PCC. However, the amount by which the PCC increases varies significantly from one household to the other, as shown by the exact values of PCC for the 15 households with batteries reported in Table 6.1 (in which "PCC without batteries" is the PCC of the original demand profile of the loads).

Table 6.1: Values of PCC and peak powers of PV systems of the 15 households with batteries of the considered simulation.

Household number	PCC without batteries	PCC with batteries	PCC increase	PV size [kW_p]
0	0.029	0.515	0.486	4.7
1	-0.088	0.435	0.523	9.6
2	0.153	0.620	0.467	3.3
3	-0.027	0.486	0.513	6.6
4	-0.064	0.677	0.740	2.6
5	-0.020	0.633	0.653	5.1
6	-0.004	0.429	0.433	10.2
7	0.104	0.472	0.368	8.0
8	-0.028	0.430	0.458	8.8
9	0.039	0.633	0.593	4.4
10	-0.038	0.536	0.573	4.8
11	-0.071	0.447	0.517	9.6
12	0.065	0.603	0.538	4.7
13	-0.068	0.427	0.495	7.3
14	-0.062	0.408	0.470	10.2

The data contained in Table 6.1 shows how in this example the increase in the PCC of a household due to the presence of batteries ranges from a minimum of 0.368 (in the case of household number 7) to a maximum of 0.740 (in the case of household number 4). Analyzing the average daily trends of the new demand profiles of these two households can allow to better understand the reasons for this difference. These trends are reported in Figure 6.8 and Figure 6.9, together with the average daily trends of the original demands without batteries and of the PV generation of the PV systems installed in these households, with their peak power relative to the represented households in the analyzed simulation.

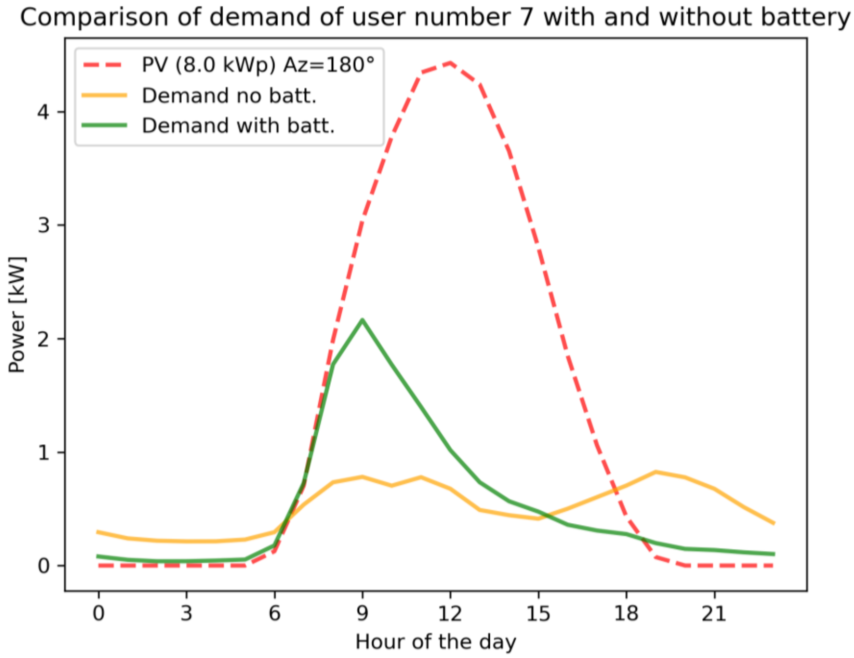

Figure 6.8: Average daily trends of demand with and without batteries and of PV generation relative to the household (number 7) whose PCC had the lowest increase due to batteries.

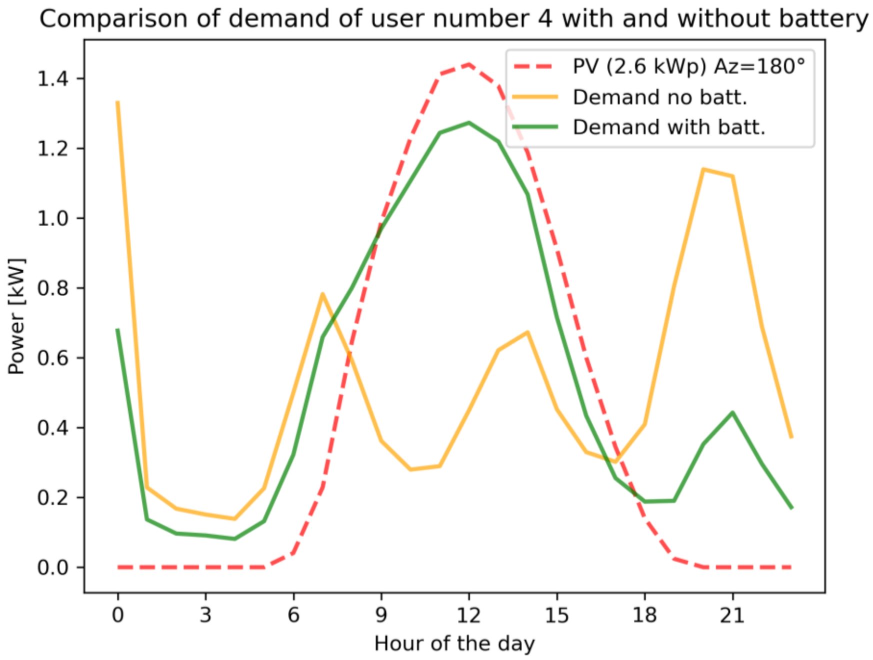

Figure 6.9: Average daily trends of demand with and without batteries and of PV generation relative to the household (number 4) whose PCC had the highest increase due to batteries.

The first thing that can be noticed looking at Figure 6.8 and Figure 6.9 is that in both of the represented cases the average trend of the new demand profile (with batteries) follows the average trend of the

PV generation more closely than the average trend of the original demand profile (without batteries), as expected since in both cases the presence of batteries increases the PCC.
However, it is clear why household number 4, represented in Figure 6.9, has a higher PCC than household number 7, represented in Figure 6.8: on average, the new demand of the former follows quite closely the PV generation for most of the hours of sunlight, while the new demand of the latter, on average, follows the PV generation closely only for the first hours of sunlight. The reason for this is that the battery installed in household 4 generally has space to store most of the surplus energy produced by the PV system, while the battery installed in household 7 on average is fully charged after a few hours of sunlight and thus cannot store most of the PV energy surplus. This occurs because the two households have equal battery capacities (10 kWh each), while the peak powers of the PV systems installed in the two houses are very different: 2.6 kW for household 4 and 8.0 kW for household 7. Therefore, the battery installed in household 4 appears to be oversized compared to the size of the PV system, while the battery installed in household 7 appears to be undersized.

Comparing the increases of PCC (due to the presence of batteries) and the sizes of PV systems, both reported in Table 6.1, the general trend seems to be that the greatest increases in PCC tend to happen in households with a low peak power of PV (such as households 4, 5, 9, 10), while the lowest increases tend to occur in households with high peak power of PV (such as households 6, 7, 8, 14). The reason for this trend is what was explained for households 4 and 7: since all of the batteries considered in the simulation have equal capacity, households with PV systems of lower sizes tend to have oversized batteries, which generally have room to store most of the PV surplus, while households with PV systems of higher sizes tend to have undersized batteries, which are often fully charged during times of PV surplus.
A notable exception to this trend is constituted by household 2, which has a low peak power of the PV system (3.3 kW) but presents an increase of PCC due to the presence of batteries that is relatively low compared to other households. The reason for this is the relatively high PCC that this household already had without batteries (0.153), which makes so that the very high PCC reached with batteries (0.620, among the highest reached by the analyzed households) does not differ so much from the initial value of PCC. This is most likely due to the fact that going above a certain value of PCC installing batteries is difficult, for example since there are periods of the year in which the daily PV production is quite low, and its surplus may not be enough to satisfy the demand of the household's loads during the hours without sunlight, in particular if the size of the PV system is quite low, as in the case of household 2.

In conclusion, in the example of the energy community simulated, the distributed batteries produced slight increases in the yearly demand and high increases in the PCC of the households in which they were installed. Batteries that were oversized compared to the size of the PV systems tended to produce higher increases in PCC. However, it is important to keep in mind that installing an oversized battery is more costly and a part of the battery's capacity may be utilized only for a low number of hours in a year. Therefore, achieving higher values of PCC should not be the only objective when sizing the distributed batteries, which should be designed taking into account various factors, such as their initial cost and the size of the coupled PV system.

7 Conclusions and future work

This thesis analyzed energy communities through the characterization of demand profiles of users belonging to energy communities considering their synchronism with PV generation and their yearly demand, and through simulations performed with an open-source Python-based program adapted from the literature.

In section 3, simulations were performed for four different scenarios, with each having all of the demand profiles in one quadrant of the PCC-demand plane. The results of these simulations differed significantly between the scenarios, showing a possible relevance of the PCC-demand plane as a tool to represent the demand profiles of energy communities in a way that could help to partially predict some effects that the demand profiles may have on the communities' KPIs.

In section 4, the effects that the inclination and orientation of PV systems can have on the distribution of demand profiles in the PCC-demand plane and on the KPIs of energy communities were studied. The inclination of PV systems was found to produce some slight changes in the values of normalized demand but no relevant changes in the values of PCC of the great majority of the demand profiles considered. In line with these limited changes in the distribution of demand profiles in the PCC-demand plane with normalized demand, the changes in KPIs of energy communities produced by different inclinations of PV systems were also found to be very limited.
The orientation of PV systems was found to have more significant impacts than the inclination on the values of normalized demand and PCC of the demand profiles considered and on the KPIs of energy communities. The West orientation was found to be the one that produced the most significant changes in the distribution of values of PCC, tending to increase the PCC of profiles that had negative PCC in the case of South orientation and to decrease the PCC of profiles that had positive PCC in case of South orientation. Considering the KPIs of the energy communities, the South orientation proved to be the best even when performing simulations with only demand profiles whose PCC increased with orientations different from South, suggesting that the average increase of PCC that these orientations can produce is not enough to compensate the drawback of the decreased PV yearly energy production that they cause.

In section 5, a tool for creating new custom datasets of demand profiles with given characteristics with regard to yearly demand and PCC was presented and utilized.

Simulations were conducted with two different datasets of demand profiles that presented similar values of four characterizing parameters (their averages and standard deviations of yearly demand and PCC). These simulations produced similar KPIs, suggesting that the four characterizing parameters could be a possibly effective way to identify demand datasets that could produce similar performances in energy communities using them as inputs.
Then, the impacts on the KPIs of energy communities caused by the variations of three of these four characterizing parameters were studied.
Varying the standard deviation of the yearly demand produced very limited changes in the KPIs (in particular in the case of the absence of batteries), with the exception of the demand peak, which showed a small but non-negligible increase with the increase of the standard deviation. The results suggested a limited relevance of the standard deviation of the yearly demand in determining the performances of energy communities.
Varying the mean of the yearly demand produced significant changes in the KPIs, with the most relevant ones being a significant increase in community self-consumption and a decrease in self-sufficiency with increasing average demand. Batteries proved to be more effective in improving self-consumption and self-sufficiency, compared to the absence of batteries, for lower values of demand, due to the higher availability of PV surplus energy to store. The P2P strategy for battery management produced significantly better values of self-consumption and self-sufficiency than the SC strategy for low values of average demand, while the two strategies produced similar results for high values of average demand.
The mean of the PCC was also found to significantly impact the KPIs, in particular, those of energy communities without batteries were affected the most. Both the self-consumption and self-sufficiency were found to significantly increase with increasing mean of PCC, showing similar increases, in percentage, for the different values of average yearly demand considered. This is a relevant result because it suggests that the increase in self-consumption and self-sufficiency due to a certain increase in the mean of PCC could be the same in percentage regardless of the average yearly demand. However, to confirm this last possibility, more simulations with more datasets and more values of average demand would be needed.

In section 6, the effects that batteries have on energy communities were analyzed in more detail, considering the cases of multiple distributed batteries and of a single centralized battery. It was found that the presence of batteries significantly affected the KPIs of the simulated example of energy community, improving them compared to the absence of batteries. A single centralized battery produced significantly higher values of self-consumption and self-sufficiency and significantly lower

values of electricity bill compared to distributed batteries, with the latter having the only advantage of slightly decreasing the demand and injection peaks. The effect that batteries have on the PCC of the simulated energy community was shown to be to significantly increase it.
Considering distributed batteries, they were shown to significantly increase the PCC (with oversized batteries tending to produce the highest increases in PCC) and slightly increase the yearly demand (due to battery losses) of the households in which they are installed.

Generally speaking, this work showed that the analysis of the PCC and normalized demand of demand profiles, through the PCC-demand plane, is a potentially interesting methodology to preliminarily investigate the characteristics and performances of energy communities.
However, this methodology needs to be investigated and tested further to definitely prove its effectiveness and to generalize its applications. The results obtained and presented in this work are inevitably limited by the impossibility of performing a larger number of simulations with more diverse settings and input data, due to the lack of computational power and the significant time required by simulations. Indeed, more, and more diverse, simulations would be required to definitively verify and generalize the obtained results.

For example, the analyses and simulations conducted in this work could be repeated using different datasets of demand profiles and different parameters of PV systems and batteries, to investigate if the results found in this work are valid in general or not. Using real demand profiles of owners of PV systems together with the associated real PV generation profiles would be preferable, to increase the realism of the simulation results.
Performing more than 100 simulations for each case considered could also be useful for narrowing the confidence intervals of the obtained results.
Moreover, demand profiles could be studied also through means different from the PCC-demand plane, for example by clustering them to find some typologies of demand profiles.
The implementation of different pricing mechanisms, trying to follow more closely the real pricing mechanisms currently adopted for energy communities, could be a useful addition to obtain more realistic values of electricity bills, enabling more detailed economic analyses.
Some of the simulations performed in this work could also be repeated considering renewable power generation from wind power systems instead of PV systems.
Finally, another interesting factor to introduce in the simulations of energy communities could be the demand side management, which could allow to alter the synchronism of the demand profiles of households without necessarily installing batteries.

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8 Appendix

8.1 Additional results on the effects of orientation on the KPIs of energy communities using only the demand profiles whose PCCs increased

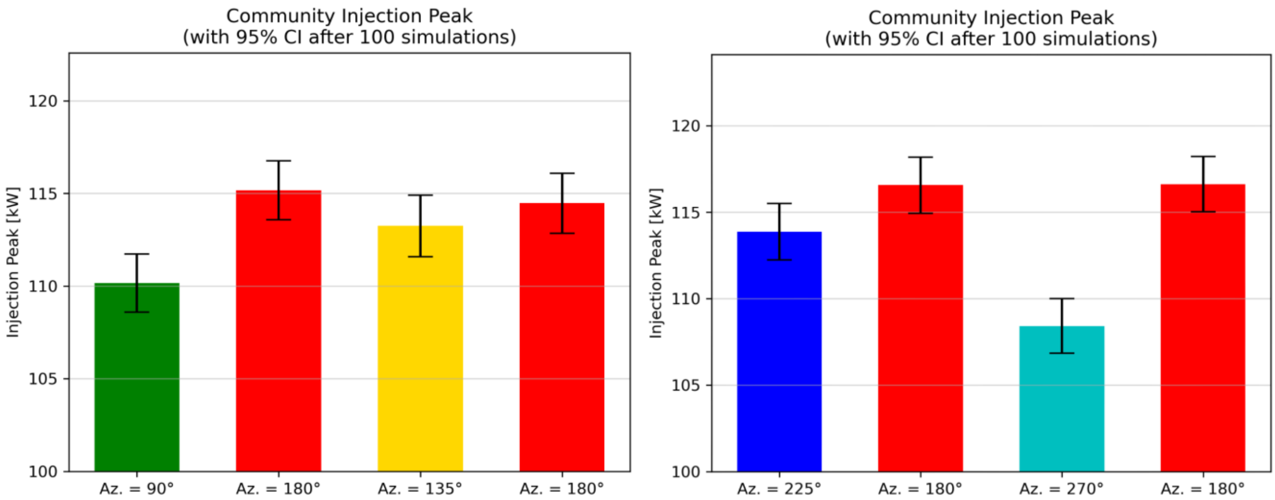

Figure 8.1: Comparisons of injection peak for different PV orientations for the four created datasets with demand profiles whose PCC increased with an orientation different from South.

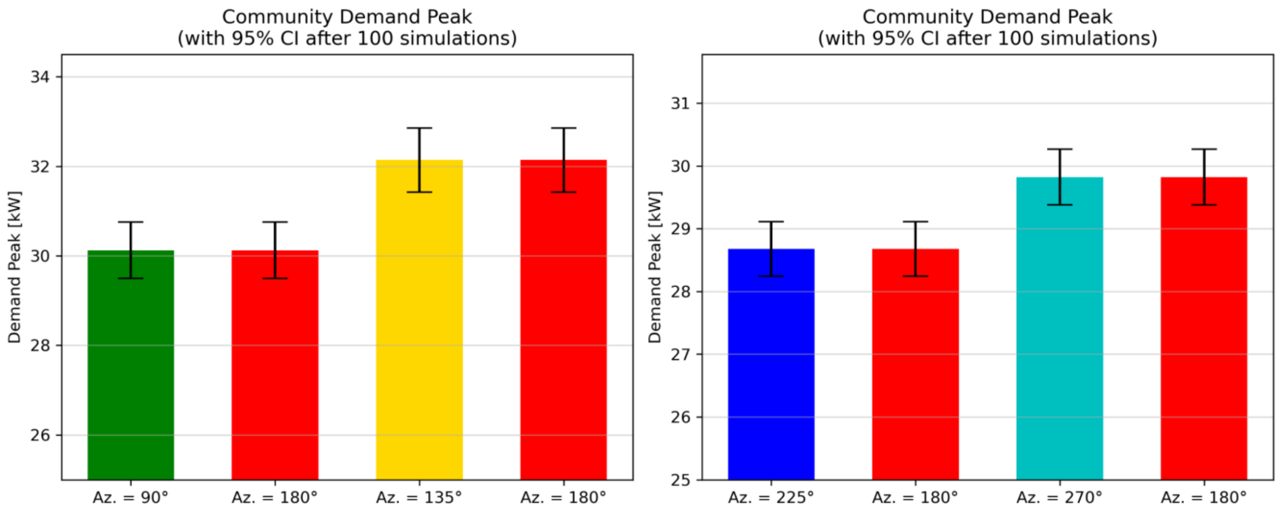

Figure 8.2: Comparisons of demand peak for different PV orientations for the four created datasets with demand profiles whose PCC increased with an orientation different from South.

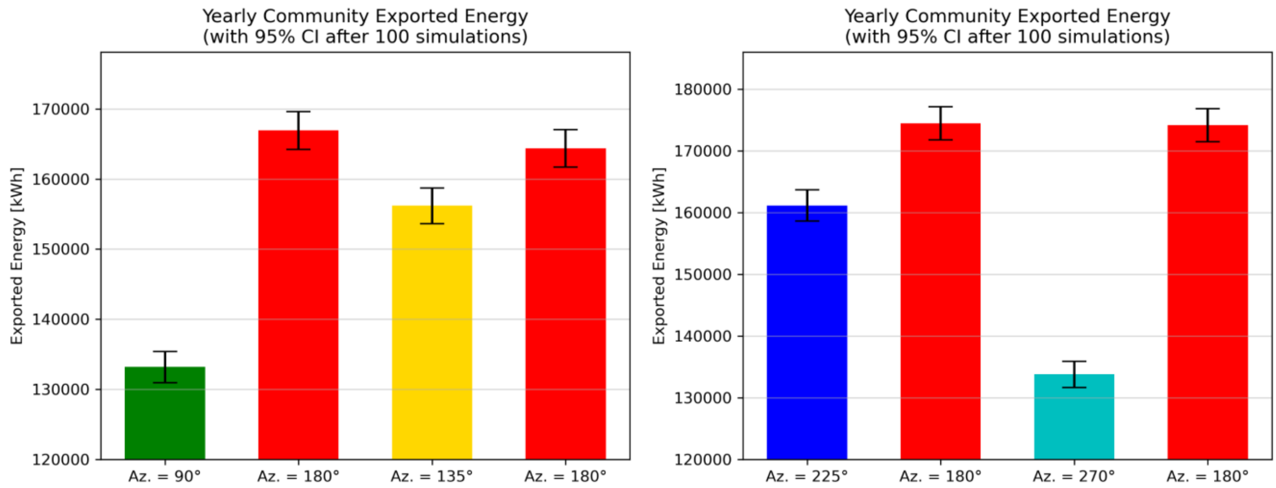

Figure 8.3: Comparisons of yearly exported energy for different PV orientations for the four created datasets with demand profiles whose PCC increased with an orientation different from South.

8.2 Effects of varying the parameters of custom demand datasets in energy communities without batteries

8.2.1 Effects of varying the mean of yearly demand in energy communities without batteries

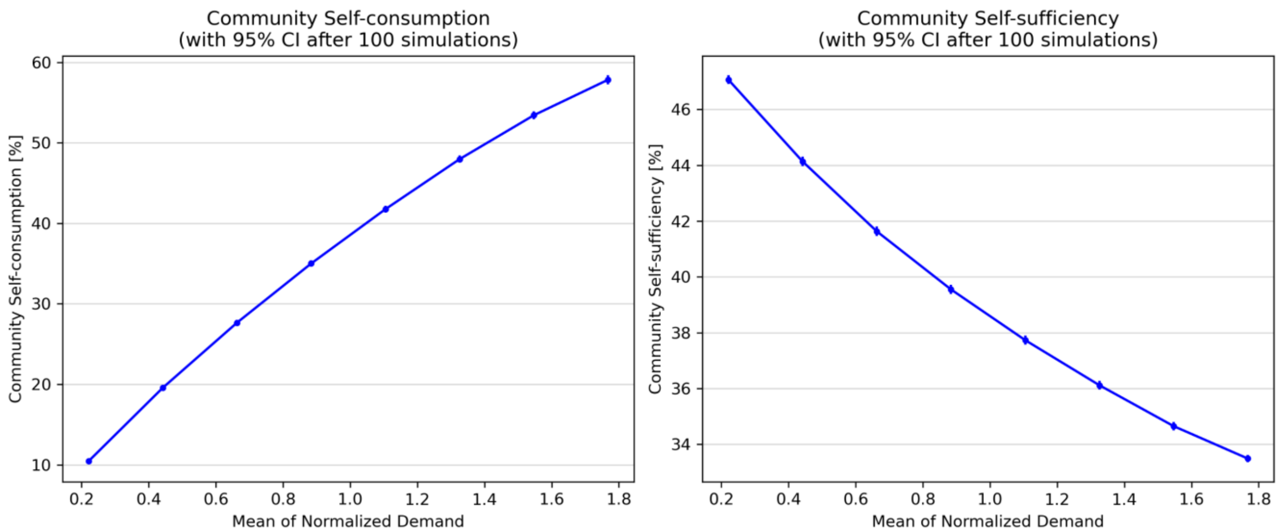

Figure 8.4: Effects of varying the mean of the yearly demand on the community self-consumption and self-sufficiency, in the case of energy communities without batteries.

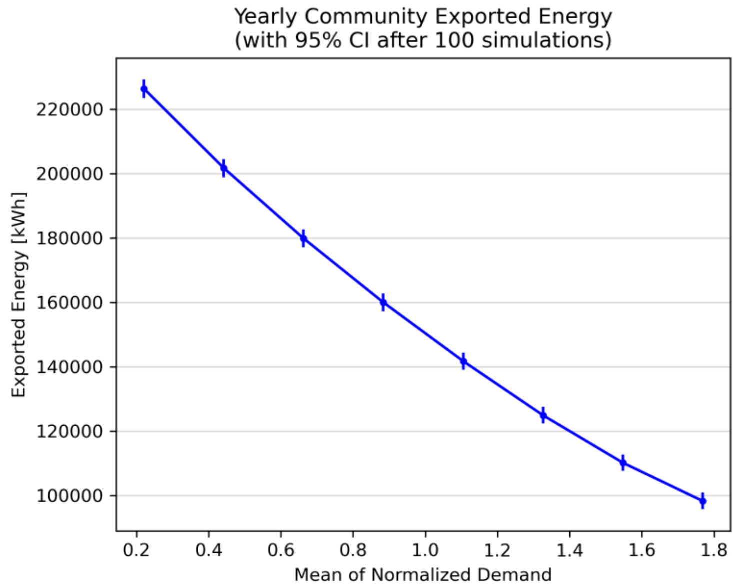

Figure 8.5: Effects of varying the mean of the yearly demand on the yearly energy exported by the community, in the case of energy communities without batteries.

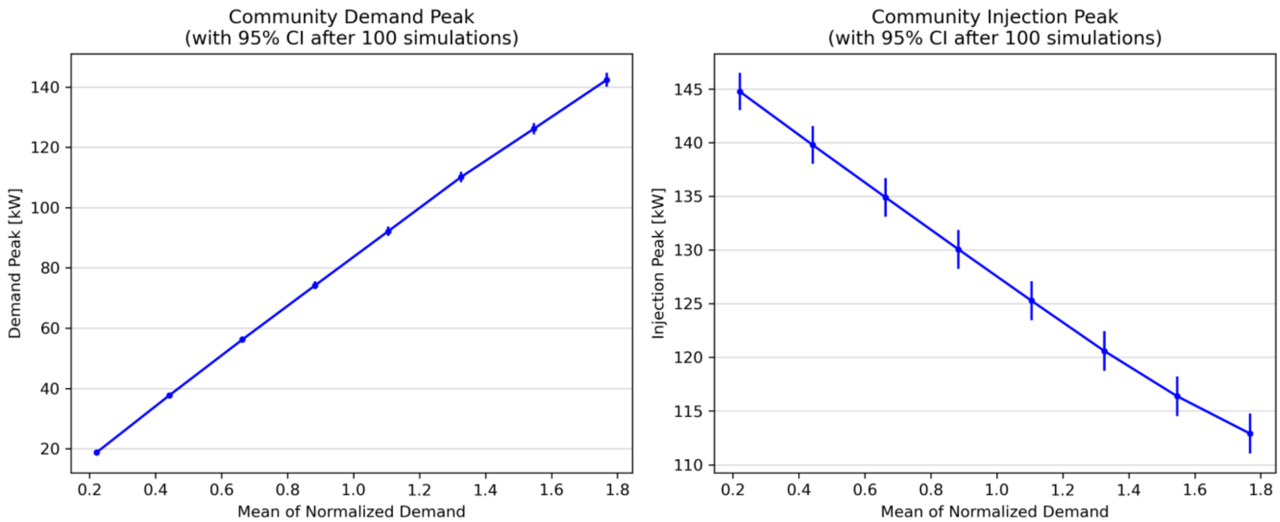

Figure 8.6: Effects of varying the mean of the yearly demand on the community demand peak and injection peak, in the case of energy communities without batteries.

8.2.2 Effects of varying the standard deviation of yearly demand in energy communities without batteries

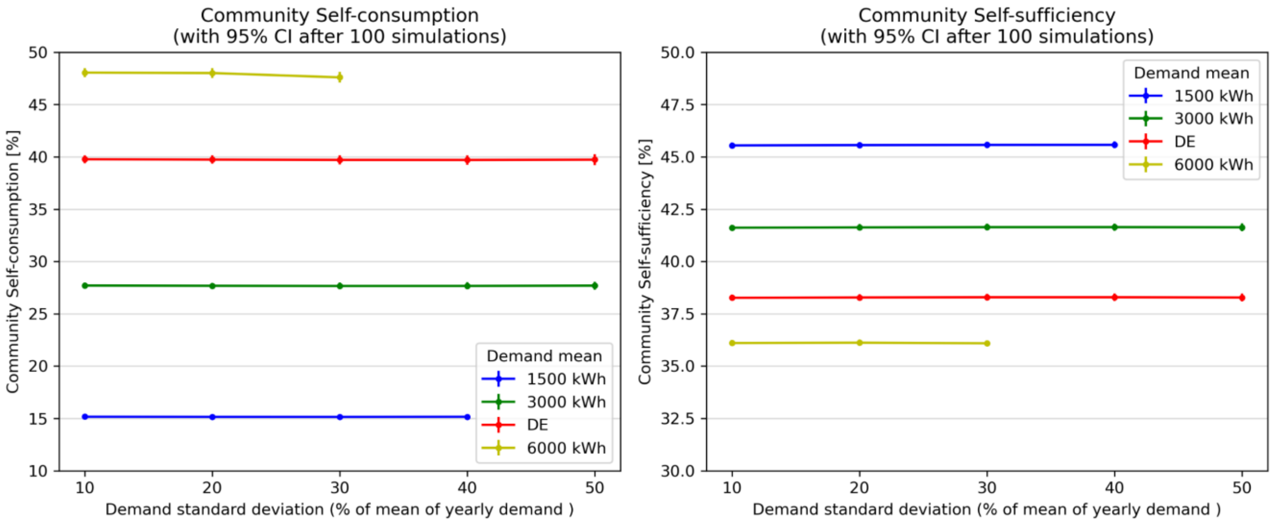

Figure 8.7: Effects of varying the standard deviation of the yearly demand on the community self-consumption and self-sufficiency, in the case of energy communities without batteries.

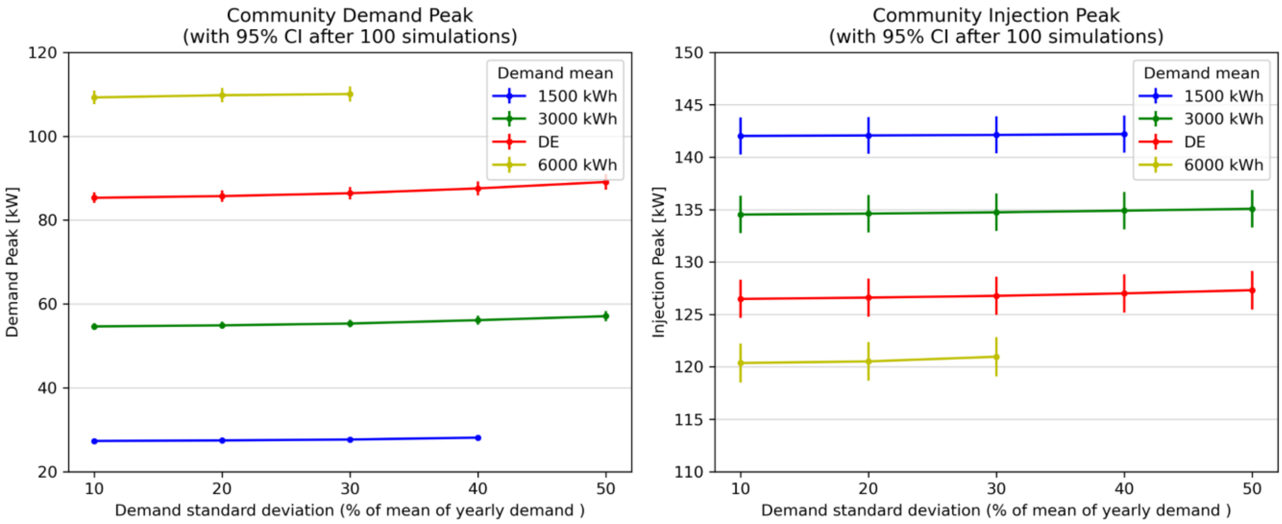

Figure 8.8: Effects of varying the standard deviation of the yearly demand on the community demand peak and injection peak, in the case of energy communities without batteries.

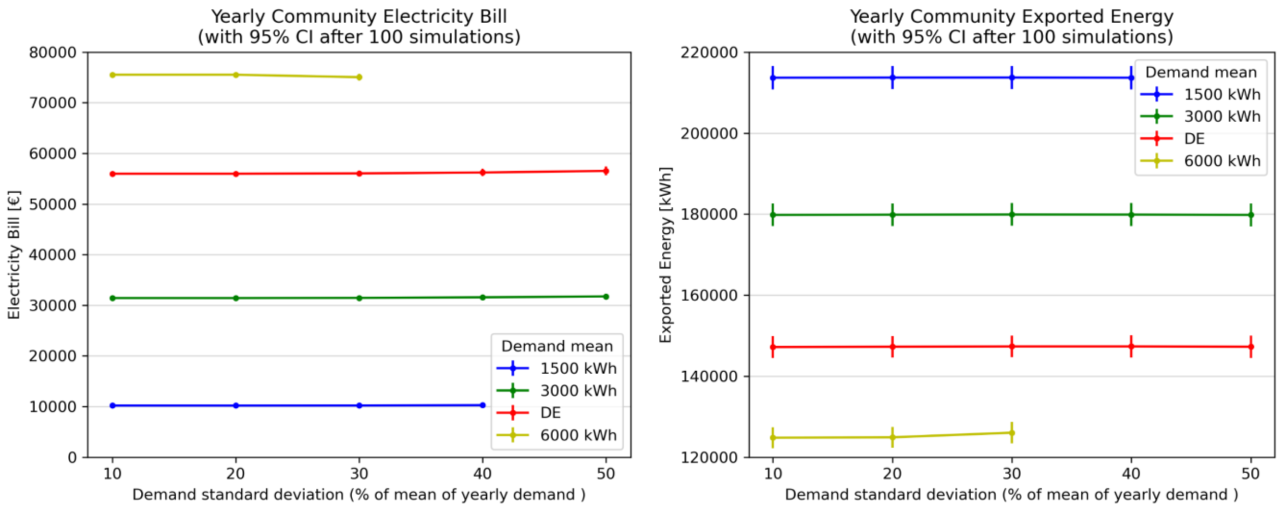

Figure 8.9: Effects of varying the standard deviation of the yearly demand on the yearly electricity bill and energy exported by the community, in the case of energy communities without batteries.

8.2.3 Effects of varying the mean of PCC in energy communities without batteries

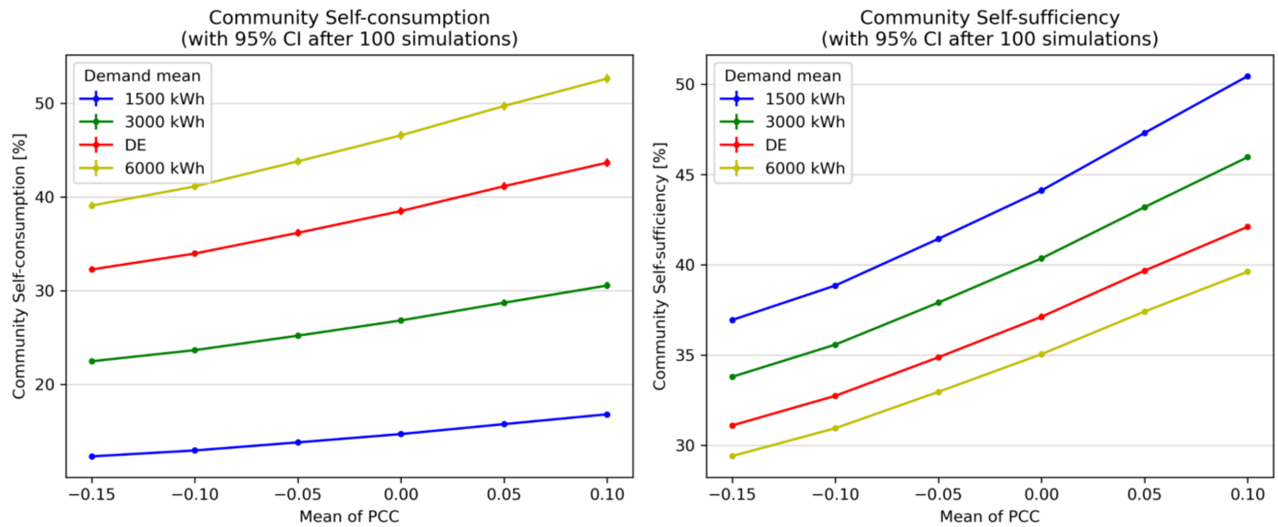

Figure 8.10: Effects of varying the mean of the PCC on the community self-consumption and self-sufficiency, in the case of energy communities without batteries.

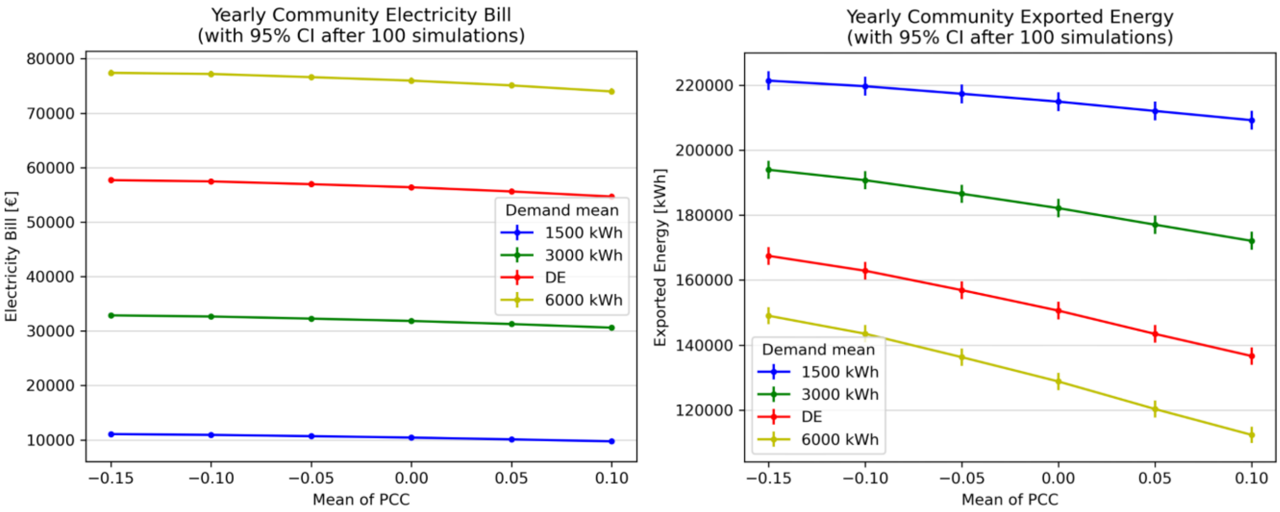

Figure 8.11: Effects of varying the mean of the PCC on the yearly electricity bill and energy exported by the community, in the case of energy communities without batteries.

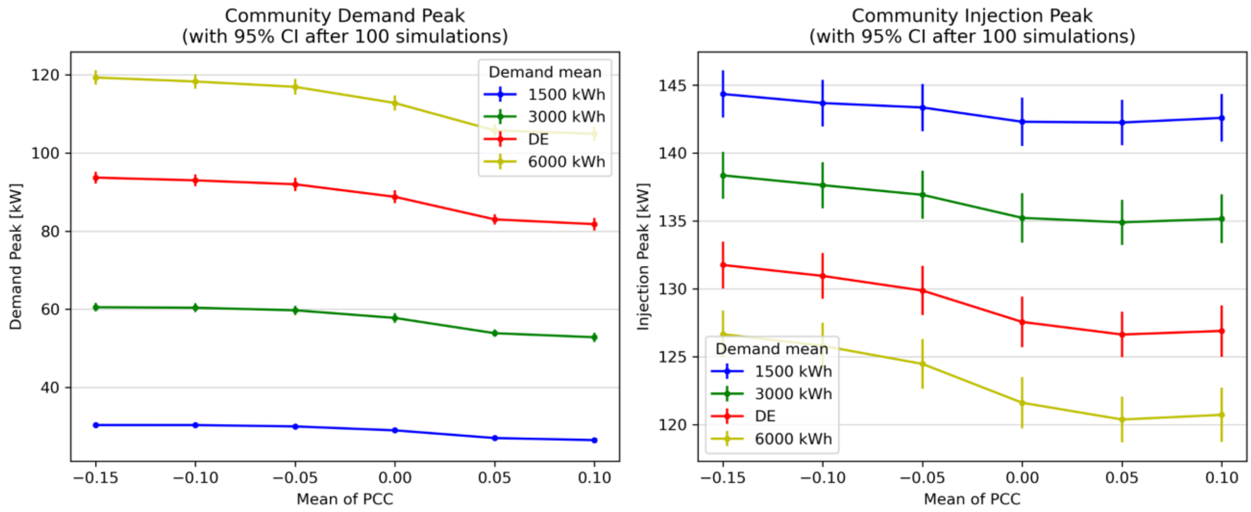

Figure 8.12: Effects of varying the mean of the PCC on the community demand peak and injection peak, in the case of energy communities without batteries.