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RESIDENTIAL ENERGY CONSUMPTION ACROSS SOCIOECONOMIC BACKGROUNDS: ADAPTING TO DISRUPTIVE EVENTS AND DER INTEGRATION IN POWER NETWORKS

TESIS PARA OPTAR AL GRADO DE
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MIGUEL ALEXIS SÁNCHEZ LÓPEZ

PROFESOR GUÍA:
RODRIGO MORENO VIEYRA
PROFESOR GUÍA 2:
EDUARDO MARTÍNEZ CESEÑA
PROFESOR GUÍA 3:
ROBIN PREECE

MIEMBROS DE LA COMISIÓN:
PATRICIO MENDOZA
FERNANDO ORDÓÑEZ
PIERLUIGI MANCARELLA

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RESUMEN DE LA TESIS PARA OPTAR
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POR: MIGUEL ALEXIS SÁNCHEZ LÓPEZ
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Esta tesis examina la demanda de electricidad residencial y los impactos de factores socioeconómicos. A corto plazo, se analiza cómo los clientes residenciales se adaptan a eventos disruptivos, como fue la pandemia de COVID-19, y a largo plazo, la integración de Recursos Energéticos Distribuidos (DER) en las redes eléctricas. Se exploran las disparidades en el consumo eléctrico entre grupos socioeconómicos, utilizando datos de 230,000 medidores en Santiago, Chile. Los resultados muestran que, durante la pandemia, los hogares más acomodados aumentaron su consumo hasta tres veces más que los menos favorecidos, influenciados también por la temperatura.

A largo plazo, se estudia la integración de DER, como la energía solar y el almacenamiento en baterías, y sus consecuencias en la desigualdad energética, ya que su despliegue tiende a ser desigual. Se examinan esquemas tarifarios que buscan una integración equitativa de los DER, destacando mecanismos que tienden a distribuciones de costos más equitativas. Al modelar el equilibrio entre inversiones en DER y redes de distribución, la investigación resalta la importancia de la tarifa de red para asignar los costos de manera equitativa. La tesis concluye subrayando la necesidad de políticas de justicia energética consideren tanto factores económicos como patrones de comportamiento.

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This thesis examines residential electricity demand and the impacts of socioeconomic factors. In the short term, it analyses how residential customers adapt to disruptive events, such as the COVID-19 pandemic, and in the long term, it explores the integration of Distributed Energy Resources (DER) into electric grids. Disparities in electricity consumption between socioeconomic groups are explored using data from 230,000 smart meters in Santiago, Chile. The results show that during the pandemic, wealthier households increased their consumption up to three times more than less privileged households, with temperature also influencing this behaviour.

In the long term, the integration of DER, such as solar energy and battery storage, is studied, along with its consequences for energy inequality, as their deployment tends to be uneven. Tariff schemes that seek to promote equitable DER integration are examined, highlighting mechanisms that lead to more equitable cost distribution. By modelling the balance between DER investments and distribution networks, the research emphasizes the importance of grid tariffs in fairly allocating costs.

The thesis concludes by stressing the need for energy justice policies that consider both economic factors and behavioural patterns, to ensure an inclusive and equitable energy transition for all socioeconomic groups.

Para mis padres y mis hermanas
Para mis seres queridos que han partido a la eternidad
Para las víctimas del COVID-19

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Nomenclature

Sets

$\mathcal{I}$ Set of users

$\mathcal{K}$ Set of hyperplanes to approximate P-Q feasible area of transmission lines

$\mathcal{L}$ Set of lines

$\mathcal{N}$ Set of nodes

$\mathcal{T}$ Set of times

Parameters

A_i^B Annuity of residential BESS of user i [$/kW]

A_i^s Annuity of residential PV pannels of user i [$/kW]

A_l Annuity of line l [$/kW]

C_t^A Marginal cost of active energy at time t [$/kWh]

C_t^R Marginal cost of reactive energy at time t [$/kWh]

$D_{i,t}^A$ Static active demand of user i at time t [kW]

$D_{i,t}^R$ Static reactive demand of user i at time t [kVAr]

H_i BESS capacity in terms of the inverter capacity [h]

$I_{n,l}$ Matrix indicating if line l enters to node n {1,0}

K_i Budget to invest in DER assets of user i [$]

$N_{i,n}$ Matrix indicating if user i is connected in node n {1,0}

$O_{n,l}$ Matrix indicating if line l depart from node n {1,0}

R_l Resistance of line l [Ω]

X_l Reactance of line l [Ω]

α_k Linearization parameter for P-Q feasible area

Δt Time step [h]

η_i^B BESS charging efficiency [p.u.]

$\psi_{i,t}^s$ Solar PV generation rate of user i at time t [p.u.]

Prosumer variables

$e_{i,t}^{ch}$ Charging power to BESS of user i at time t [kW]

$e_{i,t}^{ds}$ Discharging power from BESS of user i at time t [kW]

$e_{i,t}^{in}$ Active power injections by user i at time t [kW]

$e_{i,t}^{s}$ Solar PV active generation by user i at time t [kW]

$e_{i,t}^{w}$ Active withdrawals by user i at time t [kW]

p_i^B BESS inverter capacity of user i [MW]

p_i^s Solar PV installed capacity by user i [kW]

$r_{i,t}^{in}$ Reactive injections by user i at time t [kVAr]

$r_{i,t}^{w}$ Reactive power withdrawals by user i at time t [kVAr]

$SoC_{i,t}$ State of charge of BESS of user i at time t [kWh]

$\psi_{i,t}^B$ Battery usage rate of user i at time t [p.u.]

Distribution system variables

$d_{n,t}^A$ Active demand in node n at time t [kW]

$d_{n,t}^R$ Reactive demand in node n at time t [kWAr]

$i_{l,t}$ Square of the current in the line l at time t $[A^2]$

p_t^w Systemic active withdrawals at time t [kW]

p_t^{in} Systemic active injections at time t [kW]

$p_{l,t}$ Active power in the line l at time t [kW]

q_t^w Systemic reactive withdrawals at time t [KVAr]

q_t^{in} Systemic reactive injections at time t [kVAr]

$q_{l,t}$ Reactive power in the line l at time t [kVAr]

s_l Power capacity of line l [MW]

$v_{n,t}$ Square of the voltage in node n at time t $[V^2]$

Tariff schemes

κ Reduction factor for distribution tariff applied to energy injections

$\tau_{i,t}^{D}$ Distribution tariff for user i at time t [\$/MWh,\$/MW]

$\tau_{i,t}^{E}$ Energy tariff for user i at time t [\$/MWh]

$\tau_{i,t}^{R}$ Reactive energy tariff for user i at time t [\$/MVAr h]

φ Reduction factor for energy tariff applied to energy injections

Chapter 1

Introduction

1.1 Motivations

This thesis is motivated by the need to understand how residential electricity demand is prepared for the energy transition in relation to socioeconomic factors. Before delving further into these topics, it is worth providing some initial definitions.

First, the energy transition refers to the transformation of the global energy sector from fossil-based to zero-carbon sources by the second half of this century, with the aim of reducing energy-related CO2 emissions to mitigate climate change and limit global temperature rise to within 1.5°C above pre-industrial levels [1]. This transition implies a technological evolution, where distributed energy resources (DER), such as distributed solar photovoltaic systems, are expected to play an increasingly significant role in the energy mix [2].

Second, socioeconomic factors are related to economic capabilities, education, and other socio-demographic characteristics, such as the age of household members and their lifestyle [3]. Mathematically, socioeconomic factors can be understood as a multidimensional vector that describes a customer or a group of customers.

Thus, an analysis of how residential electricity demand is prepared for the energy transition according to socioeconomic factors can be divided into two horizons. First, it is important to observe how these differences manifest in the short term (i.e., in the current technological scenario). Second, it is essential to analyse how these differences are projected in the medium and long term (i.e., once the energy transition is complete).

Following this logic, this section (and the research) is structured as follows. Initially, the discussion focuses on how socioeconomic factors may impact electricity demand in current times and how prepared the demand is to adapt to disruptive events, where customers face significant stress in a short period of time. Consequently, from a socioeconomic perspective, different customers have varying capabilities to adapt their electricity consumption. In this context, the discussion will centre on energy fairness aspects, highlighting the unequal capabilities of consumers in current systems.

Next, the discussion moves to the increasing role of DER in distribution systems and their growing significance. A massive deployment of DER will change how power systems are understood, not only in technical terms but also from the perspective of public goods. The traditional view of passive distribution networks populated by passive customers is challenged by active networks where prosumers interact dynamically with their peers and the broader grid. In this regard, the network plays a crucial role in enabling the management of a more complex power system. Thus, the classic view of electricity as a public good may be replaced by the perspective of electricity as a tradeable commodity. This shift will inevitably create winners and losers, raising concerns that the outcomes may replicate or even widen the gap between vulnerable and wealthier customers.

The final topic addresses the incentives and how prosumers respond to them to invest in DER. In this context, regulators and policymakers create incentives to achieve multiple objectives while managing the risks associated with tariff scheme development. Different tariff schemes will impact the extent of DER integration and the distribution of benefits and costs among users.

1.1.1 Socioeconomic factors and their current effects on the electricity demand

Residential electricity demand accounts for one-third of the electricity demand in Western countries [4]. However, a significant increase in the residential share is expected as the electrification of heating, cooling, and transport progresses. Currently, electricity represents 20% of total energy consumption worldwide, but by 2050, it is projected to account for 60%, with an additional 15% for hydrogen production [5].

Understanding the drivers of electricity demand has been a longstanding research focus. For instance, the authors in [6], [7] provide a literature survey on the various socioeconomic and dwelling factors that have been studied. Figure 1.1 highlights some socioeconomic factors identified as significant for extrapolating electricity consumption. These factors include household income (3rd position), tenure type (5th position), education level (15th position), disposable income (16th position), employment status of the Household Reference Person (HRP) (19th position), and socioeconomic status of the HRP (20th position).

The variable household income has been particularly well-studied. The relationship between electricity demand and income has been debated, showing varying conclusions. Some authors find a strong correlation between income and electricity demand, while others find comparatively lower significance when considering other dwelling factors [3]. One hypothesis for this phenomenon is the Kuznets curve for electricity consumption [8], which suggests an inverted U-shape relationship between income and electricity consumption (indicating three phases: increasing, constant, and decreasing consumption relative to income).

Recognising that income may have a context-dependent impact on electricity demand, some studies have been conducted to reveal the energy burden (i.e., the percentage of income allocated to electricity bills) across different socioeconomic groups. Table 1.1 illustrates this for the United States. The findings show that low-income households have an energy burden

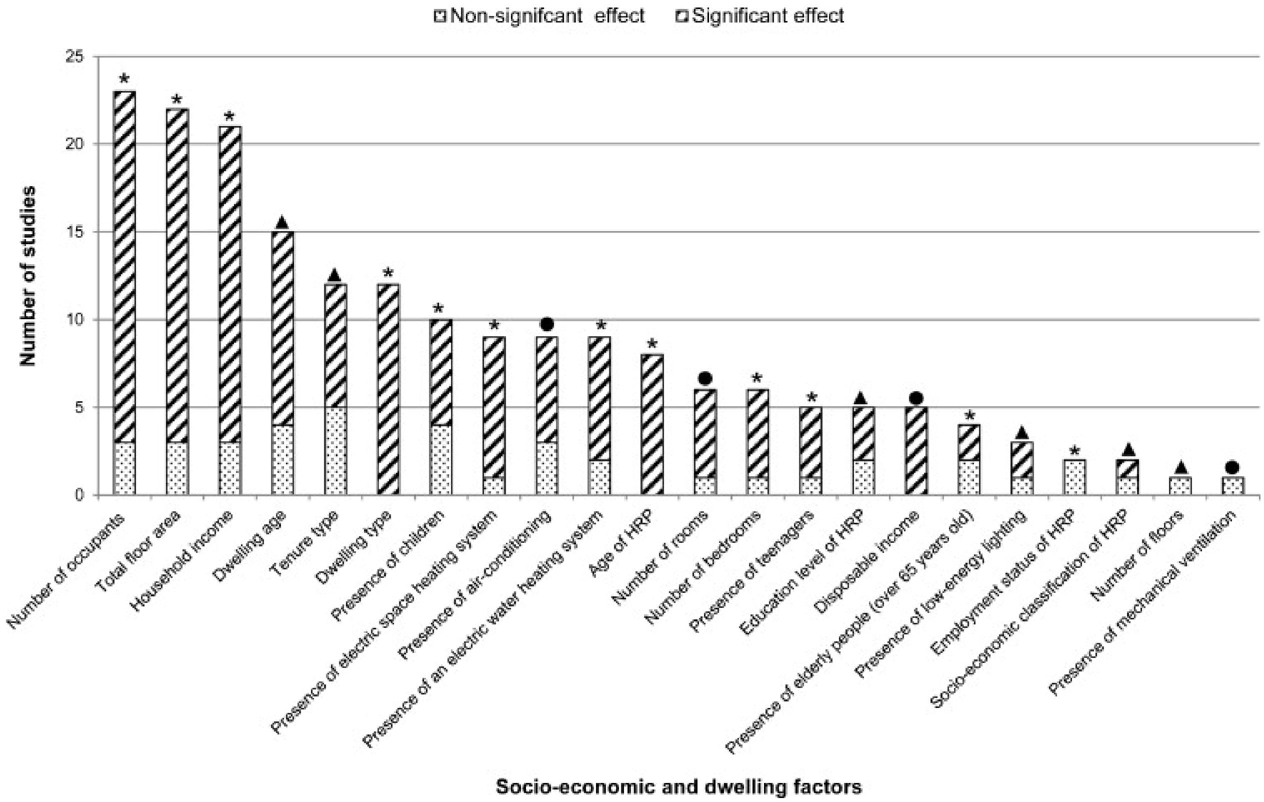

Figure 1.1: Number of studies analysing socioeconomic and dwelling factors according to the mentioned reference [6]. *Factor identified as significant in the reference. ▲ Factor identified as non-significant in the mentioned reference. • Factor not investigated in the mentioned reference.

three times higher than non-low-income households; renters have a burden 0.7 percentage points higher than owners; and the burden for African Americans is 60% higher than for the White population. In a 2015 survey in the US [9], 30% of households reported difficulty or insecurity in paying electricity bills, with the figure reaching 60% for the low-income segment. Racial inequalities in the Energy Burden is also incorporated in [10].

The disparity in energy burden across different socioeconomic groups raises concerns about the distributional aspects of energy benefits and burdens. The World Health Organization (WHO) recommends a minimum indoor temperature of 18°C in winter to minimise health risks [12]. This threshold forms the basis for the Low Income Low Energy Efficiency (LILEE) methodology [13], which combines the energy efficiency rating of a house with household income. If, after housing and energy costs, the remaining income falls below the poverty line, the household is considered to be experiencing energy poverty. In 2023, according to the Annual Fuel Poverty Statistics, 13.1% of England's population was living in energy poverty [14]. Reflecting these concerns, in 2015, the United Nations launched 17 Sustainable Development Goals, including the goal to "Ensure access to affordable, reliable, sustainable and modern energy for all" [15].

This narrative demonstrates the importance of understanding the drivers of energy poverty by analysing the specific circumstances of a region. A related topic is energy justice, a relatively new area of research with ongoing debates about the definition of energy fairness

Table 1.1: Energy burden (percentage of annual income destined to cover energy costs) according multiple socioeconomic factors. Low income is defined according to the income lower than the area medium income (AMI) [11].

	Household type	**Median annual income**	**Median energy burden**
Income type	Low-income ($\leqslant$ 80% AMI)	$24,998	7.2%
	Non-low-income	$90,000	2.3%
	Low-income multifamily ($\leqslant$80% AMI)	$21,996	5.0%
	Non-low-income multifamily	$71,982	1.5%
Building ownership	Renters	$34,972	4.0%
	Owners	$68,000	3.3%
Head of household race	White	$58,000	3.3%
	African-American	$34,494	5.4%
	Latino	$39,994	4.1%
All households	N/A	$53,988	3.5%

[16]. Despite the developing nature of this field, future perspectives on energy fairness are also a concern, given the multiple challenges such as technological evolution, climate change, and the need for low-carbon policies [17]–[19].

Given the above, the capacity of customers to adapt their consumption to future challenges is a central topic of this thesis. An initial perspective involves analysing adaptation capabilities to disruptive events—understood as unusual events with a significant impact on customers' lives (e.g., natural disasters, economic and political crises). These events directly impact the electricity system (e.g., power outages [20], [21]) and indirectly impact customer behaviour patterns [22]. Under these circumstances, customers must adapt their consumption based on their capabilities, which vary according to their economic status (for example, see [23]).

Consequently, analysing adaptation capabilities during disruptive events provides a baseline for understanding future perspectives, considering climate change and low-carbon policies. This is due to the short-term effects on residential electricity demand, where customers must adapt their consumption according to current resources, without the ability to make significant investments. The distributional analysis of adaptation capabilities has raised concerns about energy justice, given the challenging conditions of energy systems.

In summary, studies of electricity demand and its relationship with socioeconomic factors have highlighted the unequal distribution of benefits and burdens within the electricity system. This topic is gaining interest among various stakeholders involved in energy systems, including researchers, policymakers, and stakeholders. Similarly, topics such as energy justice and energy poverty have emerged as part of policy discussions, with new contributions in the research domain. This thesis contributes to this field by analysing the adaptation capabilities of different customers during disruptive events, considering these events as a baseline for future adaptation in response to evolving technological landscapes, climate change, and energy policies.

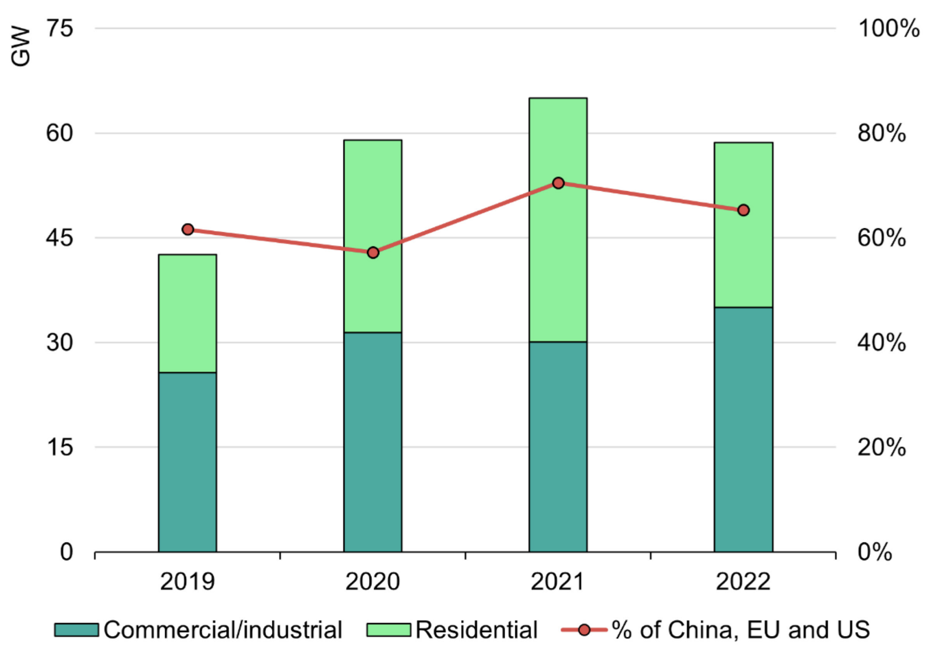

Figure 1.2: Distributed solar installations. Around of 50% of deployments are in China, EU and the US. [26]

1.1.2 The role of DER and distribution networks in future power system and their impact in energy fairness

DER powered by renewable energy sources are critical for decarbonising the energy sector. For instance, solar photovoltaic (PV) deployment is one of the three items identified as "on track" by the International Energy Agency regarding the Net Zero trajectories [24]. Distributed solar PV constitutes 49% of the total solar energy additions worldwide (representing 107 GW) [25]. Figure 1.2 shows the evolution of distributed solar PV installations worldwide. Despite this progress, most of the deployments are in China, countries in the EU, and the US [26].

In this evolving context, at least five technologies appear as prominent [27]:

- Battery Storage Systems can provide a range of services to the grid, such as storing energy during periods of excess renewable generation and discharging it during peak demand. Their main limitation is their relatively high upfront cost.
- Electric vehicles can provide a range of services to the grid, such as storing energy during periods of excess renewable generation and discharging it during peak demand. Their main limitation is their relatively high upfront cost.
- Electric water storage and heaters can provide a range of services to the grid, such as storing energy during periods of excess renewable generation and discharging it during peak demand. Their main limitation is their relatively high upfront cost.
- Grid-interactive buildings can provide a range of services to the grid, such as storing energy during periods of excess renewable generation and discharging it during peak

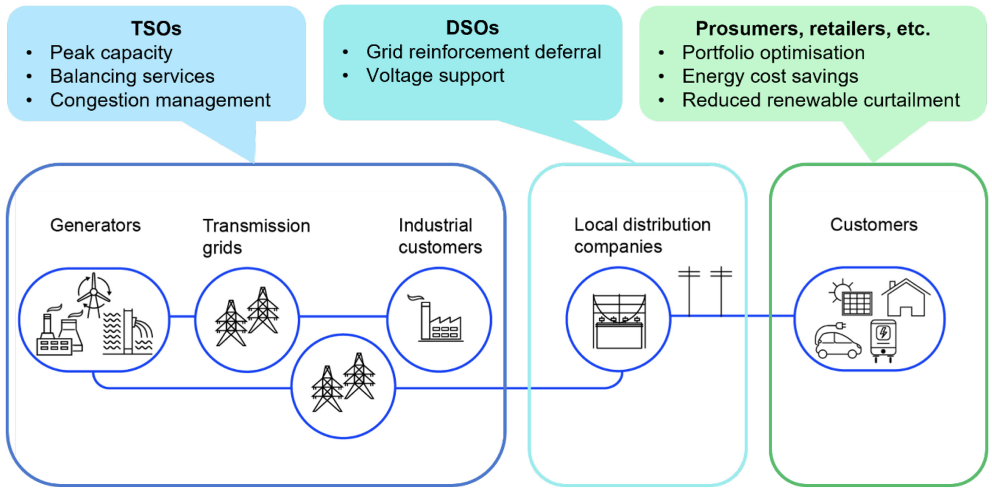

Figure 1.3: Services that DER can provide to the electric system for different stakeholders. [27].

demand. Their main limitation is their relatively high upfront cost.

- Virtual power plants (i.e., networks of decentralised power generating units, storage systems, and flexible demand) can optimise the aggregation of distributed resources across large areas by using advanced data analytics such as machine learning. Policy and regulatory issues, including value-stacking rules, are the main barriers to wider virtual power plants deployment.

In this way, DER can provide services to transmission, distribution, and prosumers, as summarised in Figure 1.3. This set of stackable revenue streams makes DER one of the most promising technologies.

However, these services require some enabling conditions. The relevant conditions to this thesis are: i) a distribution network capable of actively managing resources and demand, and ii) regulatory conditions that enable the integration of DER.

Regarding to the first point, integrating large volumes of DER into electricity distribution networks is challenging. For instance, DER can cause technical issues such as overvoltage problems, which could lead to costly distribution network investments [28]. Nevertheless, with proper planning and management, DER could alleviate network stress and potentially reduce investment costs by up to 70% [29].

Consequently, the distribution network appears as one of the main bottlenecks for DER development. In practice, some jurisdictions have identified zones with constraints on connecting load and generation [30]. Figures 1.4 and 1.5 show the example for the city of Amsterdam, where white zones highlight areas with available capacity to connect load (generation), yellow zones indicate limited availability, orange zones show availability for load (generation) supporting control management, and red zones represent areas where there is no availability and congestion management has been applied. Generally, most zones present some type of constraint. A similar situation can be observed in some regions of Germany, in the DSO Schleswig-Holstein Netz, where parts of the distribution network present a high level of

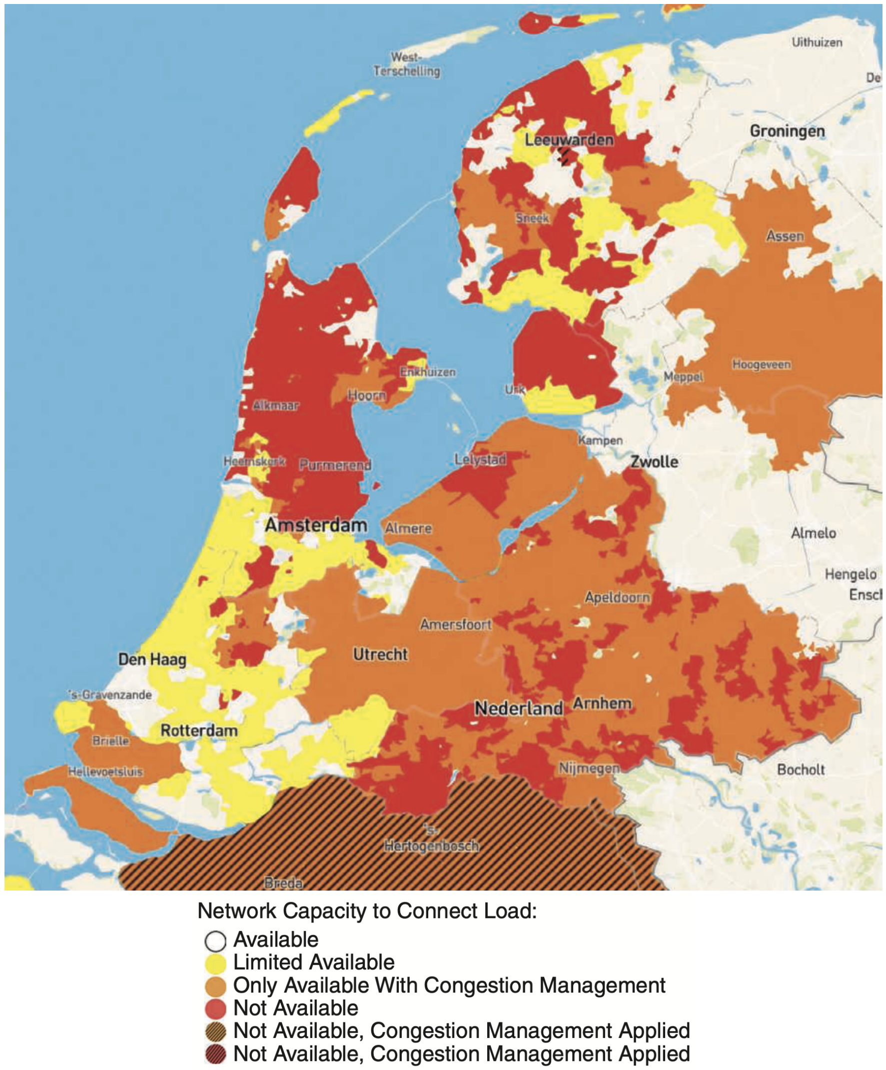

Figure 1.4: Network capacity to connect load in Amsterdam [30].

generation curtailment. Another example is in Northern California, US, where an update of distribution networks is needed to achieve DER goals [31].

The distribution network plays a critical role in the development and integration of distributed energy resources (DER), making it essential to consider its implications when analysing the future trajectory of the electric system. Any comprehensive study of future energy systems must account for the consequences of network development, not only from a technical perspective but also in terms of its broader impacts on customer choices and energy fairness [32].

In this context, the development of the distribution network extends beyond the technical aspects, as it directly influences the opportunities available to customers and shapes the fairness of the energy system. For instance, in Sweden, the hosting capacity for solar PV installations—essentially the ability of the distribution network to accommodate DER—has been found to correlate with the average income levels of the area. Regions with lower incomes, which often experience higher energy burdens, tend to have less capacity to support solar PV

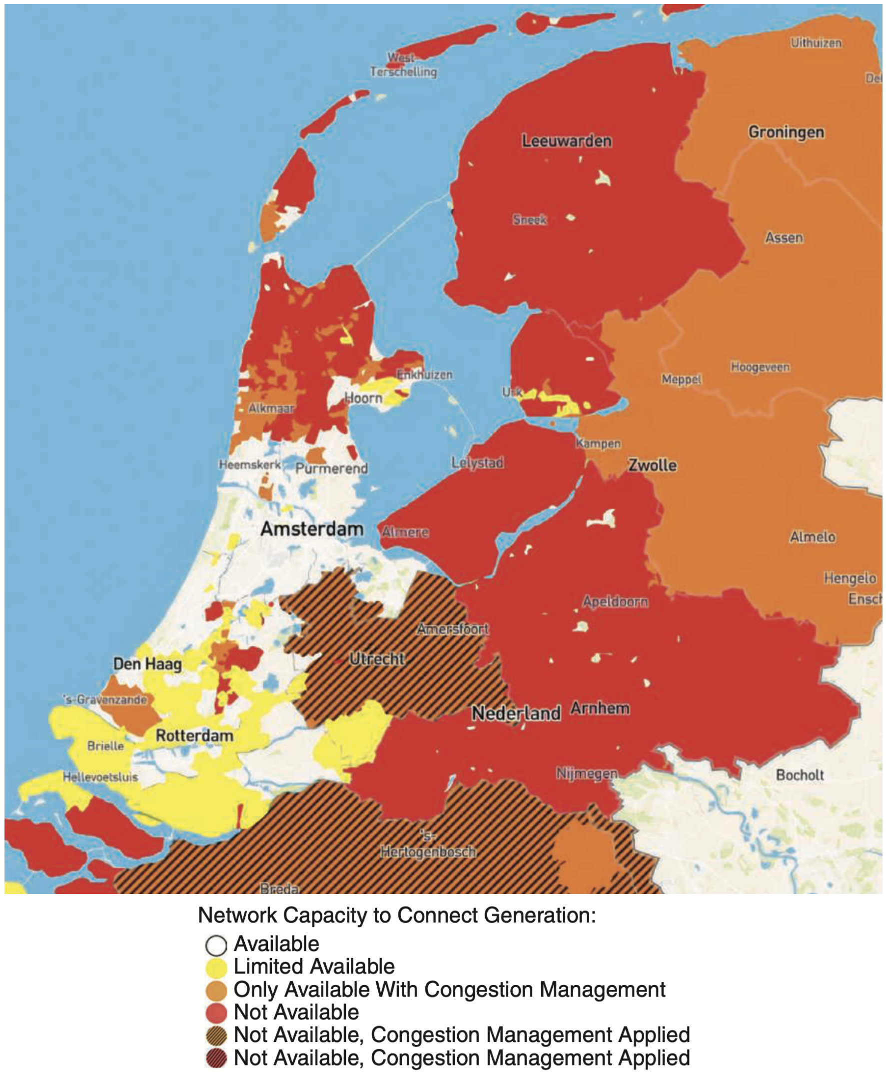

Figure 1.5: Network capacity to connect generation in Amsterdam [30].

installations [33]. This creates a situation where wealthier regions benefit more readily from renewable energy integration, exacerbating socioeconomic inequalities in energy access.

Similarly, in New York, the availability of electric vehicle (EV) charging infrastructure does not correlate with population density but instead shows a disparity in access across different socioeconomic groups. Lower-income, predominantly Black-identifying, and historically disinvested areas have fewer EV charging stations, further limiting their participation in the clean energy transition [34]. A similar pattern is observed in California, where the primary constraint for DER development is the distribution network's hosting capacity. This bottleneck is particularly pronounced in Black-identifying and disadvantaged areas, where the network's ability to integrate DERs is more limited [35].

These examples underscore how the distribution network's development can perpetuate existing inequalities, highlighting the need for equitable network planning and investment to ensure that all regions, regardless of income or demographics, can benefit from the energy transition.

1.1.3 Massive DER deployment through different socioeconomic background and the role of tariffs

As mentioned, DER will play a pivotal role in decarbonisation plans as well as in the electrification of several energy vectors (e.g., transport and heating), impacting the adaptive capabilities of customers. In this context, if the previous section about the ability to manage disruptive events represents short-term adaptation, then in this section, the deployment of DER by customers (or prosumers) reflects long-term adaptability to climate change and low-carbon policies.

Given the evolving landscape, a massive deployment of DER is expected, which will challenge the traditional view of power systems, where energy flows from large generators to passive customers (i.e., customers whose electricity consumption does not change significantly with network conditions). Instead, prosumers will interact with the distribution network and potentially with the transmission system by exchanging energy and flexibility services. In this context, Distribution System Operators (DSOs) will need to actively coordinate prosumers, consumers, and other stakeholders connected to the grid. This shift challenges the conventional perception of electricity as a public good, repositioning it as a marketable commodity [36], [37], and altering the classic paradigm of power systems, where energy traditionally flows from generators to demand centres [38].

This transformation will impact the organisational framework of the system, leading to the creation of regional markets where energy can be exchanged among peers (prosumers) in a decentralised manner, or between prosumers and a central entity that coordinates the market. This area of research, known as local energy markets, explores different types of market organisation [39]. Generally, the presence of a central entity coordinating the market depends on the market size and the number of participants. Larger markets increase coordination and transaction costs, making the presence of a central entity optimal from a market organisation perspective [40], [41].

How the central entity can coordinate resources in both the short and long term has received considerable attention. The range of solutions includes mandatory actions in the short term (such as flexibility provisions to manage contingencies [42]), flexible markets [43], and the enhancement of price signals. These solutions are not mutually exclusive and can operate at different time scales.

The use of price signals to coordinate customers is a common policy approach. For instance, feed-in tariffs have been used to encourage renewable and low-carbon generation. Under this policy, generators using certain technologies receive an additional payment for the energy they inject into the grid [44], [45]. For residential customers, electricity charges are typically based on tariffs with multiple components. The classical scheme includes [46], [47]:

- Energy tariff
- Networks tariff
- Taxes and policy-related tariffs

Clearly, the design of tariffs has a direct impact on: i) long-term investments, and ii) the distributional allocation of benefits and burdens associated with DER deployment. Regarding long-term investments, tariff schemes will influence the quantity, type, location, and timing of DER investments. Moreover, DER and network developments are mutually influential (i.e., the development of networks may encourage DER investments, and vice versa).

In terms of distributional impacts, there is currently a consensus that existing schemes—based on a single price for the entire day and uniform pricing across residential consumers—can result in cross-subsidies from less wealthy to more wealthy customers. This could pose significant challenges from political and energy fairness perspectives. Therefore, the massive deployment of DER risks social opposition, as the burden and costs could fall disproportionately on consumers (i.e., users without DER installations) [48], [49].

1.1.4 Motivation summary

The motivations and relevance of this research topic can be summarised according to the following points:

- The energy transition envisions significant changes in the energy and power sectors. In particular, residential users must adapt their energy consumption, but the impacts of these transitions vary across different socioeconomic groups. This study is therefore divided into short- and long-term analyses to explore how residential consumers may adapt their electricity consumption.
- Short-term adaptation capacity can be observed during disruptive events, where customers must adjust their consumption patterns based on their technical capabilities (determined by their current electrical devices), economic position, and behavioural patterns. As a consequence, customers may experience an increase in their electricity bills and a reduction in comfort. The distribution of energy burden in response to a disruptive event is uneven, showing a strong dependence on socioeconomic characteristics.
- In the long term, adaptation capacities depend on the development of electricity systems and the DER investments that customers may undertake. A massive deployment of DER is very likely, as these resources play a crucial role in decarbonisation. However, the benefits and burdens of DER deployment raise concerns about energy fairness.
- The critical role of the electricity network as an enabler of DER deployment and the broader energy transition. In this context, distribution networks are one of the main technological bottlenecks to advancing various DER technologies. However, the network's role is not only technical; its deployment has significant consequences for the socioeconomic opportunities available to users. This uneven network development is evident in the distribution of hosting capacity and electric vehicle charging infrastructure, which shows a higher correlation with the wealth of different regions than with demographic density.
- Energy fairness is a key objective for the energy transition efforts of the European Union, the United Nations, and several other jurisdictions. The role of tariffs in achieving this

objective is highly relevant, as price signals are crucial for encouraging the necessary investments for the energy transition. A deeper understanding of the drivers of energy inequalities is essential for developing future distributive policies related to energy burden and benefits.

1.2 General description of the research

This research examines the impacts of socioeconomic factors on residential electricity customers, taking into account the evolving landscape of energy and power systems. The analysis is structured around short- and long-term differences in adaptation capabilities.

In the short term, the focus is on how households adapt to disruptive events and how the consequences of these events are unevenly distributed based on socioeconomic background. During such events, users can only adapt by making use of their existing resources and capacities.

In contrast, the long-term perspective considers how customers might acquire new technologies or resources to expand their ability to adapt their net electricity demand, such as through the adoption of DERs. The analysis thus highlights how long-term investments in energy systems can create “winners” and “losers,” influenced by the tariff structures in place and the socioeconomic profiles of different customer groups. This underscores the importance of equity and fairness in tariff design as the energy landscape continues to evolve.

To analyse short-term adaptation capabilities, this research examines how residential users responded to the disruptive event caused by the COVID-19 pandemic during 2020 in Santiago, Chile. Data from 230,000 clients, measured by smart meters on an hourly basis from January 2019 to September 2020, is used. The analysis is conducted by administrative zones (communes) and types of clients to estimate how the pandemic and the lockdown measures impacted electricity consumption. Furthermore, socioeconomic data published by the government is utilised to observe correlations between adaptation in electricity consumption and socioeconomic factors.

The previous analysis faces two major challenges. First, in Chile, the first wave of the COVID-19 pandemic coincided with the winter period and lower temperatures. These effects naturally increase electricity consumption due to heating and lighting, thereby mixing with the impact of lockdown measures on electricity consumption. Second, the high volume of data poses a challenge for analysis. To facilitate the process, an online platform was developed to make the information publicly available, enabling reproduction of the analysis conducted in this research or any related analysis within a user-friendly framework.

For the long-term analysis, this research examines the long-term economic equilibrium between DER deployment by prosumers and the distribution network operated by a proactive distribution planner who plans the network to minimise systemic costs.[1] The distribution network is connected to the bulk power system at the primary substation, where energy injections and withdrawals are valued at the marginal price. The incentives perceived by

[1]The objective of minimising costs can be replaced by welfare maximisation.

prosumers are shaped by energy and network tariffs. Various energy tariffs are explored; in all cases, the energy tariff reflects exogenous retail offers, with average costs matching the average of marginal costs. Meanwhile, various network tariffs are designed to recover the distribution network costs but follow different rules, such as volumetric or peak tariffs.

The distinctive features of this research include the detailed modelling of the network and the budget constraints for investing in DER for each prosumer. Regarding network modelling, an AC power flow suitable for low-voltage networks is used. This modelling approach has two advantages. First, the equilibrium will consider the technical feasibility of incorporating DER resources in the long term. Second, network development enables the analysis of the social consequences of uneven development of the distribution network, as the proactive distribution planner will develop the network based on DER development and the efficiency of the investment.

Regarding budget constraints, each prosumer is characterised by different budgets to invest in a portfolio of DER devices, linking the maximum capacity of DER to purchasing power as a proxy for socioeconomic background. This framework relies on the assumption that prosumers behave as rational economic agents, minimising their electricity costs. Thus, the results of this approach serve as a benchmark for more complex outcomes where the behavioural patterns of prosumers may impact their decisions, leading to more expensive outcomes (or less favourable ones in social terms).

1.3 Hypothesis

The hypotheses of this research are:

- The adaptation capabilities[2] of residential customers are significantly influenced by socioeconomic factors, which are critical in the context of the energy transition. Consequently, there is a substantial risk that the energy transition could exacerbate issues of energy fairness and energy poverty, leading to unequal access to energy resources and services.
- In the short term, adaptation capabilities can be observed and characterised through how different customers adjust their electricity consumption during disruptive events[3]. Wealthier customers have a broader range of options to manage their electricity consumption compared to less affluent customers, resulting in disparities in electricity costs and access to comfort levels. Thus, the distribution of adaptation capabilities during disruptive events provides a baseline for analysing future inequalities in the distribution of benefits and burdens from the energy transition.
- In the long term, the higher capability of wealthier customers to invest in DER among customers can lead to an uneven distribution of energy benefits and costs, potentially

[2]Adaption capabilities is understood as different measures that users may adopt to enhance the balance of benefits and cost of energy consumption

[3]As previously stated, a disruptive event is understood as unusual events with a significant impact on customers' lives (e.g., natural disasters, economic and political crises)

resulting in undesirable effects on energy fairness. This inequality will be affected by the tariff schemes used, and so can be mitigated by designing energy tariff schemes that strike a balance between economic efficiency and equitable cost allocation.

1.4 Aim and objectives

1.4.1 Aim

Building on the above mentioned hypotheses, this research project aims to analyse how socioeconomic factors affect the adaptation capabilities of residential electricity consumers in both short-term disruptive events and long-term energy transitions, focusing on the implications for the distributional aspects of benefits and burdens, and equitable DER deployment.

1.4.2 Specific objectives

The specific objectives are

1. To review the relevant literature and identify the current state-of-the-art concerning the role of socioeconomic impacts on electricity consumers, DER deployment, and the notion of energy fairness.
2. To extract relevant information from high-dimensional data related to the hourly electricity consumption of residential consumers and present it in a clear and comprehensive manner.
3. To evaluate the short-term adaptation of residential electricity demand during disruptive events, such as the COVID-19 pandemic, and to examine how these adaptations vary according to different socioeconomic groups.
4. To model the long-term economic equilibrium between DER deployment by prosumers and the development of distribution networks, considering various tariff schemes and the technical feasibility of network integration at the low-voltage level.
5. To assess the distributional impacts of different energy and network tariff designs on the costs and benefits of DER deployment, with a focus on achieving a balance between economic efficiency and equitable cost allocation among different socioeconomic groups.

1.5 Contribution of this research

The first contribution is related with the literature survey, which accomplish the specific objective 1, and is stated as follow:

A An extensive review of the literature on the role socioeconomic factors play in shaping electricity consumption, DER deployment, and energy fairness. This review consolidates existing research to reveal gaps and trends in how socioeconomic disparities impact energy consumption, how DER and distribution network interacts, and how those technologies may impact the notion of fairness in energy systems.

The remaining set of contributions is divided into two parts: first, the contributions related to the adaptation capabilities of residential electricity consumption in response to short-term disruptive events; second, the consequences of long-term economic equilibrium between DER development and distribution networks.

The first set of contributions focuses on short-term adaptations and includes the following detailed points. Contributions B and C specifically relate to objectives 2 and 3:.

B A comprehensive analysis of how residential electricity consumption adapted during the disruptive event of COVID-19 pandemic. Using data from 230,000 smart meters across Santiago, this study captures the evolving patterns of hourly electricity demand during the disruption caused by lockdown measures. The analysis distinguishes between behavioural shifts directly attributable to the pandemic and natural seasonal variations in demand, offering critical insights into the adaption capacities of residential energy consumption in during disruptive events.

C A detailed examination of socioeconomic disparities in electricity usage impacts. This study explores the differing effects of the COVID-19 pandemic on residential consumers across various zones in Santiago, highlighting the relationship between the intensity of demand changes and underlying socioeconomic factors. The findings provide valuable knowledge for policymakers aiming to mitigate the unequal burdens on vulnerable populations during disruptive events.

The second set of contributions focuses on the long-term equilibrium between DER development and distribution networks. In this context, Contributions D and E relate specifically to objectives 4 and 5, as outlined below:

D A long-term equilibrium model where both network capacity and DER investments are determined through equilibrium conditions. The model incorporates an AC power flow suitable for low-voltage networks, thereby avoiding physically infeasible solutions and, unlike previous formulations, considers network capacity as part of the equilibrium problem.

E A pioneering study that considers the long-term equilibrium between distribution networks and DER investments takes into account the varying purchasing power of different socioeconomic groups as a factor limiting DER deployment. This study contributes to the field by comparing the impacts of long-term tariffs on both prosumers and network investments. The findings underscore and quantify the crucial role that tariffs play in achieving fair cost allocation across different customer segments, showing how certain tariffs may offers fair solution without compromising efficiency.

1.6 Thesis overview

The remainder of this thesis is structured into five additional chapters, briefly described as follows:

Chapter 2 provides the literature review, covering articles related to the impact of socioeconomic factors on residential electricity demand. It then reviews the modelling of DER deployment and concludes with a discussion of equity and fairness notions in energy systems. This chapter identifies the research gap that this thesis aims to address.

Chapter 3 analyses how Chilean residential consumers adapted their electricity demand during the disruptive event of the COVID-19 pandemic. The chapter presents the methodology, results, and discussion of the analysis.

Chapter 4 explains the mathematical modelling of equilibrium models between DER deployment and distribution networks. It details how budget constraints can be incorporated into the equilibrium assessment and provides the mathematical definition of the distribution networks used in this research.

Chapter 5 presents a case study based on a modified version of the IEEE 37-bus feeder. This chapter assesses the long-term economic equilibrium between the network and users with different budgets for investing in DER devices. It includes an analysis of how socioeconomic factors impact the distribution of costs among users and how tariffs can mitigate the effects of these factors.

Chapter 6 concludes this thesis by summarising the main findings of the research and suggesting potential areas for future work.

Chapter 2

Literature review

This chapter presents various perspectives on a central theme: the relationship between socioeconomic factors and the electricity usage patterns of residential consumers. In doin so, the firs specific objective of Section 1.4.2 is fulfilled.

This connection between socioeconomic factors and electricity usage patterns can be analysed in both the short and long term. In the short term, especially in regions with lower levels of distributed energy resources (DER) development, such as many Latin American countries, customers may exhibit a more passive attitude towards their electricity consumption due to limited options for interaction with the grid. In contrast, in the long term, as DER deployment grows, electricity customers will have the ability to actively engage with the network, influencing both their consumption patterns and the overall grid dynamics.

The chapter focuses on literature that incorporates socioeconomic factors into the analysis of the drivers behind electricity consumption. This is important for understanding the transition from passive to active energy consumers and how socioeconomic realities shape this evolution. The logic behind this structure is to illustrate the various stages of the energy transition and their potential implications for energy consumption patterns. Figure 2.1 presents a representative scheme of the literature review.

In the early stages of the energy transition, where electrification levels are still low and most customers remain passive, understanding the role of socioeconomic factors in energy demand is important for addressing energy fairness. As the transition progresses and DER integration increases, the role of active prosumers—customers who can produce and manage their own energy—becomes more significant. Therefore, in the later stages, understanding the impact of socioeconomic factors on DER integration becomes increasingly relevant, as more customers become capable of interacting with the grid in an active way.

Finally, the concept of energy fairness is expected to grow in importance as the energy transition advances. Electricity demand is projected to become the dominant energy vector for residential heating and transport, and the widespread integration of DERs will create a greater divergence in electricity costs among consumers. If these cost disparities are perceived as unfair, they may generate social opposition, potentially jeopardising the success of the energy transition [37], [48]. Thus, incorporating socioeconomic considerations into the analysis

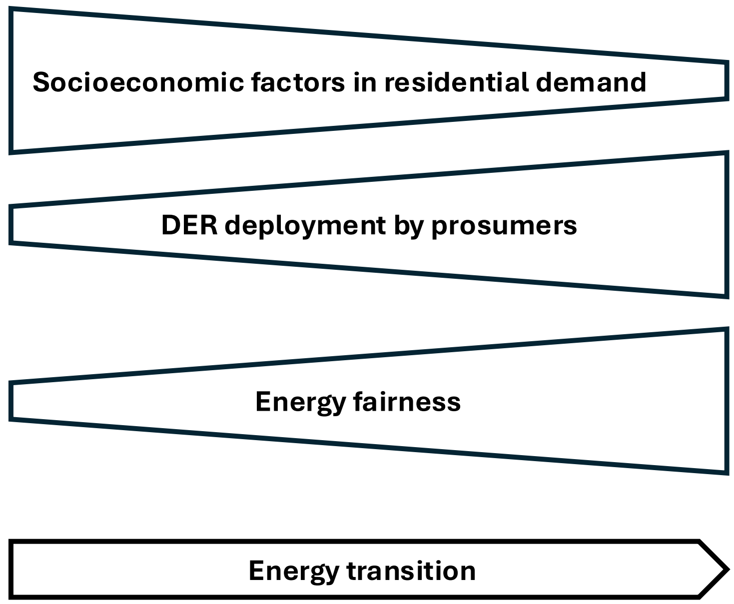

Figure 2.1: Scheme of literature review. The bottom arrow represent the energy transition timeline. The figures represent the relevance of the topic depending on the stage of the energy transition. Thus the shorter side represent a lower relevance in comparative terms and vice versa.

of DER integration and electricity consumption is essential for ensuring a fair and just energy transition.

Thus, this chapter is structured as follow. The first subsection of the literature survey examines the impact of socioeconomic factors on electricity demand, with a particular focus on the role of income in shaping residential electricity consumption patterns. This section explores how varying income levels influence energy usage and highlights the disparities in consumption between different socioeconomic groups.

The second subsection reviews literature on the integration of distributed energy resources (DER) in local energy markets. It delves into the economic structures of these markets and their mathematical modelling, with an emphasis on evaluating equilibrium models. Additionally, this subsection examines principles of tariff design and how tariffs can be incorporated into mathematical models to assess their structural impacts on energy systems and customer behaviour.

The third subsection focuses on the concepts of equity and fairness in energy systems. It explores how equity and fairness are defined in the context of power systems and reviews the key trends in the modelling of energy justice. This section also considers the importance of fairness in ensuring a just and inclusive energy transition, especially as DER adoption becomes more widespread.

2.1 The impact of socioeconomic factors in residential electricity demand

Studies aimed at identifying the drivers of residential electricity demand have been common for a long time, for instance, in 1980 is possible to register to attempt to relate the customer income with their electricity consumption [50]. However, the role of socioeconomic factors in electricity demand is still a current discussion topic, given the rising concerns of energy fairness in the energy transition [51], and considering how new methodologies can improve the understanding of residential electricity demand.

The relevance of residential electricity demand to power system development is largely due to its higher variability compared to industrial or commercial demand. Residential consumption fluctuates based on a variety of factors, such as the sociodemographic composition of the household occupants, weather conditions, education levels, and other socioeconomic factors. In contrast, industrial and commercial demand tends to be more predictable and stable [52].

Furthermore, the residential sector accounts for a significant portion of national electricity demand, comprising approximately one-third of the total [3]. In Western countries, for instance, electricity demand from the building sector alone constitutes between 40% and 68% of net electricity consumption [4]. This makes residential demand a key focus for power system planning and management. Looking ahead, the electrification of energy consumption—particularly in heating, cooling, and transport—will likely drive further growth in residential electricity demand, enhancing its importance to overall energy system development.

In this vein, [3] offers a review of the state of the art in identifying the different factors driving residential electricity demand. These identification frameworks are based on top-down, bottom-up, or hybrid approaches. A top-down approach uses national data (or data grouped by large zones) as input and attempts to extract household-level data considering different home features. Conversely, bottom-up approaches consider individual household features and attempt to derive features for their respective zone or jurisdiction.

This is an indicative summary of different factors that can impact residential electricity demand, elaborated in [3]:

- **Economic capability**: Economic capabilities, such as overall wealth or monthly income, have been studied in different jurisdictions with varying conclusions. While some authors find no clear evidence of a relationship between income and electricity consumption [53] or note only a marginal impact [54]. In those studies, the role of other variables as the education level of customers shows a comparative higher relevance. Other studies suggest a strong positive correlation between income and electricity consumption in Brazil [55], Ireland [56], and Portugal [57], among other countries. Therefore, in most cases, economic capabilities have a recognizable impact on residential electricity demand, but in some cases, this impact is minor or even negligible [3]. In consequence the impact of economic capabilities is case dependent.
- **Cost of energy**: The energy price and price structure (e.g., flat tariff or time-of-use

tariff) impact residential electricity demand. The impact of tariffs has been measured through econometric models [56], [58]. For instance, in Portugal, it has been estimated that a 1% increase in the energy tariff results in a 0.23% decrease in electricity consumption.

- **Climate and location of the dwelling**: The literature survey highlights studies demonstrating that in regions dominated by hot weather, such as Australia [59] and Thailand [60], electricity demand tends to be driven by cooling systems. As a result, there is clear evidence of increases in residential electricity consumption as temperatures rise. In contrast, in colder climates, such as the UK [61], electricity consumption is primarily influenced by heating needs, leading to peak demand during winter months. For instance, in the UK, electricity demand in winter is approximately 36% higher than in summer, reflecting the significant impact of heating requirements on the power system

- **Physical characteristics of the dwelling**: This refers to construction features such as building materials, insulation quality, surface area, and other related factors. According to certain studies, these dwelling characteristics can account for 2-5% of residential electricity demand in the US [53]. Key features influencing energy consumption include surface area (with a positive correlation to electricity use), dwelling type, and the insulation properties of building materials. These factors are crucial in understanding variations in residential energy consumption, especially in relation to heating and cooling efficiency.

- **Household activities and services**: Household activities impacts the number of hours of occupants stay in their homes and consumer behavior can explain between 2-25% of electricity demand [53] in the US. According to [3], in general, the impact of household activities affects the time of consumption, which could have a strong impact on peak energy demand. For instance, in greece the use of refigrerators and air conditioning system could increase the peak demand in 16% [62].

- **Socio-demographic characteristics**: Factors like lifestyle [54], [56], occupants' age [56], education, number of occupants [53], and the presence of children and elderly people [63] can all influence electricity demand. However, the level of impact is case-dependent, with different magnitudes of impact in different jurisdictions.

- **Potential drivers of future residential consumption**: The technological landscape will change the energy consumption patterns. The massive integration of electric vehicles and home applications such as heat pumps will increase residential electricity consumption and peak electricity demand. For electric vehicles, some estimates suggest that 1 kWh of electrical energy can power 5 km, imposing requirements on system flexibility. Thus, some studies [64] the peak electricity demand of a dwelling can increase 3.9 times the peak without electric vehicles.

Beyond of specific details, the main findings through the literature is that the relevance of a determined feature is case dependent. It means that the same feature for different jurisdiction can be significant and for others it can show no correlation.

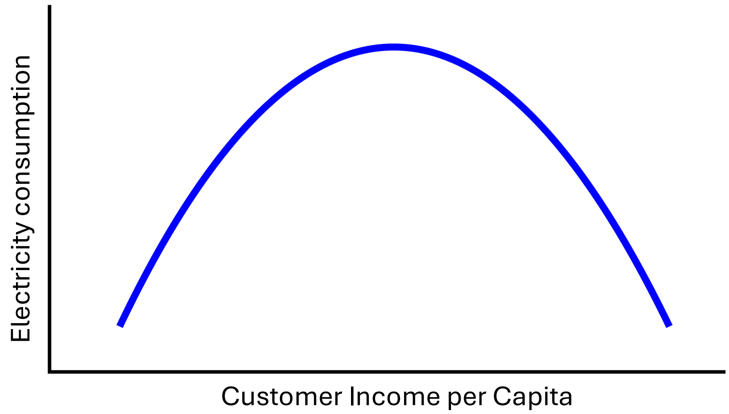

Figure 2.2: Inverted U-shape or Kuznets curve to relate the income of a sample of customers and their electricity consumption.

The electricity demand, and peak electricity demand can be explained by several factors from different sources (e.g., temperature, households characteristics, etc). Some of the factors may have a high correlation among them, which make some variables more effective to explain the residential demand.

Particularly, considering income as a explanatory variable, in most of the cases, literature indicate that income is an important factor to explain the level of electricity demand. However, the impact for different jurisdictions is not the same. Some studies find a strong positive correlation (for instance [55]–[57]), others studies, a negligible correlation (for instance,[53], [54]). Thus, the previous studies based their analysis in econometrics models that depends in multiples variables. In those analysis, the role of income as a variables have different significance compared with the complete set of variables.

In the same line, some authors have claimed the existence of a inverted U-shape between income and energy consumption [65], [66], also known as Kuznets curve (see Figure 2.2), which indicates that the curve that relates electricity consumption with income have approximately three distinctive zones: i) For low income, a monotonically crescent electricity demand with income, ii) for ”medium-income”, a flat electricity consumption with respect to income, and iii) for high income, a monotonically decreasing electricity consumption with respect to income. The existence of this curve has been demonstrated in at country level, however with nation-wide data at residential demand is more complicated to observe (an example is Guatemala [65]) and it depend of how diverse is the income in the sample. Thus in a very limited variation of income in the sample of customers, it is expected that income does not incorporates much information in the understanding of the residential demand.

In recent years, the increased availability of data has enabled research leveraging electricity demand collected from smart meters, alongside the use of machine learning techniques. In this context, [67] provides a literature survey highlighting how various studies utilise smart meter data. One of the key findings is related to the role of income, which, in many cases, does not significantly impact electricity consumption. The explanation for this is that socioeconomic status encompasses more than just the income of the household head—it also involves consumption behaviours and dwelling characteristics (For instance, wealthier socioeconomic households may have better insulation, or lightly spaces).

Similarly, [68] demonstrates that the high-resolution data from smart meters, such as hourly measurements, can reveal patterns that are not apparent in yearly aggregated data. For instance, the study shows that certain inequality indices may increase by 13.4% when more granular consumption information is considered, illustrating the importance of detailed data in uncovering deeper insights into electricity usage patterns and socioeconomic disparities. For instance, two customers may have the same consumption during a month, but one of the could concentrate their consumption in few hours, this feature may correlate with socioeconomic features.

In this vein, the authors in [57] study 265 houses in Portugal, mixing the information from the smart meters and door-to-door surveys. They find that income is relevant to explain the energy consumption of consumers, but with other variables such as the features of dwellings, and the equipment's of the house.

In a similar way, the authors [69]–[71] have performed analysis with smart meters to analyse the relevance of different factors. In all of them, they found that income have a lower importance compared with the square footage and the occupants features (a house with children or elderly people) and temperature.

Finally, in [53] analyse the information from smart meters of workers of Silicon Valley. The role of income (in statistical terms) was negligible. The authors' explanation is that the sample on consumers do not have enough diversity, then all consumers may have similar incomes that does not explain differences in energy consumption.

In summary, the relation between electricity consumption and exogenous factors has been vastly studied. Particularly the role of income have been analysed having different and opposite results. The explanations given by different authors are the followings:

- The sample of users is not diverse in terms of income, so the income cannot explain the variation in electricity consumption within the sample.
- There are other factors associated with socioeconomic status, such as education or certain features of dwellings, that have a stronger impact on electricity consumption.
- The relationship between electricity consumption and income has an inverted U-shape, indicating that there are three types of relationships between these variables. As income increases, the slope between electricity consumption and income tends to decrease or even present a negative slope.

Those studies focus on short-term electricity demand, where the role of DERs is still limited due to current integration rates. This raises the question: what can be expected in the future when DER adoption and electrification become more prominent in the energy system? How can mathematical models help us understand the evolving relationship between socioeconomic factors and electricity consumption or generation in this future context?

The next subsection explores this question by examining how mathematical models can be used to project and analyse the long-term interactions between socioeconomic variables and energy behaviours as DER integration increases and electrification expands.

2.2 DER deployment by prosumers and local energy markets

Before to discuss the role of DER deployment by prosumers, it is convenient to understand what local energy market refers. The term "local energy market" does not have a common definition across the literature. Authors in [40] define local energy markets as:

> *A market, a physical or virtual space (in this case local), in which the transactions between the actors are carried out taking into account the rules defined for the exchange of products or services in agreed temporal horizons. The main market elements are: actors, territory, transactions, market rules, products, services, physical or virtual space.*

The definition emphasises the transactional aspect of local energy markets rather than focusing on the physical or virtual environment where these transactions occur. Additionally, the "local" context limits the scope of analysis to a smaller number of actors, in contrast to the broader scope seen in global or regional markets. This focus on local interactions highlights the importance of understanding market dynamics at a community or neighborhood level, where fewer participants are involved, and localised factors play a more significant role in shaping energy transactions

As the name "local energy market" suggests, compared to conventional energy markets, the distinctive feature is their local structure. Within this framework, two key challenges arise. First, in local markets, certain actors may gain greater relevance, thereby holding more market power. This occurs because the number of actors in a local context is smaller, which increases the comparative influence of individual participants. This situation prompts researchers to apply market modelling approaches that account for imperfect markets, exploring how certain actors may exploit their market power through strategic behaviour.

At the same time, coordination among a larger number of participants is crucial, as there is a significant risk that DER development could become more costly than the current situation [28]. This is because poor planning of DER integration into the distribution network may lead to voltage and congestion issues. However, with proper coordination, total system costs can be significantly reduced—by up to 70

Firstly, in peer-to-peer (P2P) markets, different actors share their electricity through bilateral arrangements among consumers and prosumers (see Figure 2.3), enabling the markets to be more autonomous and flexible. The main feature of this market is its decentralized structure, lacking a coordinator (i.e., a central authority). Further details can be found in [72].

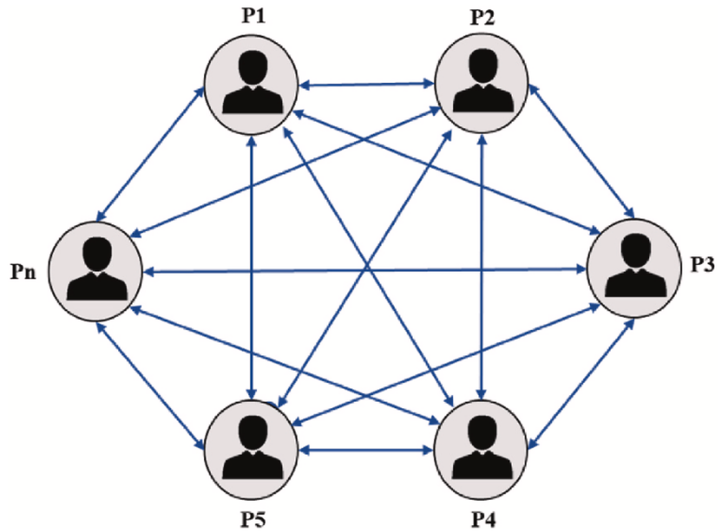

Figure 2.3: P2P market structure [40]

To study P2P markets, game theory approaches have been applied, such as Stackelberg games or non-cooperative games [73]. In these cases, agents make optimal decisions to pursue an optimal figure-of-merit (e.g., prosumers investing in DER to minimise their overall electricity costs). Another type of modelling is agent-based simulation, where prosumers follow certain rules according to specific parameters (e.g., prosumers investing in solar panels if their bill surpasses a predefined cost threshold). Those models attempt to incorporate behavioural aspect into the modelling. See [40] for more details.

Secondly, in a community-based markets, there is a local market operator (LMO) that coordinates the market clearing for consumers and prosumers (see Figure 2.4). In some cases, this structure can also be referred to as peer-to-platform. Depending on the research context[1], this local operator can serve as an energy trader, buying and selling different services (i.e., energy and other flexibility products), controlling network services, managing demand response resources, and potentially optimising energy transfers to the main grid, similar to what a Distribution System Operator (DSO) does (see [74]).

When the local energy market is connected to the main grid, the local market operator can maximise the profit of the actors operating within the local energy market. Conversely, when the network is isolated from the main grid, the local market operator usually minimises system costs. See [40] for more details.

Considering the maximisation profit or the minimisation costs of LMO, optimisation techniques based on: i) optimisation methods such as deterministic or swarm optimisation, ii) equilibrium models, or iii) agent-based methods.

Thirdly, a group of communities-based market can be understood as a mix of the P2P and community-based structures. That is, these markets are formed by several community-based markets (each with their LMO) that can trade energy and other services among themselves using P2P arrangements (see Figure 2.5). This type of arrangement can occur in a smart

[1]If the research is focused in the relation of DER and Generation, the LMO could be an aggregator or a virtual power plat that interact in the wholesale market. Instead if the objective is to analyse the role of DER with distribution network the LMO could be an a distribution system operator

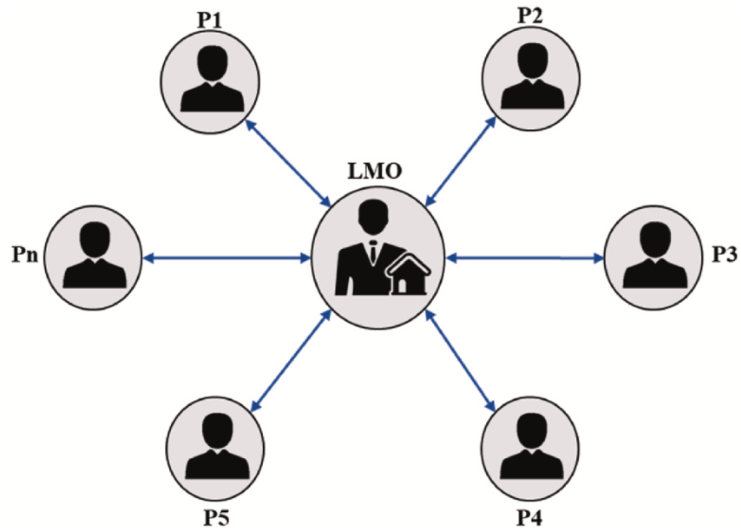

Figure 2.4: Community-based market structure [40]

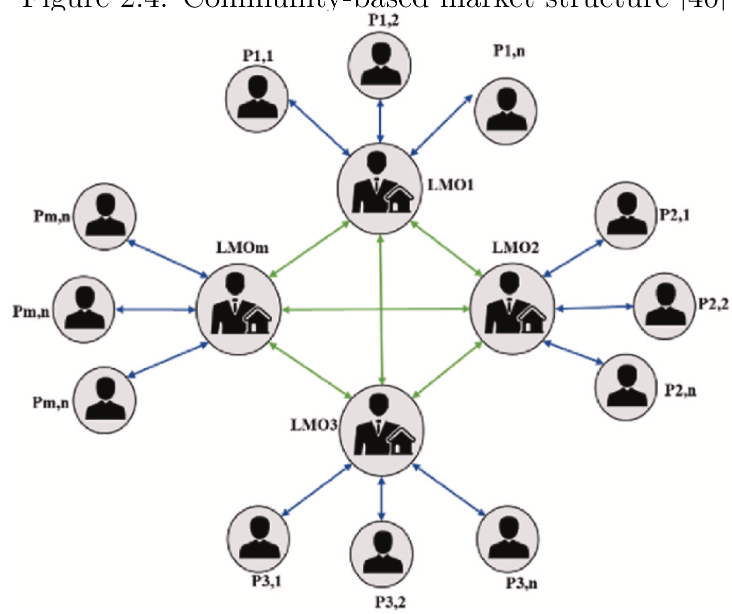

Figure 2.5: Group of community-based market structure [40]

grid environment, where different neighbourhoods or organisations can exchange their energy or services. This arrangement has the potential to create standards for different services to improve coordination among communities and the bulk power system. See reference [40] for further details.

Hereinafter, the literature will refer to the community-based market structure. The justification for this focus lies in its practicality for regulatory bodies in different jurisdictions, considering that the energy systems are evolving from passive to active systems. That is, traditionally, the electricity system is planned and operated under the assumption that customers are passive and thus unable to provide any forms of support to the energy system. This assumption is no longer valid as customers have been investing in energy technologies (e.g., storage, renewable energy sources, etc.) that allow them to actively manage their energy consumption and offer services to the energy system.

Table 2.1: Suitability of local energy markets suitability markets for different stakeholders. In the case of consumer, prosumer and producer the classification is done for residential, commercial and industrial scale [40].

Stakeholders	Role	Scale	LEM proposed structures		
			P2P	**Community-based**	**Group of community-based**
Consumer	Buyer	Residential	X	X	
		Commercial		X	X
		Industrial			X
Prosumer	Buyer and seller	Residential	X	X	
		Commercial		X	X
		Industrial			X
Producer	Seller	Residential	X	X	X
		Commercial			X
		Industrial			X
Aggregator	Intermediary			X	
Local market operator	Market operator		X	X	
DSO				X	X

In this context, there is a higher relevance of grid operators, known as Distribution System Operators (DSOs), in charge of operating, maintaining and developing the distribution network to ensure that electricity is delivered to end-users in a secure, reliable and efficient manner [75]. Thus, in the Electricity Directive (EU) 2019/944 [76], which states that DSOs have the duty to "ensure the long-term ability of the system to meet reasonable demands for the distribution of electricity, for operating, maintaining and developing under economic conditions a secure, reliable and efficient system," thereby imposing the presence of a central entity, provided by the DSO, to manage networks at the low-voltage level. Similarly, the authors in [77] conducted a survey in European countries in the context of analysing the Electricity Directive (EU) 2019/944 and how to improve regulation considering the decarbonisation ambitions for the coming years. They concluded that there is a need to empower DSOs in their innovation capacity, coordination with Transmission Sysmtem Operators (TSOs), and other areas. Again, the trend is to strengthen the role of the central entity, and this trend is extrapolated to other markets.

Another reason to focus the analysis on community-based markets is the broad range of actors that can be reasonably included in the modelling. According to [40], the size of production and consumption by users is key to determining which market structure is suitable. Consequently, they recognise three size categories with increasing scale: i) residential, ii) commercial, and iii) industrial. Table 2.1 shows the suitability for different stakeholders according to their size. Community-based markets allow the participation of stakeholders with residential and commercial-scale operations, which aligns with the objective of analysing the impact of DER integration on various residential customers.

Finally, as mentioned before, the techniques applied to a community-based market include general optimisation models, agent-based models, and game theory models (non-cooperative games). In this context, classical optimisation models can identify the optimal solution assuming a social perspective (minimising total cost or maximising social welfare), however this optimisation rely on idealistic conditions, such as a perfect information of the central planner, prosumers without market power, no transactional costs, among others. Another approach, provided by agent-based modelling, involves stakeholders making decisions based on specific rules that takes in account the behavioural aspects of prosumers. This practical approach is useful for realistic regulatory frameworks and considers practical customer choices. Lastly, the game theory approach considers the rational decisions of each stakeholder, particularly prosumers. The main assumption of those models is that prosumers decision are led by economic rationality, beyond behavioural (or non-economic) motivations.

In a game theoretical model, depending on the specific rules of the community, the game can be classified as either cooperative or non-cooperative. Cooperative games are used to study coalitions of stakeholders and the allocation of profits among participants. The main focus is often on finding an allocation that makes the coalition of all players stable, meaning that no subset of members has an incentive to leave the coalition. Non-cooperative games, on the other hand, focus on analysing the behaviour of players who compete with each other. Typically, the study aims to characterise the existence of a market equilibrium (i.e., a situation where no player can be better off by deviating) [73].

The next subsection analyses the case where prosumers integrate DER into the distribution network individually and without coordination with other stakeholders. Note that this is the classical approach in typical regulatory frameworks (e.g., net billing, net metering [78], [79]). If each prosumer follows rational behaviour, then the situation corresponds to a non-cooperative game.

2.2.1 Prosumer as a non-cooperative agents: Equilibrium models

Before studying the role of prosumers in the deployment of DER in equilibrium with the network, it is important to define what is meant by equilibrium. In general terms, consider n players that make choices to maximise their utility (analogous analysis can be performed for minimising cots). For the player i, s_i represents the strategy chosen, and $u_i(s_i, s_{-i})$ denotes the utility of player i, given their strategy s_i and the strategies of all other players, denoted by the vector s_{-i}. A strategy profile $s = (s_1, s_2, \ldots, s_n)$ is said to be a Nash equilibrium if:

$$u_i(s_i, s_{-i}) \geqslant u_i(s_i^*, s_{-i}) \quad \forall s_i^* \tag{2.1}$$

This means that no player can increase their utility by unilaterally changing their strategy. This concept was originally studied by John Nash, who demonstrated that for a finite set of strategies and a finite number of players, an equilibrium exists [80]. The extended version to a continuous set of strategies is also valid, but it requires a compact and convex set, as well as continuity and concavity of utility functions.

In the context of market modelling, non-cooperative games are used to study imperfect competition, which is a type of competition that could have one of this features[2]:

[2]The features presented are relevant in this work, but there are others features, for instance entry barriers, price-making firms [81]

Table 2.2: Market structure according regarding the number of participants [82]

		Supply-side		
		Free competition	Oligopoly	Monopoly
Demand side	Free competition	Free competition	Oligopoly	Monopoly
	Oligopoly	Demand oligopoly	Bilateral oligopoly	Reduced Monopoly
	Monopoly	Monopsony	Reduced Monopsony	Bilateral Monopoly

- Players in imperfect competition have some degree of market power, which means they can influence the price of their goods or services rather than being price-takers, as in perfect competition.
- Players in an imperfectly competitive market often do not have complete information. Consumers may not be fully aware of all the prices or product qualities, while firms may lack complete information about their competitors.
- Imperfect competition typically involves a small number of players relative to perfect competition, where there are many firms. This leads to some degree of monopoly power or oligopoly structures.

According to Heinrich von Stackelberg [82], nine types of market structures can be recognised. These types are differentiated based on the number of participants on the supply side or the demand side. These structures are shown in Table 2.2.

In power systems, oligopoly structures are the most widespread due to entry barriers and the cost structure of electric power. Moreover, distribution systems are considered natural monopolies because they exhibit strong economies of scale, which, for the sake of efficiency, require that a single company provide the service [83].

Two types of oligopoly models are distinguished: i) non-cooperative oligopoly models (the focus of this thesis) and ii) cooperative oligopoly models. The latter include collusion, cartels, and strategic competition. Although these effects could occur in the context of DER inclusion, they are outside the scope of this thesis.

In the modelling of non-cooperative oligopolies, three different approaches have commonly been utilised, each with its own characteristics:

- Cournot model: In this approach, each player determines its production level while assuming that changes in its output will not directly influence its competitors' actions. The Cournot model is symmetric in nature, as all firms are assumed to make their decisions simultaneously, focusing on how much to produce rather than at what price.
- Bertrand model: Here, each player competes by determining its bid price for the entire output, rather than by setting the quantity. Players in a Bertrand model compete primarily on price, and the firm offering the lowest price tends to capture the market, making this model especially relevant in industries where price competition is the primary driver.

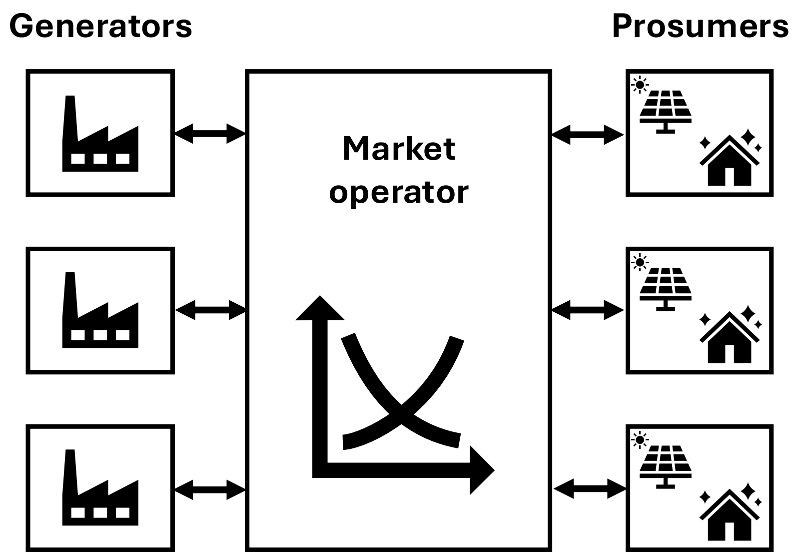

Figure 2.6: Representative schemes for research that study the interaction between prosumers and utility scale generators.

- Stackelberg model: This approach introduces an asymmetric game where some players, referred to as leaders, make strategic decisions first. The remaining players, known as followers, then react to these decisions. The Stackelberg model allows for a hierarchical structure, where the strategic advantage lies with the leader due to its ability to influence the decisions of followers.

In the context of power systems, Stackelberg games are one of the most widely used models [40], particularly for their versatility in modelling oligopolies, as they impose few constraints on the modelling process. Studies involving DER integration can be broadly categorised into two groups: i) those that explore the relationship between DER and large generators, and ii) those that focus on the interaction between DER and local networks. Although these perspectives are theoretically distinct, in practice, research tends to analyse them separately rather than combining both views.

In this regard, the first group of papers that relates DER inclusion (local energy markets) with large generators (wholesale markets) includes the following studies [84]–[89]. Typically, these studies focus on features such as carbon emissions, flexibility, and market design. Table 2.3 summarises the leader and the follower in the mathematical models.

The second group of papers focuses its analysis on local structures, considering the study of tariffs, the role of distribution networks, among other aspects. In this group, the following studies are highlighted [90]–[98]. Table 2.4 summarises these articles, including the leader, follower, and DER inclusion features. Regarding DER inclusion features, there are three options: i) Fixed DER capacity (i.e., DERs are not part of the decision variables), ii) Equilibrium DER (i.e., DER decisions are made by prosumers), and iii) Optimised DER by aggregator (i.e., DER is optimised at the neighbourhood level).

Table 2.3: Leader and follower definition for studies that relates generation and DER

Article	Leader	Follower
[84]	Generators	Prosumers
[85]	Retailer	Prosumers with demand response
[86]	Retailer	Aggregator with DSM
[87]	Electricity supplier	Prosumers and consumers
[88]	Generators	Distributed generators
[89]	Generators	Distributed generators

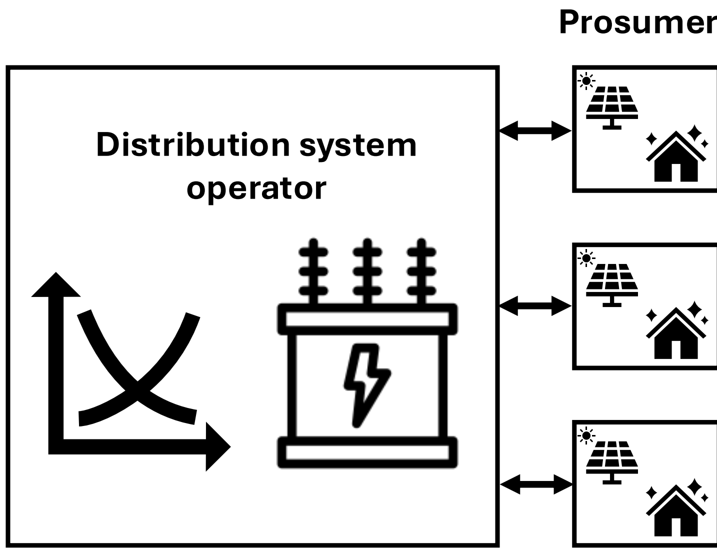

Figure 2.7: Representative schemes for research that study local interactions between prosumers and distribution networks.

2.2.2 Distribution network modelling in equilibrium models

Table 2.5 categorises the types of network modelling used to quantify the equilibrium. Regarding network modelling, studies show different levels of complexity. Some studies on equilibrium models have not considered network modelling within their scope [85]–[88], [90], [91], [98], because they centred their in the relation of DER with the generation companies, then they do not model the network. A DC power flow in a fixed network (i.e., the network capacity is fixed and is not part a variable within the optimisation) is applied in [84], [89], [95]; however, a DC power flow can be inaccurate in the LV context, underestimating the impact of physical issues (e.g., voltage limits or reactive power management), however, in other context, authors [28], [30] shows that distribution network is one of the main bottleneck in the DER deployment, constrained by voltage and congestion issues. To address this limitation, studies such as [94], [96] use AC power flow models (quadratic and linearised representations, respectively), but still the the caveat of fixing the capacity of the network, i.e., overlooking the impacts of DER on the optimal capacity of the distribution network, and centring the analysis in the short-term. Finally, in [92], [93], the distribution network is represented by two nodes (connecting the rest of the system with the neighborhood); in this case, the simplified

Table 2.4: Leader and follower definition for studies that study local energy markets

Article	**Leader**	**Follower**	**DER inclusion features**
[90]	Microgrid operator	Prosumer with PV	Fixed DER capacity
[91]	Microgrid operator	Prosumer with PV	Fixed DER capacity
[92]	Distibution sytem operator	Prosumers	Equilibrium DER
[93]	Distibution sytem operator	Aggregator	Equilibrium DER
[94]	Distibution sytem operator	Prosumers	Equilibrium DER
[95]	Distibution sytem operator	Aggegator	Optimised DER by aggregator
[96]	Distibution sytem operator	Prosumers	Fixed DER capacity
[97]	Distibution sytem operator	Prosumers	Equilibrium DER
[98]	Distibution sytem operator	Prosumers	Optimised DER by aggregator

Table 2.5: Network modelling in equilibrium models.

Network	**Article**
Single node model without network considerations	[85]
	[86]
	[87]
	[88]
	[90]
	[91]
	[98]
DC power flow model	[84]
	[89]
	[95]
AC power flow model with a fixed network	[94]
	[96]
Bi-nodal model with variable network	[92]
	[93]

network is optimally sized, but physical constraints are neglected.

Based on the information presented in the table, and as far as the author of this thesis is aware, only two research articles have analyzed the role of AC power flow in DER integration [92], [93]. These papers focus on short-term equilibrium modelling and assume network capacities are fixed (i.e., capacities are not variable within the equilibrium model). This leaves space to explore how network investment impacts long-term equilibrium.

The role of networks in a decarbonised energy future has been recognised at the transmission level (for instance, see [99]), by enabling the renewable deployment and providing enough transmission capacity; however, at the LV level, it remains an emerging research area, where not only the thermal capacity of power lines matters but also voltage and reactive constraints need to be considered.

This gap has been identified by other authors [40], [73] concerning local energy markets. In particular, to the best of the thesis author's knowledge, there is no other study that simultaneously includes:

- DER as a decision variable in the equilibrium model.
- Distribution network capacity as a variable in the equilibrium model.
- AC power flow modelling included into the equilibrium model

2.2.3 The role of tariffs in equilibrium models

Total electricity tariffs paid by end users have three main components: i) the energy cost, that is, the price of electricity generation, trade, and supply; ii) network charges, for both transmission or distribution; and iii) taxes and other charges, including Value Added Tax (VAT), various tax contributions, and support measures [100]–[102].

In general, energy costs comes from a competitive market given by the retail sector or general supply auctions. Therefore, the final price is exogenous to the regulations and give an account of the supply costs, competitive conditions and the risk profile of the industry [103].

Instead network charges, due to it monopolistic condition is regulated business whose revenue is reviewed by the regulation. In this context, the pricing schemes are a political/regulatory decision to recover the network costs. Thus, the analysis is focused in network tariff, due to their definition derives from a regulatory decision instead of a competitive process.

General studies on tariff design are a classical topic in power systems, as this design should collect the network costs, however the allocation of those costs in different customers can be done in many ways. However the tariff making process follow certain principles. Note that under certain conditions and this has gained greater relevance as DERs become more affordable for many prosumers. In this context, theoretical frameworks have been developed by [104]–[106], among others. In general, the tariff-making process can pursue multiple principles such as [100]:

- Cost reflectiveness
- Infrastructure and operational cost- efficiency
- Cost recovery
- Non- discriminatory
- Transparency, simplicity, and predictability
- Fairness as a necessary balance of interests

Regulators must carefully balance these objectives in line with broader policy goals. However, it is important to note that there are no universal rules for this process, and the prioritisation of these principles often depends on the specific regulatory context, market

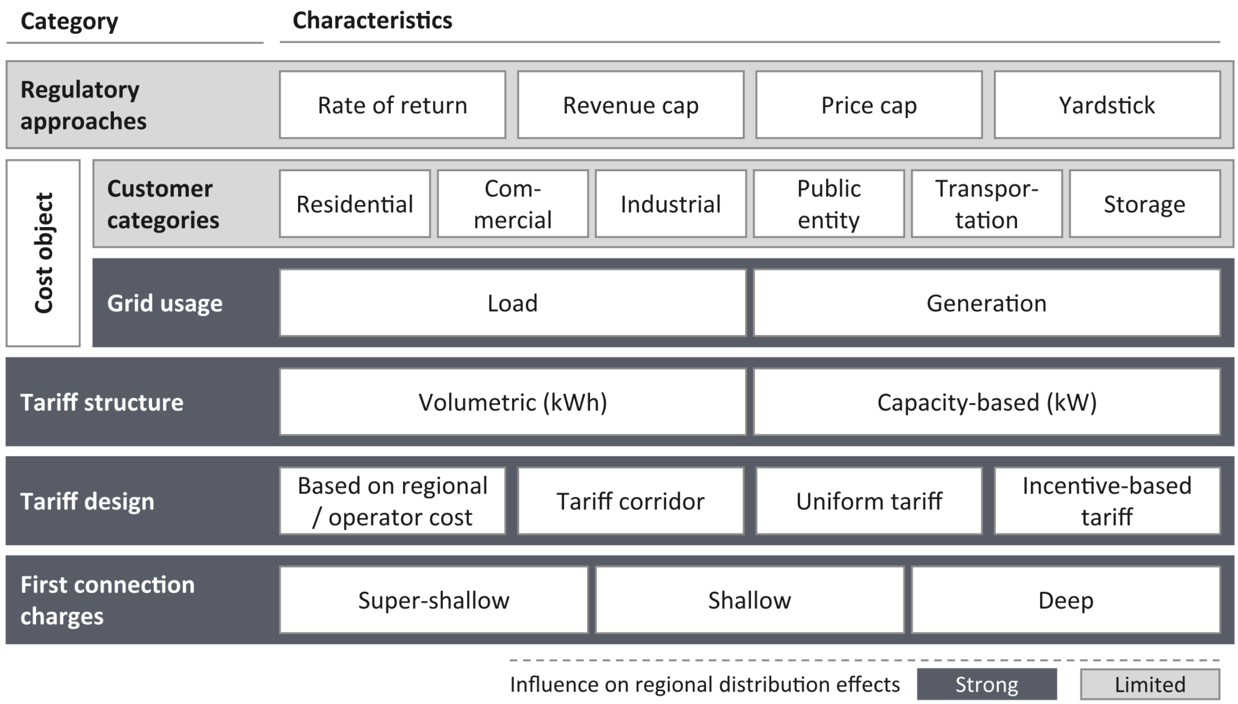

Figure 2.8: Tariff composition considering different components [108].

conditions, and social or economic priorities of the region in question. As the energy transition continues and DERs proliferate, the challenge of designing tariffs that are equitable, efficient, and sustainable will only grow, requiring ongoing adaptation and innovation in regulatory practices.

In practical terms, tariff schemes typically have predefined structures. Figure 2.8 shows the classical tariff components for distribution networks in Europe, recognising the regulatory approaches to define the allowance revenue for distribution network owner, types of customers according to their activities of type of grid usage, Finally, the figure shows the first connection charges, based on the cost of the new infrastructure required (deep), or the marginal cost of the infrastructures (shallow).

In this work, the focus is related with the tariff structure for recovering distribution network costs. There are two main structures: volumetric (associated with energy demand in kWh) and capacity-based (associated with demand consumption during peak hours in kW). Figure 2.9 shows different structures used in European countries. Similarly, in Latin American countries, a volumetric tariff is the most utilised for residential customers [107].

Currently, in most countries, tariffs are the main economic signal for proper DER development due to prosumers are exposed to electricity tariff and DER deployment my diminish their annual bills. For instance, [109], [110] shows the impact of different tariff schemes on DER installation, highlighting that cost-reflective tariffs (i.e., tariffs aligned with the incremental cost of the system) incentives higher integration of DER. Similarly, the authors in [40] demonstrate the close relationship between structures studied by academic models and practical regulatory frameworks. [111] explores studies on the integration of DER in developed and developing countries. Many developing countries have initiated DER deployment, but their local energy market structures rely on regulated tariffs, often a combination of retail and

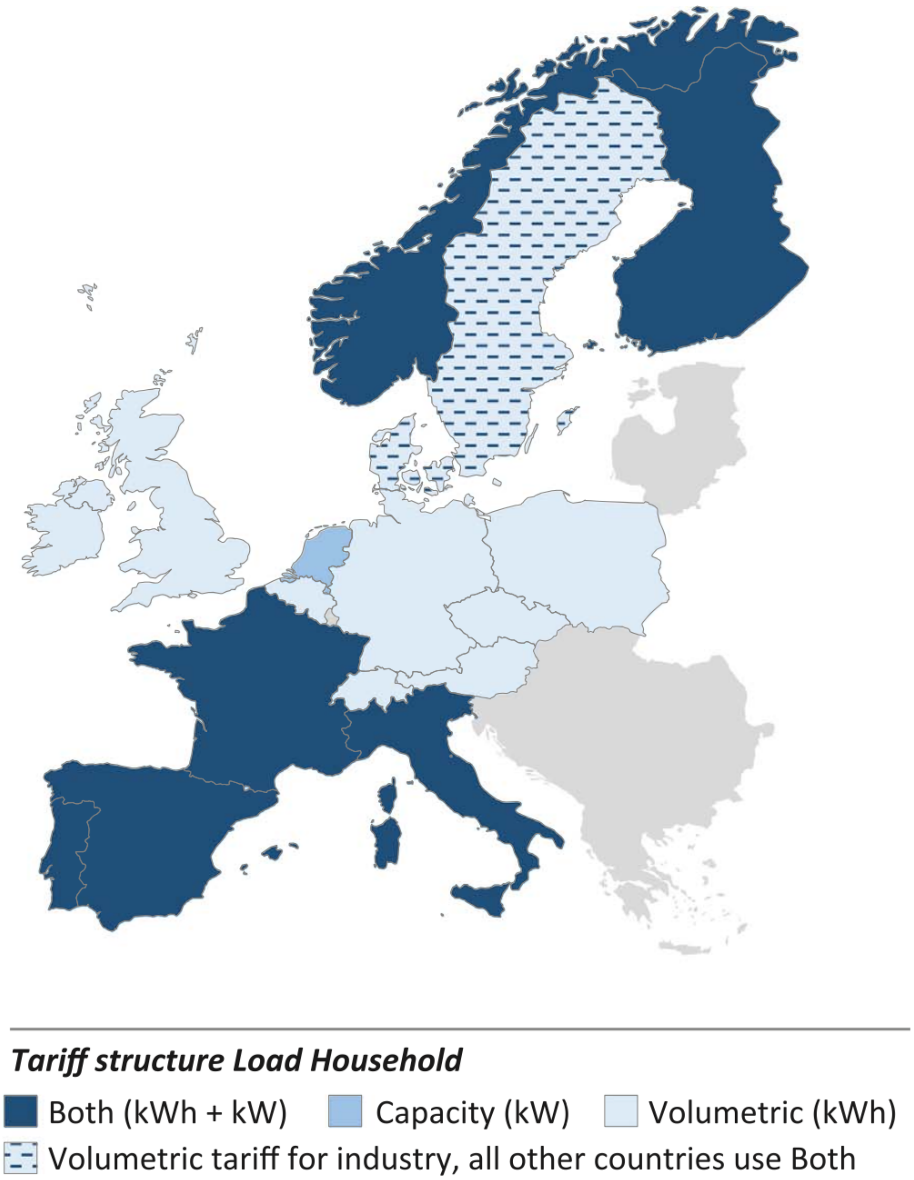

Figure 2.9: Tariff structures for different countries in Europe in 2018 [108].

network tariffs expressed in volumetric terms, which fail to incorporate actual distribution network usage and energy availability. Therefore, studying tariffs and their consequences is crucial to analyze DER integration levels and the social effects of equilibrium.

The inclusion of tariffs in equilibrium models inspired by game theory serves to analyse the structural implications of tariff design. It means that, the game theory assumes that prosumers act following an economical rational behaviour. Under this assumption, the equilibrium reflects the minimum costs. Evidently this is an idealistic scenario that can be understood as a structural. The difference between the practical application of tariffs and equilibrium models can be understood as a behavioral pattern of prosumers that goes beyond rational decisions, and may have a positive or negative impact in the total cost of the system. For instance, if the behaviour of customers make them act following the central planner decision, the overall system cost will decrease. That would imply that some actors may have an altruistic behaviour.

Consequently, the role of distribution tariffs in the deployment of DERs has been extensively examined in various studies, with a strong focus on efficiency. These studies primarily explore how tariffs can incentivise an equilibrium that minimises overall system costs, often highlighting the importance of cost-reflective tariffs in promoting optimal DER integration. However, the distributional impacts of tariffs, particularly in terms of how they affect consumers who are less able to benefit from the energy transition, have received comparatively less attention.

For instance, several studies [88], [89], [92]–[97], [109], [112]–[118] analyse various tariff structures, underscoring the need for cost-reflective tariffs to efficiently incorporate large volumes of DERs into the grid. These works stress that achieving global efficiency through well-designed tariffs is critical to managing the transition toward a decentralised energy system.

Additionally, several of these studies [88], [89], [92]–[97] employ Stackelberg game theory to model and analyse tariffs under different equilibrium conditions. Their primary objective is to evaluate the impact of tariffs on overall system efficiency, leaving the distributional effects of cost allocation largely unexplored. As a result, while these studies advance the understanding of tariff efficiency, they often overlook how different consumer groups—particularly low-income or vulnerable consumers—are affected by the costs associated with the energy transition, a gap that remains critical for ensuring fairness in future energy markets.

2.3 Equity and Fairness notions in energy systems

This subsection elaborates on these concepts, starting from their basic definitions and progressing to their implications for energy systems. The motivation behind this discussion is to demonstrate that the lack of clear definitions for equity and fairness can lead to different approaches in addressing energy fairness. To begin, it is important to distinguish between equity and fairness, as they represent two different principles in the tariff-making process [100], [119].

With regard to equity, the concept has been defined as follows:

> *Equity or non-discriminatory access to the service and cost allocation. As a rule, non-discrimination is agreed to mean that equal power consumption should be charged equally, regardless of the nature of the user or the use to which the energy is put. Equity does not mean, then, that the same costs should be allocated to all grid users (to make this perfectly clear, this principle is often referred to as the fairness rather than the equity principle). From the standpoint of the electric power business, this principle ensures that the rates applied do not provide a given competitor (in this case, customers) any advantage over any other within the electricity system...* [119]

Consequently, this concept is primarily related to how customers are treated within the energy market, ensuring that no arbitrary discrimination is applied between users. For example, this principle has significant implications for first connection charges, where the fee must adhere to a general rule and not vary arbitrarily for two similar stakeholders seeking connection to the grid. Equity, therefore, focuses on maintaining consistent and non-discriminatory treatment for all participants, ensuring fair access to services and cost allocation across the energy market.

There is no consensus on the definition of fairness. That said, the work in [16] provides an extensive review on fairness in local energy systems, three different principles are analysed: equality, meritocracy and the John Rawls principle. The root of the concept of fairness can be tracked to ancient Greece, specifically to the following quote from Aristotle:

> *Good should be distributed between people proportionately to what each person deserves...* [120]

In this regard, the question of what is deserved arose. Thus, the basic principle is *equality* distribution, nevertheless in many cases it is acceptable to deviate from the equality distribution, arguing in favour to a *meritocratic* distribution.

Following the narrative in [16], some theorist have challenged the meritocratic approach by arguing that certain goods, for instance, basic health care shold be allocated regardless to merits and contribution. In this line appears the work of John Rawls and the Theory of Justice. Rawls argues that:

> *it is legitimate that individual efforts result in higher gains but only if these gains also go hand in hand with considerable advantages of least advantaged members of society* [121]

In base to those three principles: i) Equality, ii) Meritocracy, and iii) Rawls' principle (also known as a min-max principle) can be summarised as follow:

- Equality: the main objective of the principle that agents receive an as equal as possible share of the goods or burdens of a respective good.
- Meritocracy: The main objective of the principle is that distribution of a good and burdens is subject to the agents merits and contributions. Thus participants that invest more in a cooperative practice are rewarded accordingly in the distribution.
- Min-max principle: The main objective of the principle is to ensure an allocation of resources that maximises the minimum benefit received by any agent.

In recent years, energy justice, including the distributional aspects of the benefits and costs of new technologies, has gained significant interest. Reference [48] provides a literature survey. Most of the articles that study distributional fairness focus their analysis in geographical (or spatial) fairness.

In this line, the analysis of how tariffs schemes might impact in the cost allocation among prosumers and the fairnes of the outcome. In this line, reference [36] highlights a gap in the comparison framework among different policies and tariff schemes. Authors in [49] partially addressed this gap by analysing 11 different tariff structures and their distributional impacts. However, their approach relies on historical data and does not consider prosumers' ability to adjust their demand patterns in response to changes in economic signals.

2.4 Summary and Gap Identification

This section summarizes the literature review and identifies the research gaps that this thesis aims to address.

2.4.1 Impact of Socioeconomic Factors on Residential Electricity Demand

The literature provides evidence that socioeconomic factors significantly influence demand patterns and consumption levels. However, the impact of income as a variable is case-dependent. The explanations for this include: First, the inverted U-shape relation between income and electricity consumption. Second, residential electricity demand results from multi factorial processes, making the correlation of income weaker compared to other aspects such as consumers' education levels or demographic composition (e.g., the presence of children).

These studies through statistical collected under normal conditions (i.e., the typical and stable conditions that customers face). However, these conditions do not account for understanding customer behaviour during disruptive events when customers need to adapt to new conditions. How different customers have varying capabilities to adapt their patterns and consumption levels is an area that remains underexplored and represents a gap in the research.

2.4.2 DER Deployment by Prosumers and Local Energy Markets

DER deployment has been extensively studied from various perspectives, including the economic structures (i.e., P2P-based, community-based, and group-of-community-based structures). The appropriate economic structure depends on the context of the analysis and has implications for mathematical modeling.

In the context of the energy transition, from passive customers to actively engaged ones, the community-based structure is the most likely to become the typical structure (for instance, the DSO fits under this market structure definition). Consequently, research has focused on analysing the external relationship between local energy markets and wholesale markets, as well as the internal relationships within local energy markets. Classical methodologies involve mathematical modelling based on game theory and agent-based methods, allowing for the modelling of decentralised decisions.

These studies typically focus on short- or mid-term analysis, which means they do not examine equilibrium conditions where both DER and distribution network capacities can adjust in response to market conditions. This limitation may obscure the full impact of network constraints on DER adoption, which is currently a significant bottleneck in DER deployment in advanced countries like Germany or the Netherlands. Furthermore, it may overlook the role of the network in the allocation of distribution costs, potentially placing a disproportionate burden of DER deployment on specific segments of prosumers.

As a result, there is considerable scope to contribute to the understanding of the network's role in achieving long-term equilibrium, especially in terms of how it influences both DER integration and the equitable distribution of costs across different consumer groups.

2.4.3 Equity and Fairness Notions in Energy Systems

Equity and fairness have gained increasing interest in academic literature, as energy systems are trending towards electrification, and DER integration may lead to unequal electricity costs among customers. However, there is still debate on what constitutes fairness. In this context, definitions supporting equal distribution, meritocracy, and Rawls' principle are considered.

Most studies on local energy markets focus on defining fairness within this context and understanding distributional fairness, with particular emphasis on geographical fairness, and less attention on social fairness.

Regarding social fairness, many studies rely on statistical and optimisation methods that tend to overlook the dynamic interaction between prosumers and the network. These approaches often fail to fully capture how prosumers can impact the network and how network constraints, in turn, affect prosumer behaviour. In an evolving technological landscape, where DERs and grid technologies are advancing rapidly, past statistical data may not be a reliable predictor for future scenarios. However, despite these limitations, such statistical and optimisation-based methods remain the primary approach used to analyse the impact of tariffs on prosumers and the wider network.

This reliance on past trends could lead to oversimplified conclusions, especially as the energy landscape becomes more decentralised and prosumers play a larger role. Moving forward, it will be critical to incorporate more dynamic models that better account for these interactions to ensure that tariff designs and network policies are equitable and reflective of future realities.

While several studies have worked on understanding the impact of tariffs on efficiency, comparatively fewer have examined the impact on cost allocation across distinct socioeconomic groups. In this context, equilibrium models have not incorporated an energy fairness analysis for different tariff schemes, revealing a gap in the literature.

Chapter 3

Influence of socioeconomic factors on electricity demand adaptation among customers

3.1 Chapter overview

This chapter analyses the relationship between socioeconomic factors and how customers adapt their electricity consumption in response to a disruptive event. In this case, the disruptive event is the first wave of the COVID-19 pandemic and its impact on electricity consumption among regulated demand, with a specific focus on residential demand in Chile. In doing so, the second and third objective of the Section 1.4.2.

The adaption of electricity consumption in response to disruptive event shows the short-term adaptation capacity, where customers must adjust their consumption patterns based on their technical capabilities (determined by their current electrical devices), economic position, and behavioural patterns. As a consequence, customers may experience an increase in their electricity bills and a reduction in comfort in their quality life during the disruptive event.

In this chapter, to conduct this analysis, the hourly electricity consumption data of 230,000 clients, obtained from smart meter devices installed in the Metropolitan Region, is processed. The information captures from the 1st of January, 2019 to 30th of September 2020. This way, it includes the first COVD-19 wave in Chile.

The results are presented with respect to geographical zones that exhibit significant variation in their socioeconomic backgrounds. As a proxy for social background, the study uses the mean income of each zone as a variable. This way, the analysis shows how the electrictity customers were adapted and how was the difference between different socioeconomic backgrounds.

The findings indicate that the electricity demand of residential consumers increased during the first COVID-19 wave, however the effect of pandemic is mixed with the natural seasonality of the residential electricity demand on Chile, where due to low temperatures the energy consumption increases during winter.

Considering the above mentioned, a methodology to isolate the weather with the pandemic effects is developed. The results shows that the residential increased their consumption motivated by the lock-down measures. Furthermore, the study demonstrates how these effects vary across different communes of Santiago, revealing a strong relationship with socioeconomic factors. Specifically, the results show that different demand response patterns are influenced by the socioeconomic status of consumers.

3.2 Introduction and motivation

As mentioned above, the aim of the work presented in this chapter, is to analyse the relationship between socioeconomic factors and how customers adapt their electricity consumption when facing a disruptive event. For this purpose, the energy patterns of different types of customers were analysed during a disruptive event (i.e., COVID-19 pandemic).

In this work, a disruptive event is defined as an unusual circumstance that affects several aspects of customers' lives. Accordingly, disruptive events can include natural disasters [22] (such as hurricanes [122] or earthquakes [123], [124]), climate change [125]–[128], economic [129], [130] and political crises [131], pandemics, and others. These events can have multiple impacts on economic and social aspects, including changes in energy consumption due to the circumstances, e.g., during a hurricane, customers may demand more energy for heating, or during a pandemic, lockdown measures may increase energy demand. Under these circumstances, consumers with higher socieeconomic backgrounds, and thus access to more resources (e.g., energy generation, transport, space, etc.), may have distinctively different behaviours (quantified here as energy consumption) than customers with lower access to resources.

The potential differences in the adaptation capabilities among various socioeconomic groups reveal how the benefits and burdens (costs) of the energy system are distributed. This raises important questions about the fairness of the energy system, particularly when examining electricity consumption during disruptive events. This chapter tries to analyse the underlying drivers of these unfairness and how they contribute to an unequal distribution of costs and benefits. Understanding these drivers is crucial for addressing fairness and ensuring that energy systems are designed to reduce disparities among different groups.

Regarding the impact of pandemics, studies have quantified the global (regional or national) effects on electricity demand during the COVID-19 pandemic. Table 3.1 provides a summary of the global impacts of the COVID-19 pandemic on the electricity consumption of 17 countries. Even though this information facilitated aggregated, country level analysis, it does not discloses what happens across different economic sectors (e.g., industrial, commercial and residential) or even among various socioeconomic groups within a specific sector.

Focusing on the residential sector, wealthier customers generally have more options to adapt their electricity consumption compared to less affluent ones. They can choose to reduce their consumption (with some loss of comfort, such as cooler homes in winter), adjust

Table 3.1: Summary of publications about country-related COVID-19 impacts on electricity demand.

Source	Country	Economy	Findings
[132]	Australia	Developed	Reduction of 7% of national-wide electricity demand during March 2020 compared to 2019. Residential demand grew by 14% during March 2020
[133]	Canada (Ontario)		Reduction of 14% of overall electricity demand during April 2020 compared to 2019
[134]	France		Reduction of 20% of national-wide electricity demand during the third week of lockdown period compared the same period of 2019
[135]	Germany		Reduction of 6% of national-wide electricity demand during May 2020 compared to 2019
[136]	Ireland		Increment of 11% in residential demand comparing two weeks before and after lockdown
[137]	Italy		Reduction of 20% of national-wide electricity demand during May 2020 compared to 2019
[138]	Japan		Reduction of 8% of overall electricity demand (in Kansai) during April and May 2020 compared to 2019
[139]	Sweden		Increment of 2% of overall electricity demand in 2020 compared to 2019
[140], [141]	UK		Reduction of 16% in overall electricity demand during the first lockdown period compared with the average of the last three years. Residential demand shows a growth of 17%
[135], [142]	US		Reduction of 19% of overall electricity demand during April 2020 compared to 2019. In Austin, residential demand increased 32% during the first three weeks of lockdown
[143]	Serbia	In transition	Simulation shows that the residential demand sector could increase up to 58% of their electricity demand due to containment measures
[144]	Bangladesh	Developing	Reduction of 14% of national-wide electricity demand during 2020 compared to 2019. Residential demand increased 15% during 2020 compared to 2019
[145]	Brazil		Reduction of 19% of overall electricity demand (south subsystem) comparing periods before and after implementation of containment measures
[135], [146]	China		Reduction of 11% of national-wide electricity demand during March 2020 compared to 2019
[135]	India		Reduction of 4% of national-wide electricity demand during 2020 compared to 2019
[144]	Nepal		Reduction with a range between 21%-28% in nation-wide electricity demand during 2020 compared to 2019
[147]	South Korea		Reduction 10% of national-wide electricity demand during April 2020 compared to 2019. An increment of 5.5% in residential demand during March 2020 compared to 2019

their usage patterns, or invest in energy-efficient technologies (such as better insulation or distributed generation systems like solar panels to lower long-term energy costs). These investments help wealthier customers not only manage their energy use but also reduce their overall costs in the long run.

In contrast, less wealthy socioeconomic groups often have fewer options and are typically constrained to one primary strategy: limiting their energy consumption, which can come at the expense of significant discomfort. For example, they may be forced to endure inadequate heating or cooling because they lack the financial resources to invest in energy efficiency or alternative energy solutions.

A deeper understanding of the extent and nature of these differences in adaptation capabilities is critical for identifying the sources of inequality in energy outcomes. By investigating how different groups respond to energy costs and disruptions, policymakers can better address the structural drivers of these inequalities and promote more equitable energy solutions.

3.2.1 The disruption of the COVID-19 pandemic

The COVID-19 pandemic began in November 2019 in the Chinese province of Hubei. Since then, it has gained global attention due to the rapid increase in daily infections and the resulting collapse of health systems. In March 2020, COVID-19 was declared a pandemic by the World Health Organization (WHO) [148].

To contain the spread of the virus and alleviate pressure on health systems, several countries around the world adopted policies restricting people's mobility. In Chile, a state of catastrophe was declared on 18 March 2020, and quarantines were first implemented at the end of that month, applied by zones (usually communes[1]). In Santiago, the capital city of Chile, where the largest population is concentrated, a total quarantine was declared on 15 May 2020 [149], which will describe further in the subsequent subsections.

In the context of the pandemic, the containment measures developed to curve the spread of the virus had strong impacts in the electricity demand of several countries. The International Energy Agency (IEA) reports the variation in electricity demand with respect to 2019 for some countries in Europe, as well as China and India [150]. The report finds that Italy experienced the sharpest drop in electricity demand, with a decrease of over 25% during April 2020. Similarly, the work presented in [151] reports decrease in the overall consumption in electricity demand for seven Regional Transmission Operators (RTOs) in the United States. The New York Independent System Operator (NYISO) and Midcontinent Independent System Operator (MISO) jurisdictions showed the largest decreases in the US experience (around 10%) in demand compared to 2019.

In Chile, the reduction in mobility prompted by quarantines and other containment measures also affected economic activity, which decreased by 14.1% in the second quarter of 2020 compared to the same period in 2019 [152]. Consequently, national electricity demand declined by approximately 3.5% compared to the previous year during the period from May to August 2020, as shown in Fig. 3.1.

3.3 Methodology

This section explains the methodology used to analyse the impact of the disruptive event caused by COVID-19 on the electricity demand of residential customers in the metropolitan region. The subsection begins with a general explanation of the methodology used for the analysis. Following this, an overview of the specific methodology applied to the Chilean case is provided, presenting the four specific cases analysed. The subsequent subsections will then detail the specific methodology used for each of these cases.

[1]The commune is the basic administrative division of the city. For example, the city of Santiago—formally called the province of Santiago—is divided into 32 communes.

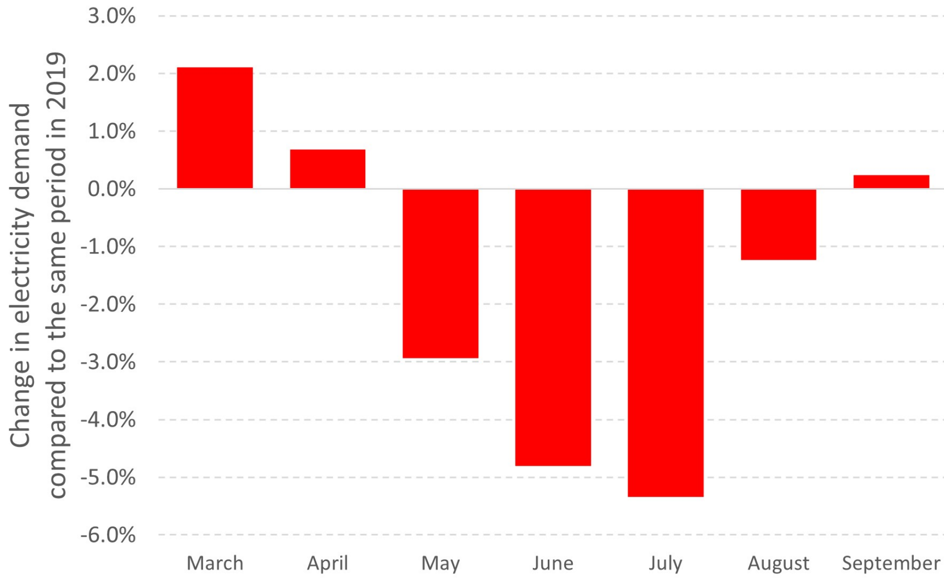

Figure 3.1: Variation in electricity demand with respect to the same period in 2019 (The first case of COVID-19 in Chile was reported in March 2020). [153].

3.3.1 General methodology

The methodology relies on both qualitative and quantitative comparisons between electricity consumption during (or after) a disruptive event and a benchmark of electricity consumption prior to the event, as illustrated in Figure 3.2.

The general approach involves comparing electricity consumption under normal conditions, before the disruptive event, with consumption patterns after the event. The pre-event consumption, considered the benchmark, can be selected in various ways. For instance, the benchmark might be the electricity consumption from one week before the event, such as the start of a pandemic, or alternatively, it could be based on consumption from the same period in the previous year. The selection of the benchmark is critical, as it can significantly influence the conclusions drawn from the comparison.

This benchmarking approach can be applied to different customer segments, depending on the study's objective. For example, a study might focus on the role of having children in the household and how this affects electricity consumption patterns. In such a case, the analysis would be divided into clusters—one including households with children and another without. As this study aims to analyse multiple dependencies across different socioeconomic backgrounds, the clustering method should include relevant socioeconomic variables.

At this stage, it is essential to consider data availability for clustering customers. Selecting measurable attributes, such as a customer's location or income, is crucial for identifying correlations that may explain differences in electricity consumption patterns. The benchmark and the electricity consumption during a disruptive event are then compared for each socioeconomic cluster.

Finally, the size of the sample is directly linked to the methodology used. Regression-based

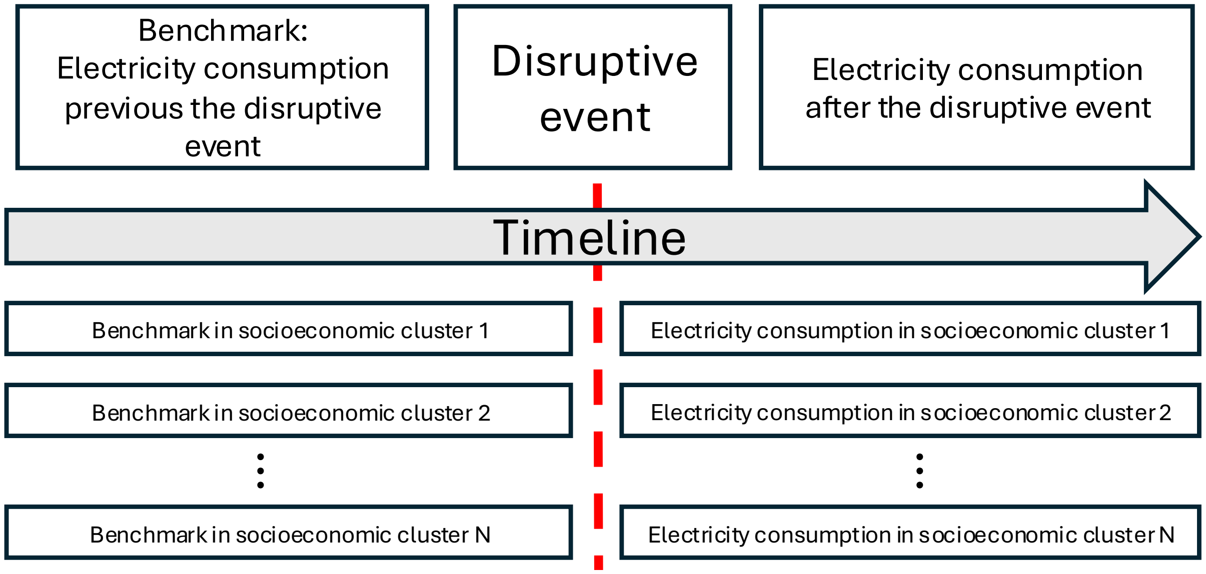

Figure 3.2: Basic scheme to analyse the impact of a disruptive event.

models, such as those using optimal least squares, or machine learning tools like decision trees (see [22], [123], [131], [154] for examples), require relatively large datasets to produce statistically significant results. In contexts where such data is unavailable, analysts may need to create fit-for-purpose ad-hoc methodologies tailored to the specific study.

3.3.2 Methodology for the case of the pandemic COVID-19 in Chile

This section describes the methods to process a the high volume of data, and the statistical methods used to analyse the electricity demand of residential consumers (also are included small commercial consumers) during a disruptive event such as the COVID-19 pandemic.

To study these residential and commercial segments, data from 230,000 smart metering devices installed by Enel Distribución [155] in Santiago's capital city (covering 32 communes) were used. This data is protected by a Non-Disclosure Agreement and has been sufficiently aggregated in this work to ensure consumer privacy (notably, approximately 10% of consumers have a smart meter installed). The data is available for the period from 2019 to September 2020 considering hourly resolution. Thus, the data base consider around 3500 millions of electricity consumption data. It is worth mentioning that the socioeconomic aspect is done according to the location (or commune) of the customer. Thus, each commune is characterised by the average income.

The time series of demand per smart meter is then characterised based on the communes where consumers are located and their type (i.e., residential or commercial). By examining the evolution of demand data during the first wave of the pandemic, trends across various time scales (hourly, daily, weekly) are identified. Additionally, demand evolution is compared across different types of consumers and communes. This analysis presents both average consumption and other percentiles that give a better understanding of the density of consumption in each commune and for each type of consumer. The analysis is focused in 5 of 32 communes in the

Table 3.2: The methodology decomposition in four cases.

Case	Benchmark	Analysis
Case i	The week before the pandemic	Weekly demand evolution through different communes
Case ii	The same period in the previous year	Isolate the pandemic effects with those related with temperatures
Case iii	The week before the pandemic	Behavourial changes at hourly level of residential demand
Case iv	The week before the pandemic	Overview of the impact across the 32 communes of Santiago

Metropolitan Region, which are representative of the spread of income across the different communes.

To understand the impacts of the pandemic, demand changes are evaluated using two benchmarks: (i) energy consumption immediately before the pandemic (March 2020), and (ii) energy consumption during the same period in the previous year (2019). To further isolate the pandemic's impact from seasonal effects, a method is employed to identify consumers who are weather-insensitive. This approach characterises consumers whose electricity consumption is less responsive to temperature variations, meaning that changes in their electricity consumption are more likely attributable to the lockdown measures rather than seasonal weather changes. In other words, the behaviour of these weather-insensitive consumers provides a more accurate reflection of the pandemic's effect, allowing for the isolation of demand shifts unrelated to temperature fluctuations.

In the subsequent subsections four different cases are analysed. Table 3.2 briefly summarises those cases and the benchmark considered in the analysis. Those cases are independent, it means that the results of a specific case does not depend on the others.

3.3.3 Case i: Trends in weekly demand of residential and commercial consumers during the pandemic

The weekly variation in electricity demand is analysed using the first week of March 2020 (week 10) as the benchmark. During this week, the Chilean Government had not yet declared a state of catastrophe for the country, so the energy consumption patterns of residential and commercial consumers were not yet impacted by the pandemic.

For the analysis, the demand data from each smart meter is aggregated (summed) for each week, and the weekly demand is averaged within each commune. This method provides the average weekly demand for both residential and commercial consumers in each commune. In addition to the average weekly demand, the respective 10th, 25th, 75th, and 90th percentile ranges are presented using box and whisker plots to illustrate the distribution of consumption.

These data are used to track the evolution of average demand from March 2, 2020, to September 21, 2020, offering insights into how electricity consumption changed throughout the early months of the pandemic across different consumer segments and communes.

3.3.4 Case ii: Isolating pandemic effects from seasonal weather effects on residential demand trends

The methodology for this case aims to examine changes in the electricity demand of residential consumers whose demand is not sensitive to temperature variations. For this specific segment of non-temperature-sensitive consumers, the increase in demand in 2020 compared to 2019 can primarily be attributed to the effects of the COVID-19 pandemic and the containment measures implemented by authorities. The benchmark for 2020 is the electricity consumption of non-temperature-sensitive consumers during the same week in 2019.

To identify these consumers, their average demand during cold weeks (April 22 and May 6, 2019) is compared with their demand during a warm week (March 4, 2019). A consumer is classified as temperature-insensitive if their average demand during cold weeks is similar to their demand during warm weeks, allowing for minor variations. This tolerance for variations is defined by a threshold, as shown in Figure 3.3 with a red dashed line.

If a consumer's electricity consumption exceeds this threshold in any cold week, they are classified as temperature-sensitive. Conversely, if the consumer's electricity consumption remains below the threshold during cold weeks, they are considered non-sensitive to temperature variations. The threshold is set at two times the electricity consumption during the first week of March, after testing other thresholds. However, future work could refine this threshold using a specific figure of merit to improve the identification process.

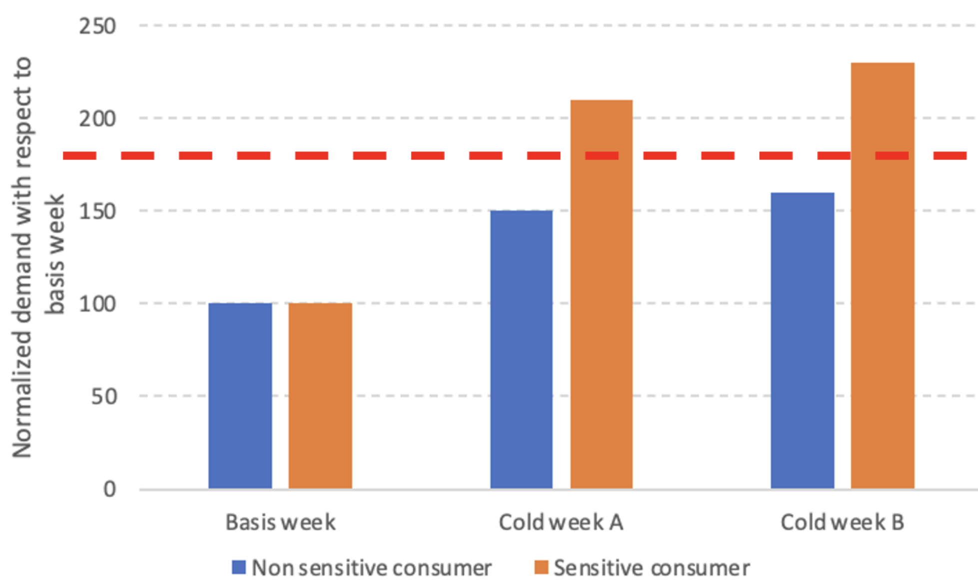

Figure 3.3: Scheme to determine if a consumer is sensitive or non-sensitive with respect to the temperatures

For this group of temperature-insensitive consumers, the variation in average monthly demand in 2020 is compared to their average monthly demand in the same months of 2019.

These variations are attributed to the effects of containment measures aimed at curbing the spread of COVID-19.

Note that other, arguably more advanced methodologies based on regressions, and machine learning (for instance, see [22], [123], [131]) cannot be applied in this study, as the collected smart metter dataset is not long enough to meet the training set needs of such methodologies. For instance, for every customer within the database there are information of electricity consumption during only one winter (2019). In addition, the income is only available to the commune level (32 communes). Thus, having income as a explanatory variable imposes a limitation for the methodology selection. Therefore, the proposal methodology considers a trade-off between complexity and data availability.

3.3.5 Case iii: Behavioural changes (at an hourly level) of residential demand

Unlike the previous cases, this case study focuses on hourly variations in electricity demand within representative weeks, offering a more detailed look at changes in consumption patterns throughout different phases of the pandemic. The periods analysed include the pre-pandemic week (March 2, 2020, which serves as the benchmark), the initial phase of intensive quarantines (week of April 20, 2020), the period of total lockdowns (week of June 22, 2020), and the gradual reopening phase (week of September 21, 2020).

This analysis delves into changes in daily demand patterns, which are closely linked to shifts in consumers' daily routines, such as wake-up times, work schedules, meals, and breaks. Additionally, the study examines temporal shifts in intra-day peak demand, revealing how consumption habits evolved throughout the pandemic. The analysis is carried out for two of the five selected communes, Las Condes and Renca, which represent the two extremes of the socioeconomic spectrum. While these two communes were chosen for detailed examination, similar trends are observed in other areas as well.

For each commune, the study calculates the average hourly demand along with the corresponding 10th, 25th, 75th, and 90th percentile ranges to provide a comprehensive understanding of consumption variability across different times of day and different phases of the pandemic. This approach highlights how the pandemic and related lockdown measures impacted electricity usage across both affluent and lower-income communities, offering insights into how socioeconomic factors influenced consumption patterns during this disruptive period.

3.3.6 Case iv: Overview of the impact of the pandemic on the 32 communes of the Metropolitan Region

This case study aims to provide a comprehensive assessment of the overall impact of the COVID-19 pandemic on the Metropolitan Region by quantifying the changes in average electricity demand across different communes during selected representative weeks. These variations are measured against the baseline week of March 2, 2020 (week 10), which serves as the reference point for normal, pre-pandemic conditions. The representative weeks chosen for this analysis are the same as those described in Case iii, ensuring consistency across the study.

The study also seeks to explore the disparities in how different communes experienced the effects of the pandemic on their electricity consumption. To achieve this, the analysis incorporates socioeconomic factors, using income as a proxy for socioeconomic status. By comparing the demand trends in higher-income communes with those in lower-income areas, the study highlights the differing impacts of the pandemic, reflecting the extent to which socioeconomic factors influence changes in electricity consumption patterns.

Finally, the findings discuss how the pandemic-induced shifts in electricity demand may have disproportionately affected certain segments of the population, shedding light on the unequal burdens and adaptations across different socioeconomic backgrounds.

3.4 Results an discussion

This subsection presents the results of the four cases outlined in the methodology (as discussed in section 3.3) for residential and small commercial consumers, aimed at analysing the impact of COVID-19 containment measures on the evolution of electricity demand among regulated consumers (i.e., residential and small commercial consumers) in the Metropolitan Region (Región Metropolitana). The study covers the period from the week of March 2 (week 10) to the week of September 21 (week 39), 2020.

Through this analysis, the results provide insights into how the pandemic-related restrictions influenced electricity consumption patterns across different consumer segments, shedding light on both short-term and longer-term effects.

3.4.1 Database content

The demand data from each smart metering device includes the following information for each consumer:

- **Location data:** This includes geographical coordinates, address, and commune of the consumers.
- **Commercial data:** This covers the type of billing (used to differentiate between residential and small business consumers) and the type of tariff or plan the consumer is on.
- **Electricity demand:** The energy consumed (in kWh) from January 2019 to September 2020, recorded with hourly resolution.

Additionally, the analysis includes more in-depth case studies focusing on five communes that represent different socioeconomic realities within the city. These communes are Las

Condes, Santiago[2], La Florida, La Cisterna, and Renca. The number of smart meters per commune and the types of consumers considered in the numerical studies are detailed in Annex A.

In the case of income, those data are taken from the Encuesta CASEN [156], which is a survey done by the Chilean Ministry of Social Development every 2-3 years. Thus, the average income per commune is obtained.

By examining these diverse communes, the study aims to provide a more nuanced understanding of how the pandemic impacted electricity demand across different socioeconomic backgrounds, offering a comprehensive view of how these disruptions varied within the metropolitan area.

3.4.2 Case i: Trends in weekly demand of residential and commercial consumers during the pandemic

Figures 3.4 and 3.6 show the evolution of the demand of commercial and residential consumers, respectively, throughout the period under study. Coloured areas highlight different containment measures undertaken by the Chilean government authorities, which are described in Table 3.3. Notice that residential demand increased with respect to week 10 (March 2, 2020), opposed to the systemic trend (Figure 3.1) of decreasing electricity demand from May to July.

Figures 3.4 and 3.6 show the variation of electricity demand during the pandemic for commercial and residential consumers. The figure shows that, since the implementation of school closures in week 12 (March 16, 2020), small commercial consumers (top figure) experience a gradual reduction in their demands compared to week 10 (March 2, 2020). This reduction reached its lowest point during week 15 (April 6, 2020). Particularly, the communes of Santiago and Las Condes, underwent demand reductions of 47% and 42%, respectively, compared to week 10. The other communes experienced demand reductions of around 15% during week 15.

The electricity demand from small businesses is shown in the top chart of Figure 3.4(considered commercial consumers) experiences a recovery during the period of gradual quarantine, specifically between weeks 15 and 20 (May 11, 2020). For example, Las Condes consumed 58% during week 15 (compared to week 10), figure that rises to 72% during week 20. This recovery is, however, greatly impacted by the total quarantine policy implemented during week 21 (May 18, 2020). During that week, the demand of Las Condes decreased to a 66% of the demand of week 10. Small businesses in the Santiago commune were the most affected in terms of electricity demand during week 21 (May 18, 2020), consuming around 57% of the electrical energy consumed in week 10.

Interestingly, the electricity demands of small commercial consumers on the five communes under analysis reach their peak around week 26. This week coincides with the coldest period of the winter (see Figure 3.5).

[2]Note that in this case, the reference is to the commune of Santiago, which is located within the city of Santiago.

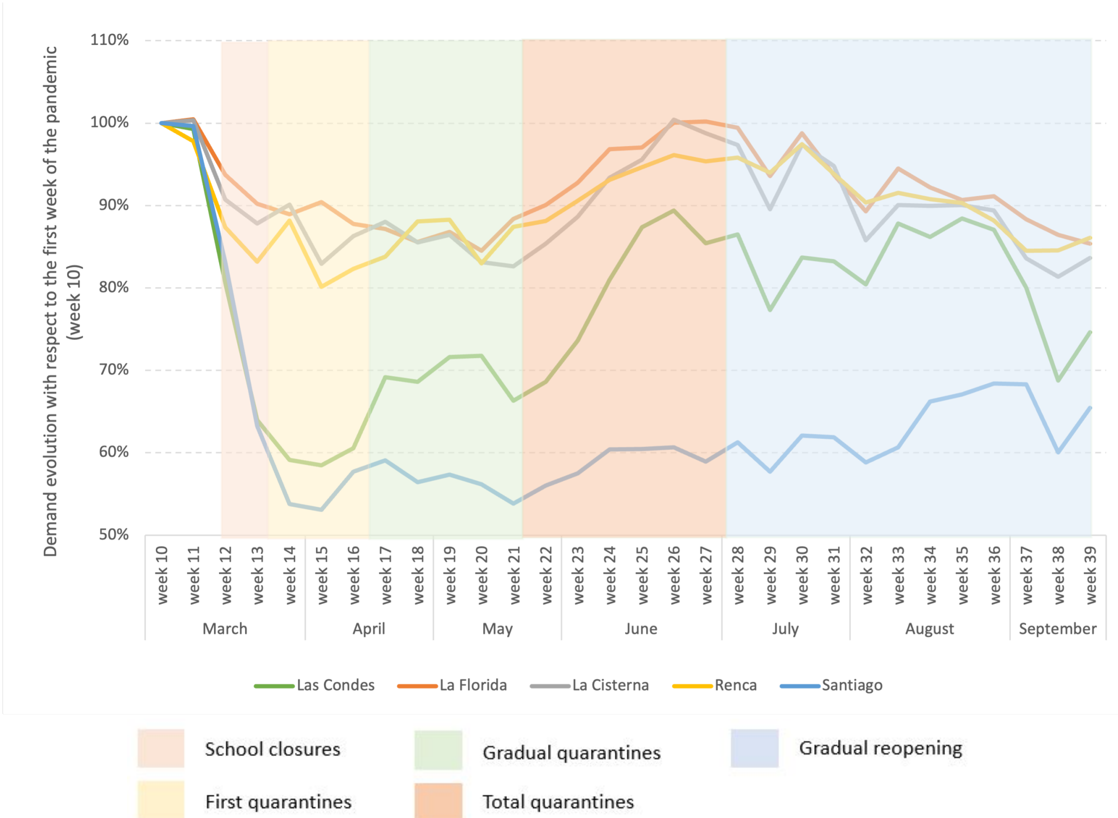

Figure 3.4: Variation in regulated commercial electricity demand during the weeks of the pandemic in 5 communes of Santiago.

Finally, during July and August, electricity demand maintained a relatively stable trend. Consumers in Santiago reduced their demand the most during this period, consuming on average around 63% of the electrical energy they consumed during week 10.

Figure 3.6 also shows trends in residential demand. During the first weeks of the pandemic, when school closures were mandated (weeks 12-14), demand in Las Condes and Santiago increased by approximately 10% compared to week 10. On the other hand, residential demand in Renca and La Cisterna increased at a lower rate of around 5%. From the end of April (week 18), residential electricity demand significantly increased as a consequence of the pandemic and lower temperatures in Santiago.

Peak demand occurred in week 26 (June 22, 2020). During this week, consumers in Las Condes increased their demand 2.7 times (on average) compared to week 10, while in Renca, consumers increased their demand 1.6 times.

After the peak-demand week, the gradual reopening policy and rising temperatures cause a reduction of residential demand. After the arrival of spring in week 39, the demand of consumers in Las Condes reached a 23% increase (compared to week 10), while in the other communes, it reached increases of around 10%.

It is important to notice that Figures 3.4 and 3.6 show the evolution of the average demand

Table 3.3: Containment measures applied by the Chilean government during the pandemic (all dates correspond to 2020).

Milestone	**Period**	**Comments**
School closures	Since week 12 (03/16)	This policy is in effect from March 16 until the end of the study horizon.
First quarantines	From week 14 to week 16 (03/30 - 04/13)	This period begins with the quarantine of four communes in the eastern part of Santiago, and ends with the reopening of these communes. At the end of this period, only two communes remain in partial quarantine (Santiago and Ñuñoa).
Gradual quarantines	From week 16 to week 21 (04/13 - 05/18)	During this period the authorities gradually increase the number of communes in quarantine. At the end of this period, all the 32 communes under study are in quarantine.
Total quarantine	From week 21 to week 27 (05/18 - 06/29)	During these weeks the authorities establish a quarantine for the whole metropolitan area (Región Metropolitana), allowing only the so-called essential activities*.
Gradual reopening	From week 27 (06/29)	Since the week of June 29, and as a result of improvements in the epidemiological indicators, the authorities begin to reopen communes.

*A set of activities deemed by the authority as critical for the society, e.g., healthcare workers,food supply chains.

per commune on a weekly basis. However, there is a significant variety of demand evolutions across consumers within a commune. In this regard, Figure 3.7 presents a box and whisker plot of demands in every commune. In all the cases, the box and whisker have their maximum width during the winter months.

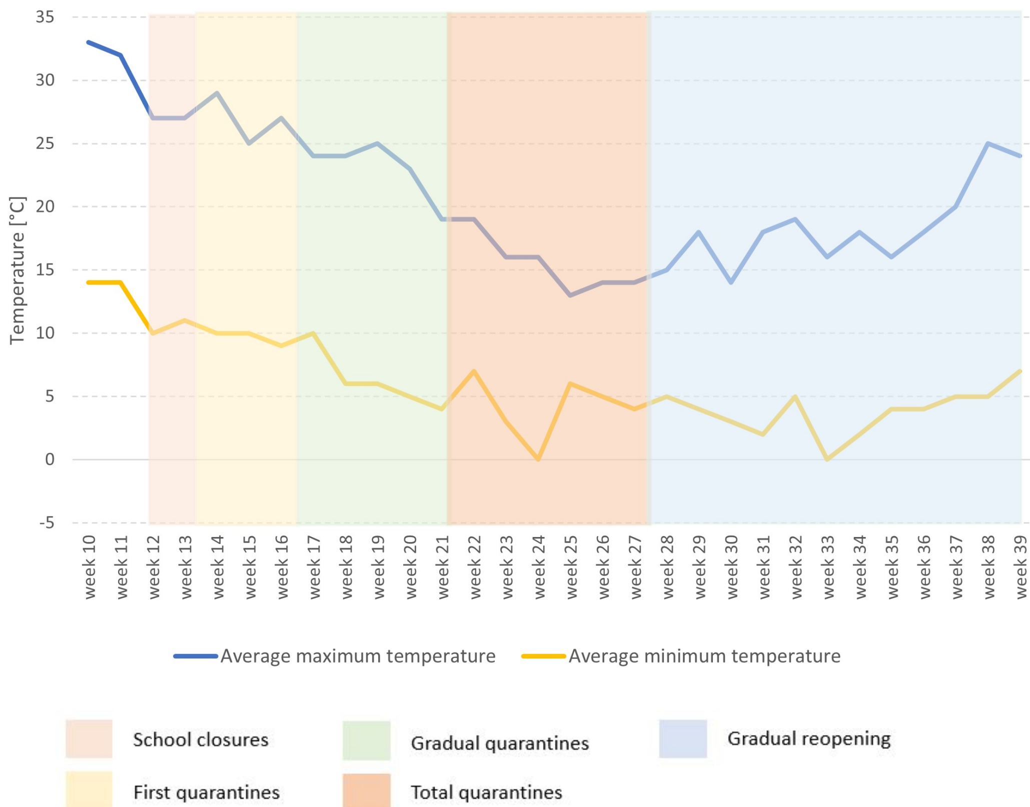

Figure 3.5: Evolution of weekly maximum and minimum temperatures (seven-day averages). The different containment measures throughout the period are described by the colored areas.

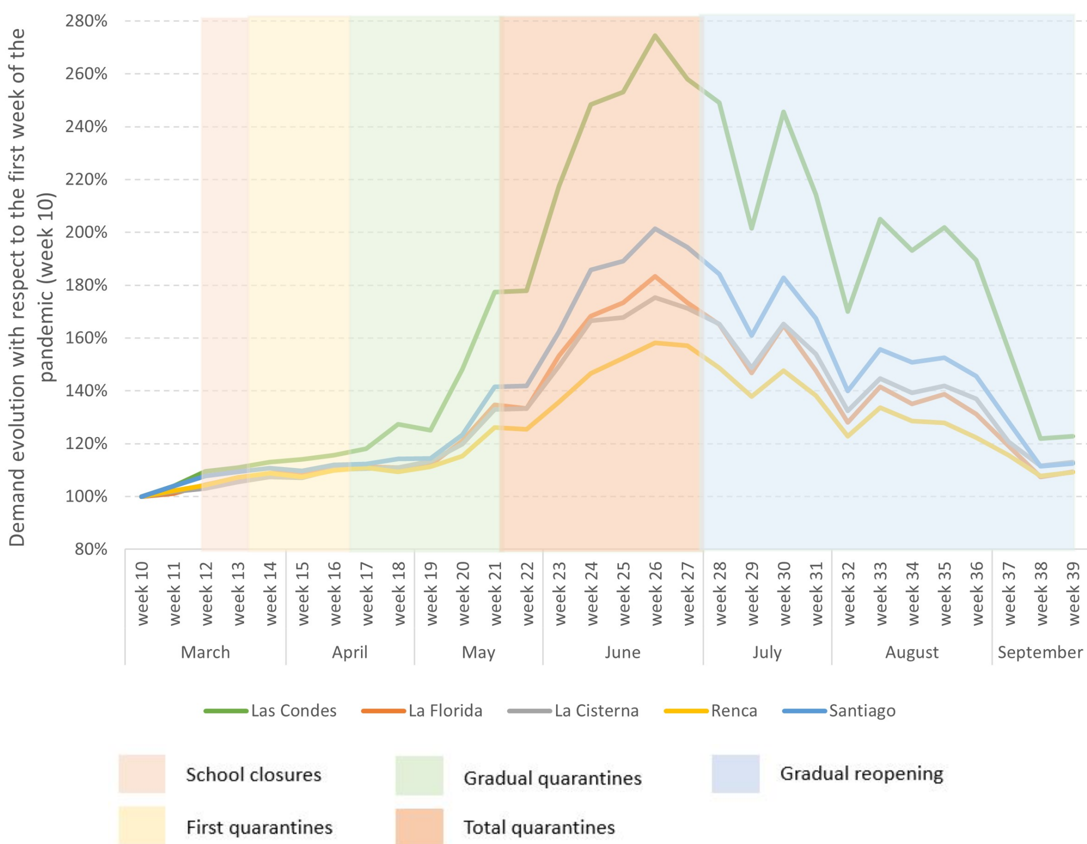

Figure 3.6: Variation in residential electricity demand during the weeks of the pandemic in 5 communes of Santiago.

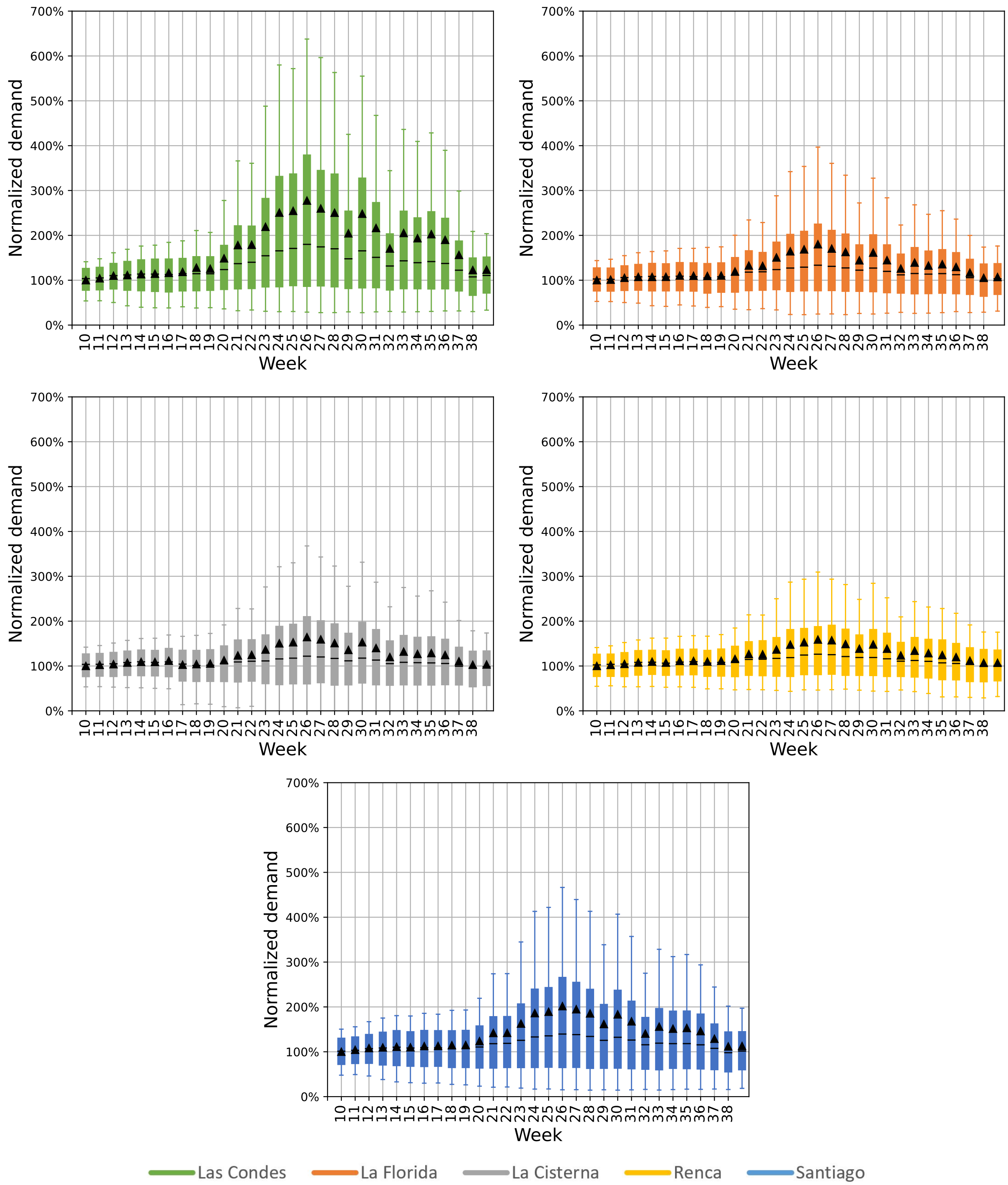

Figure 3.7: Box and whisker plot showing the residential demand normalized (divided) by the average demand of week 10. For every commune, the horizontal line and the black triangle indicate the median and average value. The lower (and upper) edges of the box are the 25th (75th) percentile. Whiskers represent the range between 10th and 90th percentile.

Figure 3.6 also shows an important relation between the demand of the different communes and the containment measures. This can be observed more clearly in the first weeks of the pandemic (weeks 12-16), where all the communes under study showed an important increase in demand (between 7% in La Cisterna and 16% in Las Condes with respect to week 10 for residential consumers) prompted by the first containment measures imposed by the Chilean government. Note that these weeks are prior to the increase in demand due to lower temperatures. During the weeks 12-16 the minimum temperatures slightly decreased from 14°to 10°. Instead during the week 26 in June the temperatures decreased to the 0°(Figure 3.5).

Finally, it is worth noting that the largest demand increases are observed in the socio-economic sectors with the highest income. Figure 3.8 shows the distribution of monthly gross salaries in 32 communes of the metropolitan area (Región Metropolitana), based on data from the National Statistics Institute [157]. Communes in the eastern part of the region, like Las Condes, present the highest salaries (around 2,300 USD per month on average). Other communes, such as Santiago and La Florida, present average salaries for the region (around USD 1,000 per month on average). Finally, communes like La Cisterna and Renca are at the lower-end of the income distribution for the region (around USD 650 per month on average).

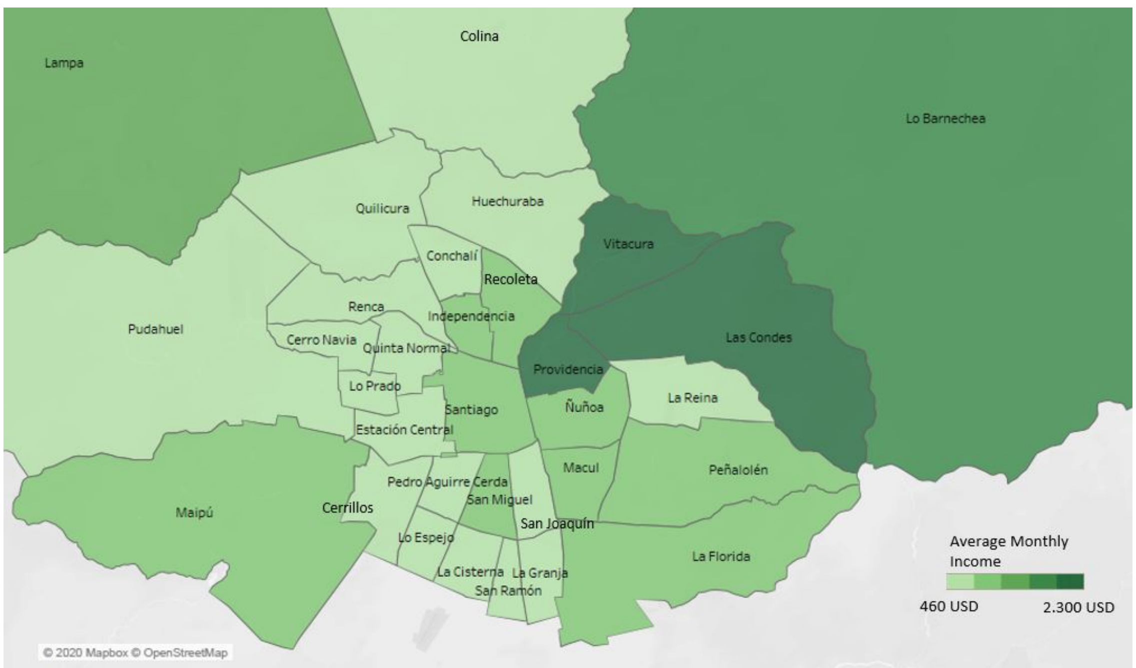

Figure 3.8: Distribution of average monthly incomes according to the National Institute of Statistics [157].

The largest increases in demand were observed in the commune of Las Condes (higher-income commune), while the smallest changes were observed in Renca and La Cisterna (lower-income communes).

These differences observed across the analysed communes may be explained by a potential lower response to confinement [158] and low temperatures (due to reduced levels of electrification of heating solutions) in lower-income communes. Interestingly, using metrics of mobility calculated with data from mobile/cell phones, the authors in [159] demonstrate dependencies between people's income and mobility levels under quarantine. In fact, [159] demonstrates that people with higher incomes are more likely to work from home, reducing their mobility levels. Conversely, people with lower incomes tend to feature higher mobility levels as they likely need to commute to undertake their work. Hence, reference [159] found that communes with higher incomes (e.g., Las Condes) present, on average, higher reduction levels in their mobility under quarantine. This is in opposition to the case in lower-income communes such as Renca, where mobility levels are, on average, higher. This relation between the mobility levels of the population and their incomes may help explain a key observation presented in our study, where higher-income communes feature, on average, a higher rise in their electricity consumption during lockdown measures. Importantly, the relation between income and mobility during lockdown was observed in several countries, and it is not particular to Chile [160], [161].

Previous studies [3], [54], [162], [163] demonstrate that income alone does not fully explain the energy-use behaviour of the consumers, but that it may be one of the factors related to household energy demand. Furthermore, studies show a variety of results, demonstrating different levels of dependencies between income and electricity demand. For instance, the study presented in [162] shows a small dependency between these factors, while [163] illustrates that their dependencies may be more important. However, none of these studies were undertaken under a pandemic; thus, previous conclusions must be taken with care under the current situation. Under the current COVID-19 pandemic, lockdown measures significantly affected the population's mobility and, thus, the time people stay at home. In several cases, like in Santiago, these mobility changes feature dependencies with the socioeconomic factors of the population. This has been studied and demonstrated for the specific case of Chile in[159], but this is not particular to one country [160], [161]. Importantly, the reader must bear in mind that, in this study, no other demographic and socioeconomic factors have been analysed (besides income).

The previous paragraph highlights the differences in how various socioeconomic groups adapted their electricity consumption during the pandemic, reflecting their differing capabilities. More vulnerable customers, often unable to fully comply with lockdown measures due to the nature of their work, had to maintain their mobility, leading to less significant changes in their electricity consumption. In contrast, wealthier consumers exhibited lower mobility, indicating higher adherence to quarantine measures, which in turn led to increased electricity consumption in their homes.

Furthermore, the disparity in consumption increases during colder periods can potentially be attributed to differences in heating technology adoption. Wealthier households are more likely to rely on electric heating solutions, whereas less affluent homes may depend on fossil fuels like kerosene or gas for heating. This technological gap reinforces the differing responses to temperature changes across socioeconomic groups.

These observations suggest that behavioural factors, beyond purely rational economic decisions, play a significant role in how consumers from different socioeconomic backgrounds respond to disruptive events like the COVID-19 pandemic.

3.4.3 Case ii: Isolating pandemic effects from seasonal weather effects on residential demand trends

The rise in residential electricity demand shown in Figure 3.6 can be explained mainly by two factors: quarantines and lower temperatures as winter approaches. These factors can act in combination (i.e., households may consume more electricity during cold days in a pandemic situation because people spend more time inside the house). This section seeks to separate them to isolate the impact of the pandemic. In this way, the increases in electricity demand in 2020 are analysed with respect to demand during the same period in 2019 for a subset of consumers whose demand is not very sensitive to temperature changes. The sensitiveness of a consumer is according the increment of electricity consumption compared with a threshold as shown in the Section 3.3.4.

The average increases in demands from consumers who are not very sensitive to temperatures are calculated for each representative commune, and the results are summarised in Table 3.4. During April, the demand of these consumers experienced an increase of 8% compared to the same period in 2019. This increase rises to 12% during May, when the gradual quarantine policy was implemented. The greatest changes are observed from June to August, when there is an increase of up to 17% compared to the same period in 2019. During these months, the containment measures implemented were total quarantine and gradual reopening (from July 29, 2020). Finally, during September, a large part of the metropolitan area (Región Metropolitana) had partially reopened its activities, so the increase in demand for this month reached 7% compared to the same month in 2019, the lowest values throughout the period. This result is consistent with the situations in the United States and Australia, which feature a growth of 20% and 14%, respectively, in their residential demand compared to 2019 [164].

Table 3.4: Variation between 2019 and 2020 of the electricity demand of consumers who are not sensitive to changes in temperature.

Month	**Increase in demand [%]**
March	9
April	8
May	12
June	17
July	13
August	10
September	7

Importantly, Table 3.4 presents average variations, but the dispersion associated with these average values should not be overlooked. In order to analyze the dispersion, Table 3.5 shows the proportion of consumers that more than doubled their demand in different communes and months. This reveals, for example, that 8% and 10% of the consumers in Santiago and Las Condes, respectively, more than doubled their demand as a result of lockdowns during May (compared to the same month in 2019). In other communes, such as Renca and La Cisterna, these consumers represent approximately a 6% of the sample examined. The most critical period ranges from June to August, where the consumers who doubled their demand represent between 10% and 17% of the whole sample.

Table 3.5: Proportion of consumers who at least doubled their demand in 2020 with respect to the same period in 2019.

Commune	**Mar.**	**Apr.**	**May.**	**Jun.**	**Jul.**	**Aug.**	**Sept.**
Las Condes	4%	7%	10%	17%	16%	17%	11%
La Florida	4%	5%	7%	17%	16%	15%	12%
La Cisterna	2%	4%	6%	10%	15%	14%	7%
Renca	2%	4%	6%	15%	14%	13%	10%
Santiago	4%	7%	8%	14%	14%	14%	10%

3.4.4 Case iii: Behavioural changes (at an hourly level) of residential demand

Behavioural changes in residential electricity demand are analysed through the hourly demand profiles presented in Figure 3.9 and Figure 3.10 for consumers in the communes of Las Condes and Renca. These two communes represent extremes in terms of income: Las Condes is one of the wealthiest communes in Chile, whereas Renca has comparatively lower-income levels.

In the figures, a pronounced daily peak at 10 pm is observed for both communes prior to the pandemic (week 10, corresponding to the week of March 2, 2020, indicated in blue in Figure 3.9). Additionally, a lower peak is seen between 8 am and 9 am on weekdays. These patterns reflect the typical pre-pandemic electricity consumption behaviour, likely tied to evening routines and morning activities before work or school.

Once the pandemic started, during week 17 (from April 20, 2020, indicated in gray in Figure 3.9), the daily peak demand increases and is shifted 2 hours before, around 8 pm. Additionally, a second daily peak appears at 2 pm (sharper during weekend, as shown in the blue demand profile corresponding to week 10), considerably increasing energy demand during the afternoon. Finally, the peak observed in previous weeks during the morning (around 9 am) on weekdays disappears. Instead of this morning peak, demand gradually increases until the 2-pm peak.

In the week of maximum demand, week 26 (from June 22, 2020, indicated in yellow in Figure 3.10), a combined effect of the pandemic and lower temperatures is observed. This explains the considerable increase in demand levels. Peak demand during these weeks occurs at 9 pm.

Finally, week 39 (from September 21, 2020, indicated in green in Figure 3.10) is characterised by a reduction in demand levels, in line with the rise in temperatures and gradual opening policies. In addition, the morning peak (at 10 am) that existed during the pre-pandemic period reappears in Las Condes during September.

It is important to highlight the difference in the intensity with which the aforementioned changes occur in both communes. While in Las Condes (a higher-income commune) these changes are more pronounced, in Renca (a lower-income commune), the changes are milder. This could be explained by a potential lower response to lock-downs (information consistent with mobility reports [158]) and by a lower response to low temperatures (reduced electrification

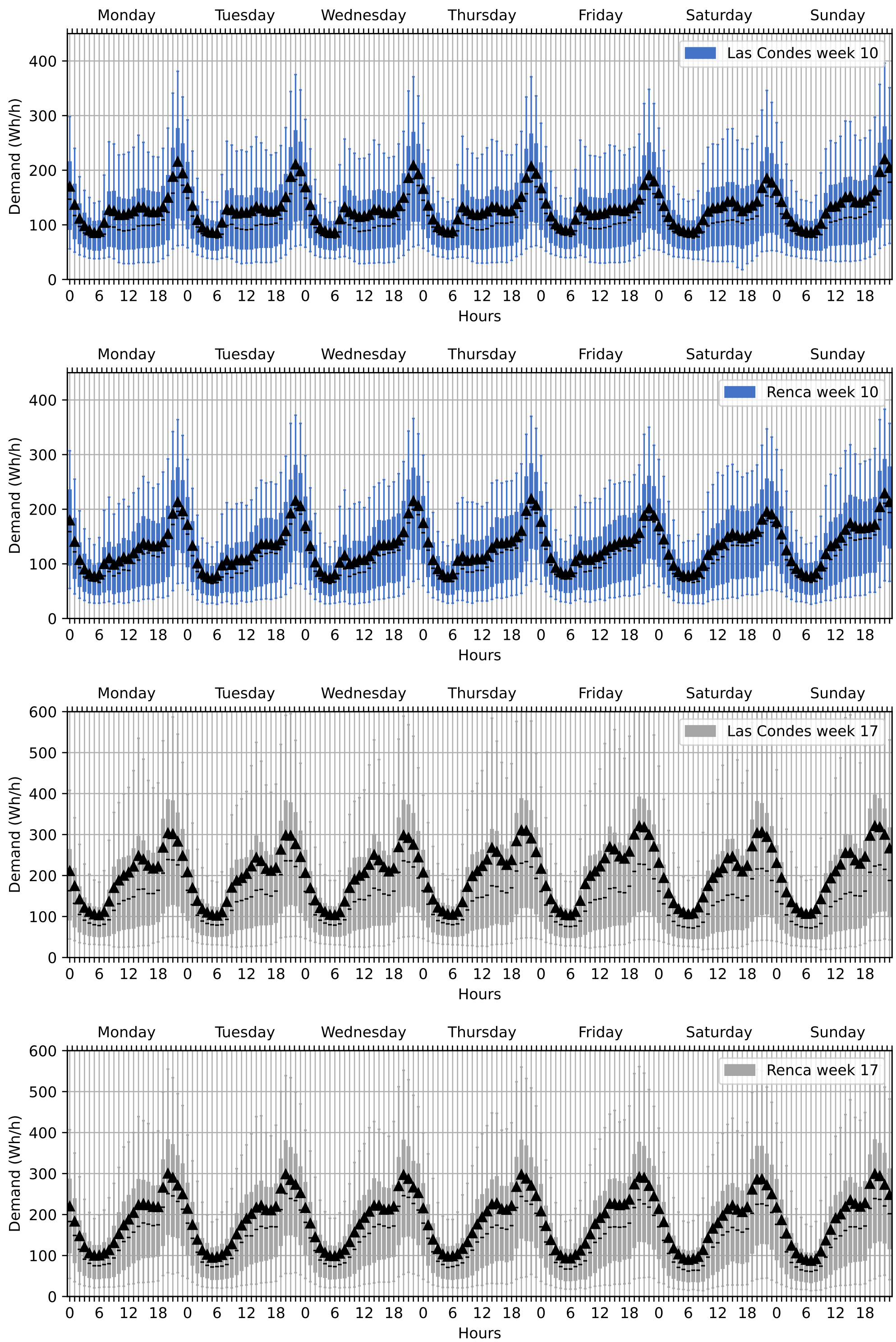

Figure 3.9: Box and whisker plot showing the hourly residential demand in two weeks (weeks 10 and 17) and two communes (Las Condes and Renca). For every plot, the horizontal line and the black triangle indicate the median and average value. The lower (and upper) edges of the box are the 25th (75th) percentile. Whiskers represent the range between 10th and 90th percentile.

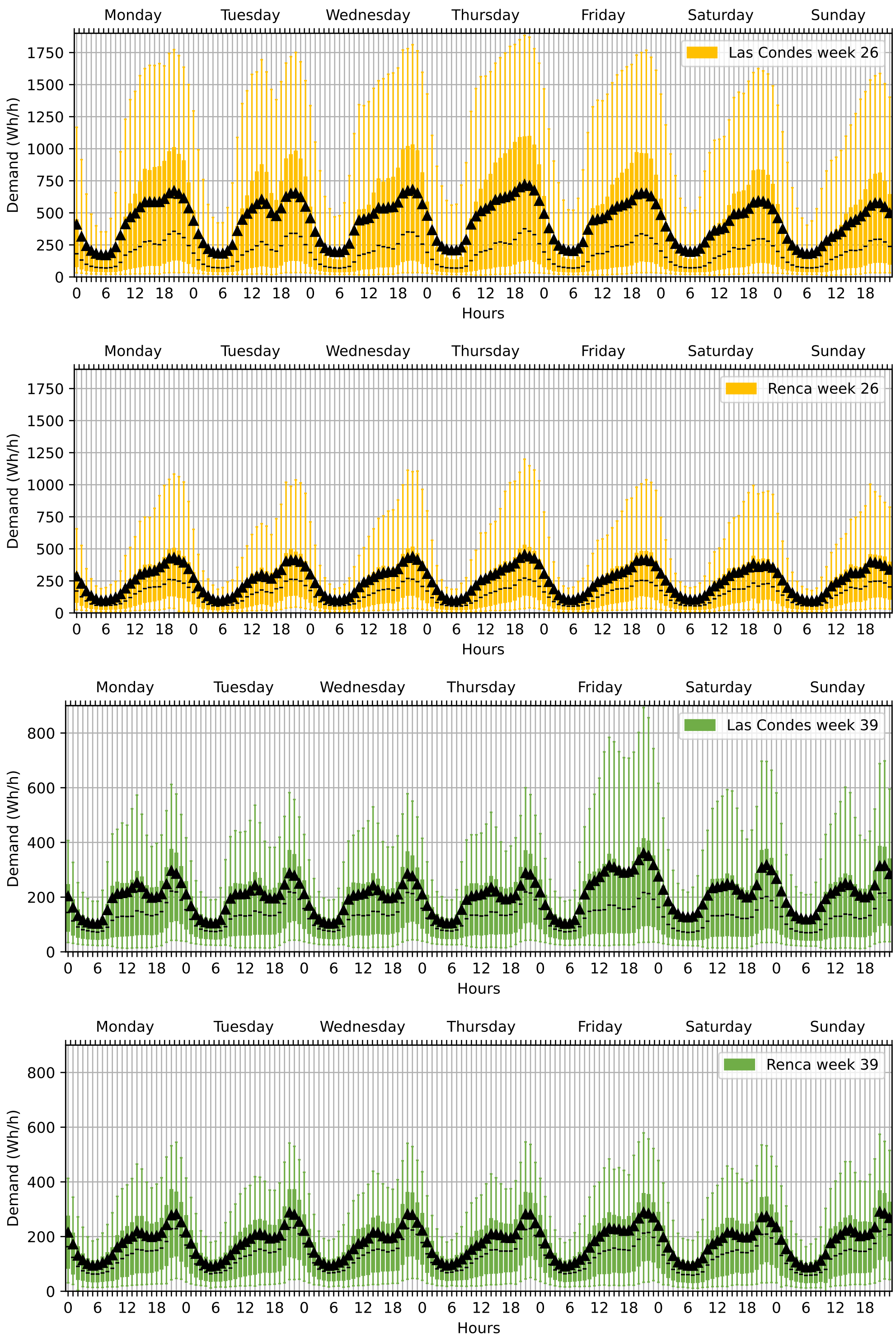

Figure 3.10: Box and whisker plot showing the hourly residential demand in two weeks (weeks 26 and 39) and two communes (Las Condes and Renca). For every plot, the horizontal line and the black triangle indicate the median and average value. The lower (and upper) edges of the box are the 25th (75th) percentile. Whiskers represent the range between 10th and 90th percentile.

in heating solutions). This is consistent with the socioeconomic levels of the communes shown in Figure 3.8, as communes with higher incomes have more access to heating solutions using electrical equipment and a higher percentage of their population is able to work from home.

3.4.5 Case iv: Overview of the impact of the pandemic in the 32 communes of the metropolitan area

Figures 3.11 and 3.12 present a general overview of how residential demand increased in all the communes of the metropolitan area (the city of Santiago) during the period under study. This increase was substantial, reaching 91% (on average for the 32 communes) during week 26 (June 22, 2020) with respect to the pre-pandemic period (March 2, 2020). These results emphasise that the greatest increase in demand has occurred in the eastern (higher-income) part of the region, in communes such as Vitacura, La Reina, Providencia and Las Condes. In Vitacura, for example, the increase in residential demand in week 26 reached 236% with respect to the demand in week 10 (March 2, 2020). On the other hand, during the same week, Cerro Navia was the commune with the lowest variation, reaching an increase of only 46% compared to week 10. These differences are in line with the socioeconomic levels of the communes, as previously observed and discussed.

3.4.6 Implementation of data analysis tool

During the development of this study, a comprehensive data analysis tool was created and published for use by a variety of stakeholders. This tool allows for the easy reproduction of all the analyses presented in this chapter via the website of the initiative named "Faro Energético" [165]. The goal of the tool is to provide accessible insights into the impact of the COVID-19 pandemic on electricity demand across different communes.

The tool was implemented using the software Tableau [166], which is designed to display processed information from large datasets in a highly intuitive and user-friendly environment. Special attention was given to the front-end design to ensure that the figures and visualisations developed in this study could be easily replicated for all 32 communes. The back-end work involved the creation of structured databases, where the data was preprocessed according to the methodology detailed in Section 3.3. This preprocessing step was essential to ensure that users could interact with the data in a seamless way, obtaining the same insights as those presented in this study.

In this tool, processed data covering the 32 communes from week 10 (beginning March 2, 2020) to week 39 (ending September 21, 2020) is made publicly available in a simplified format. This allows stakeholders to easily explore the data, analyse trends, and reproduce the findings. Figure 3.13 provides an illustration of the tool and its user interface.

Furthermore, it is worth highlighting that this initiative gained notable recognition, becoming a finalist in the prestigious Chilean innovation prize, Avonni, which acknowledges groundbreaking innovations that make significant contributions to the country. This achievement underscores the importance and impact of the "Faro Energético" initiative in the field

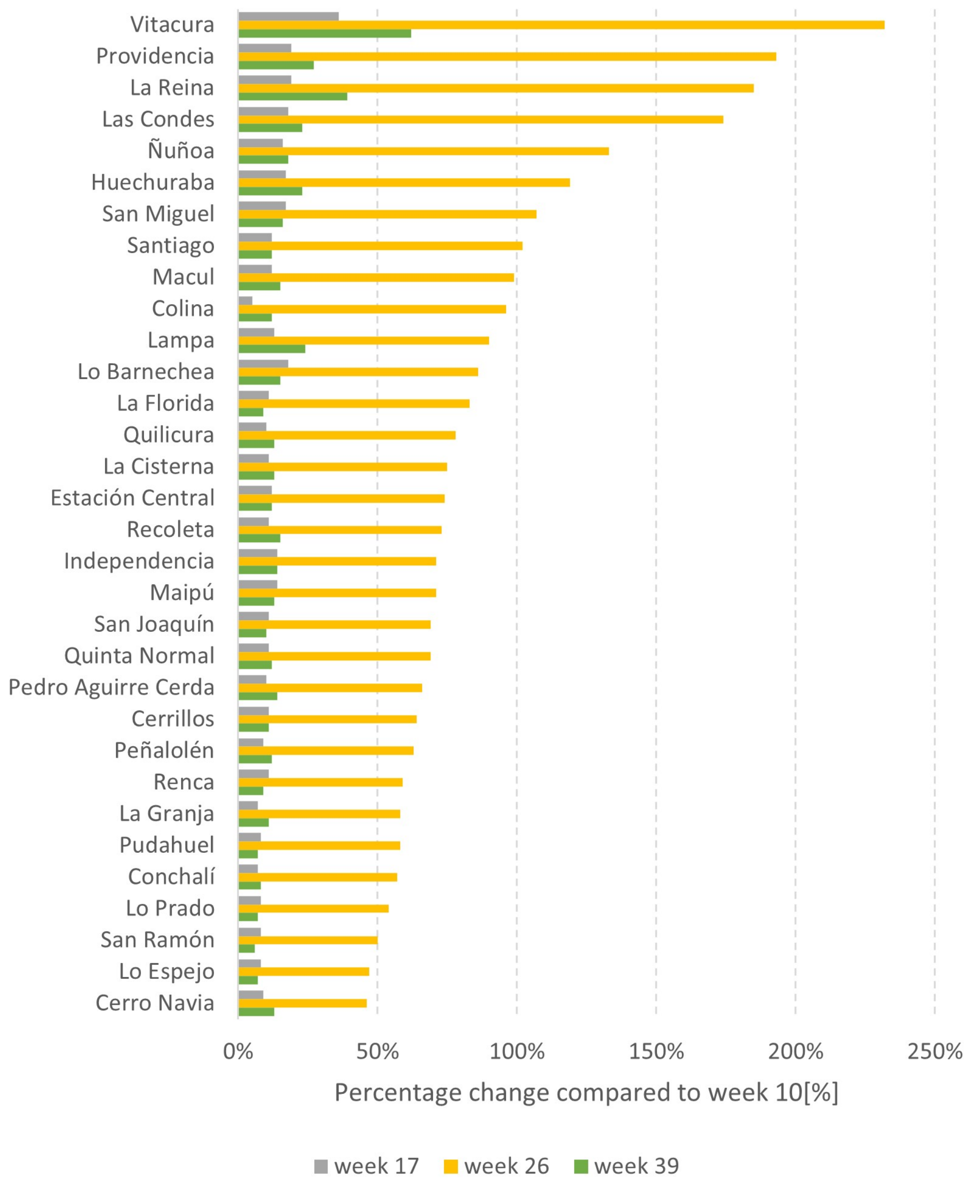

Figure 3.11: Variation in residential demands in weeks 17 (week of April 20), 26 (week of June 22) and 39 (week of September 21). All with respect to week 10 (week of March 2).

of energy data analysis in the Chilean context.

3.5 Summary

This research applied a methodology to analyse the impact of a disruptive event on the adaptation of electricity consumption across different socioeconomic factors. Specifically, the disruptive event examined is the COVID-19 pandemic and its impact on customers in Santiago, Chile.

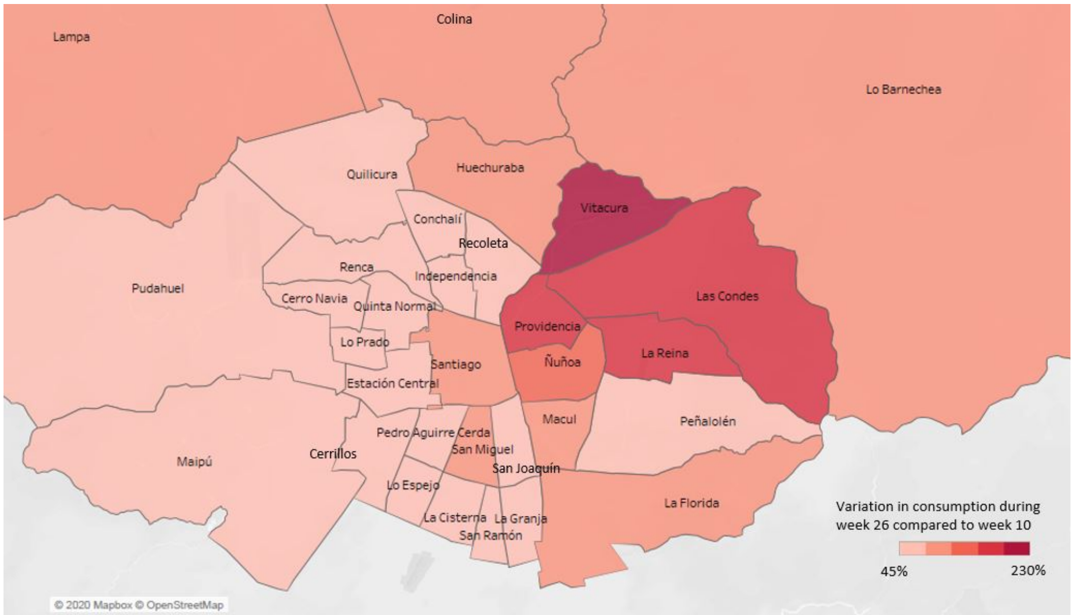

Figure 3.12: Geographical distribution of demand increases during week 26 (week of June 22) compared to week 10 (week of March 2) due to the combined effect of seasonality and the pandemic.

The analyses show that the impact of COVID-19 on electricity demand varies significantly by type of consumer. For regulated consumers, for example, the demand from small businesses dropped sharply, decreasing by more than 40% compared to the pre-pandemic period in the communes of Santiago and Las Condes. This aligns with the slowdown of the Chilean economy observed during the same period.

In contrast, residential consumers increased their demand following the implementation of the first lockdowns at the start of the pandemic. The steepest increase occurred between June and August 2020, which coincided with the coldest months and the most restrictive mobility measures. Notably, the peak increase occurred during the week of 22 June 2020, when demand was, on average, 91% higher than in the first week of March. This was the result of the combined effect of the pandemic and lower temperatures. It is estimated that the pandemic accounted for a demand increase of up to 17% in June, compared to the same month in 2019. It is worth mentioning that this effect varied significantly across different communes. In fact, the communes with the highest demand increases were those with higher income levels. Similarly, the results also show a wide dispersion in demand variation within each commune.

An important conclusion of this work, with potential implications for public policy, is that lockdowns can significantly increase residential electricity demand, imposing additional costs on families. This could pose particular challenges for vulnerable families who, in addition to facing increased costs for basic services, may find themselves in difficult financial situations due to the economic crisis associated with the pandemic.

The following possible applications and extensions of this study have been identified:

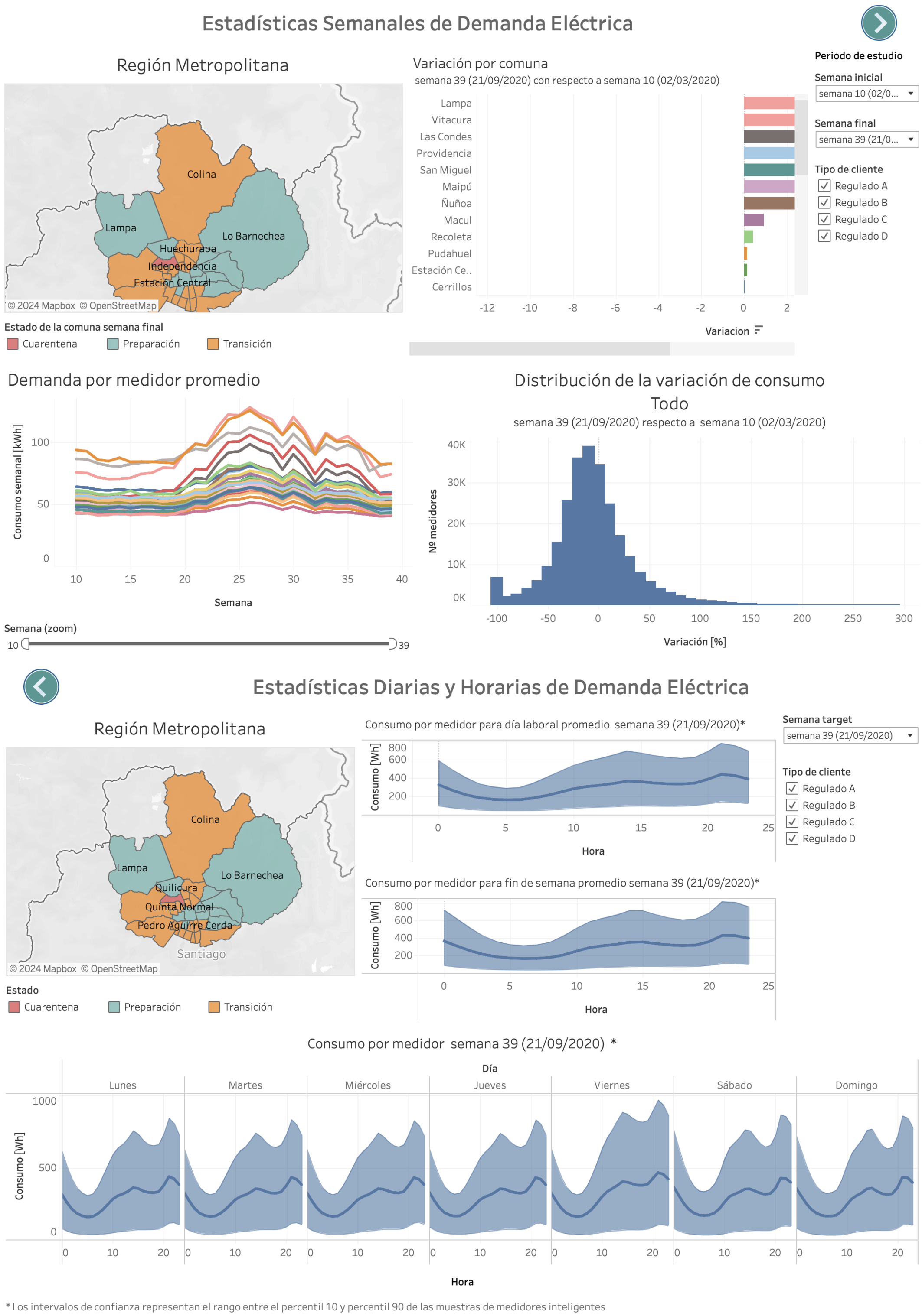

Figure 3.13: Interactive dashboards to explore the complete results for the 32 communes of Santiago.

- Better forecasting of demand responses to complex containment measures (which may vary by commune).

- More accurate estimation of the financial support needed to assist economically vulnerable families during the pandemic, which is of particular importance to policymakers.
- Improving operational practices (including demand forecasting and network operation, such as reactive compensation due to voltage issues) to manage parts of the network with significantly different load profiles.
- Identifying areas of the network with higher or lower stress levels due to the pandemic, which could justify accelerating or delaying investment plans by electrical utilities.

It is important to emphasise that such detailed studies of electricity demand are not only relevant in the context of the pandemic. In general, in-depth monitoring and analysis of energy demand data have the potential to inform and improve decisions and processes in both the public and private sectors, such as public policy decisions, regulatory design, grid tariff studies, and system investment and operation, among others.

Finally, this chapter explains the short-term adaptation of residential electricity customers to disruptive events, highlighting how these adaptation measures are closely tied to socioeconomic factors. In the short term, the response of customers is influenced by their technological capabilities, economic resources, and behavioural patterns. Throughout this study, it was observed that wealthier customers, such as those in Las Condes, experienced a higher increase in electricity demand due to a combined effect of the pandemic and colder temperatures. In contrast, less affluent customers, such as those in Renca, showed a comparatively smaller increase in their electricity consumption.

One of the key reasons for this disparity is linked to behavioural patterns. For less affluent consumers, adherence to lockdown measures often goes beyond mere economic considerations, as many were less able to comply with restrictions due to their work circumstances or other factors, even at the risk of potential exposure to the virus. As a result, the social dynamics within these communities had a direct and significant impact on electricity consumption patterns, reflecting the complex interaction between behavioural responses and socioeconomic constraints during disruptive events like the COVID-19 pandemic.

This analysis underscores the importance of considering both economic and social factors when evaluating how different segments of the population adapt to sudden disruptions, and how these adaptations manifest in their energy consumption patterns.

Chapter 4

Equilibrium models influenced by DER deployment and tariff schemes

4.1 Chapter overview

This chapter presents an economic model to analyse how different socioeconomic groups are impacted by the long-term energy transition and the integration of DER. This model assesses a long-term equilibrium between DER deployment by prosumers and distribution network investments. In doing so, this chapter fulfils the fourth specific objective outlined in Section 1.4.2.

In this model, from the perspective of prosumers and DER investment, users with a budget are able to invest in DER. The budget is determined by their purchasing power and serves as a proxy for their socioeconomic background. Furthermore, prosumers' decisions are made independently of their peers' decisions; this user behaviour is known as a selfish attitude and creates a game situation characterised by a non-cooperative structure.

On the other hand, from the perspective of distribution network deployment, the model considers a distribution system operator following a proactive distribution planner behaviour[1] that minimises the total system cost, which includes the distribution network, energy exchange, and DER deployment. The latter must consider the optimal decisions of users.

This research considers the scenario where prosumers may trade their energy with the distribution system operator, following energy and distribution network tariffs predefined by the regulator. Thus, this scheme aligns with the community-based market structure [40]. This choice is justified as the community-based market is suitable for large numbers of prosumers, with a central entity, such as the distribution system operator, facilitating the coordination of the market and technical operation.

[1]This concept is primarily used at the transmission level, where proactive transmission planning aims to maximise social welfare by anticipating the optimal decisions of generating companies [167]. At the distribution level, the proactive distribution electricity planner internalises the decisions of prosumers to minimise their electricity bills.

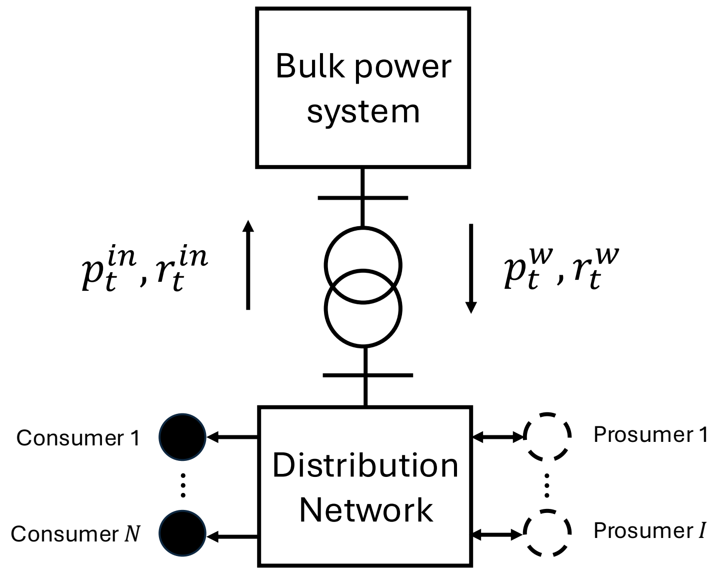

Figure 4.1: Basic network representation.

Considering both the perspectives of users and the distribution system operator, the proposed model identifies the long-term equilibrium. This means that distribution network capacity and DER installation are decision variables for each agent, and these are in a Nash equilibrium—where no agent (whether prosumers or the distribution system operator) can improve their economic position without negatively impacting the economic position of other agents.

The previous model is defined as a decentralised investment model due to prosumers make their own decision independently, without information of their peer decisions. This feature is also known as a ”selfish” attitude.

Since tariffs do not necessarily follow efficient criteria, the equilibrium is generally different from the optimal solution. Thus, this chapter defines a centralised planning model that serves as a benchmark for the equilibrium model.

The rest of the chapter is structured as follow: section 4.3 contains the central planning model formulation. Then, section 4.4 contain the formulation of a decentralised investment model to find the equilibrium. Finally, section 4.4.3 proposes a Gauss-Seidel algorithm to deal with non-linearities of the decentralised model.

4.2 Basic network representation

Figure 4.1 illustrates the basic structure of the network model used in this chapter. The figure shows the primary substation, which connects the bulk power system to the distribution network. The distribution network exchanges active and reactive power with the bulk power system through the variables p_t^{in} and r_t^{in} for the injection of active and reactive power, respectively, and p_t^{w} and r_t^{w} for the withdrawal of active and reactive power, respectively.

4.3 Centralised planning model

The centralised planning model (CPM) is formulated as a single-level linear programming (LP) optimisation problem, aimed at minimising total system costs by considering distribution network costs, energy exchanges, and installations of solar PV and BESS (see equation (4.1)). Meanwhile the constraints are given by equations (4.2) to (4.25).

The objective function is given by the equation (4.1). The first term consider the distribution network costs as it consider the sum of the investment costs $A_l s_l$ per line l. The second term considers the DER investment cost, which considers the sum of solar investment $A_i^s p_i^s$ and Battery Energy Storage (BESS) $A_i^B p_i^B$ per prosumer i. The third and fourth terms shows the active and reactive energy exchange respectively. Note that the expressions $(p_t^w - p_t^{in})$ and $(r_t^w - r_t^{in})$ denotes the hourly net active and reactive consumption at the primary substation, where the active energy exchanges are valued at C_t^A and reactive energy exchanges are valued at C_t^R.

Objective function

$$\min \sum_{l \in \mathcal{L}} A_l s_l + \sum_{i \in \mathcal{I}} (A_i^s p_i^s + A_i^B p_i^B) + \sum_{t \in \mathcal{T}} C_t^A (p_t^w - p_t^{in}) \Delta_t + \sum_{t \in \mathcal{T}} C_t^R (r_t^w - q_t^{in}) \Delta_t \tag{4.1}$$

Equations (4.2) and (4.3) denote power balance respectively. In the case of (4.2) the active power demand $D_{i,t}^A$ is supplied by the net balance between injection and withdrawals from the distribution network, the solar power injection and the net balance between charging and discharging from the BESS. Instead, for the case of (4.3), the reactive power demand $D_{i,t}^R$ is supplied exclusively by the net balance of the network. It's worth noting that PV and BESS do not provide reactive power which is aligned with most practical applications [168].

Power balance

$$D_{i,t}^A = e_{i,t}^w + e_{i,t}^s - e_{i,t}^{in} - e_{i,t}^{ch} + e_{i,t}^{ds} \quad : \lambda_{i,t}^A \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.2}$$

$$D_{i,t}^R = r_{i,t}^w - r_{i,t}^{in} \quad : \lambda_{i,t}^R \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.3}$$

Equation (4.4) shows the capital expenditure of prosumer i in solar PV and BESS. Every prosumer is constrained by their budget which is related with the purchasing power and serves as a proxy of their socioeconomic background, assuming that wealthier users dispose of a higher budget to invest in DER devices.

Budget

$$A_i^s p_i^s + A_i^B p_i^B \leqslant K_i \quad : \beta_i \quad \forall i \in \mathcal{I} \tag{4.4}$$

Equation (4.5) imposes the limit for the active generation of solar power. The solar generation is constrained by the installed capacity and the solar availability, which derives from the solar irradiance.

Solar PV

$$e^{s}_{i,t} \leqslant p^{s}_{i}\psi_{i,t} \quad : \phi^{s}_{i,t} \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.5}$$

Equations (4.6) shows the positiveness of operational variables related with the active power withdrawals and injections, reactive power withdrawals and injections, the state of charge $SoC_{i,t}$ of the BESS, the solar PV generation and the charging of discharging of the BESS. Equation (4.7) reflects the positiveness of solar PV capacity. Finally, equation (4.8) is the positiveness of BESS capacity.

Non-negativeness

$$e^{w}_{i,t}, e^{in}_{i,t}, r^{w}_{i,t}, r^{in}_{i,t}, SoC_{i,t}, e^{s}_{i,t}, e^{ch}_{i,t}, e^{ds}_{i,t} \geqslant 0 \quad : \sigma^{*}_{i,t} \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.6}$$

$$p^{s}_{i} \geqslant 0 \quad : \sigma^{s}_{i} \quad \forall i \in \mathcal{I} \tag{4.7}$$

$$p^{B}_{i} \geqslant 0 \quad : \sigma^{B}_{i} \quad \forall i \in \mathcal{I} \tag{4.8}$$

Note that all the previous equations from (4.2) to (4.8) have their dual variable. For simplicity, the notation for the dual variable of equation (4.6) $\sigma^{*}_{i,t}$ have a * as superscript, representing all the left hand variables.

Additionally, from (4.9) to (4.13), the model for the BESS operation in the centralised planning model is presented. Note that the BESS model for the decentralised investment model differs and will be introduced in subsequent sections. Equations (4.9), (4.10), and (4.11) represent the upper limits for charging, discharging, and the state of charge of the BESS, respectively. In the case of (4.11), the storage capacity is constrained according to the BESS power capacity p^{b}_{i} and the predefined number of storage hours H_i. Equation (4.12) shows how the state of charge of the battery evolves, also referred to as the energy inventory of the BESS. Finally, equation (4.13) imposes the condition that the state of charge at the initial time and at the end of each day remains the same.

CPM BESS operation

$$e^{ch}_{i,t} \leqslant p^{b}_{i} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.9}$$

$$e^{ds}_{i,t} \leqslant p^{b}_{i} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.10}$$

$$SoC_{i,t} \leqslant H_i p^{b}_{i} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.11}$$

$$SoC_{i,t+1} = SoC_{i,t} + \eta^{B}_{i} e^{ch}_{i,t} - e^{ds}_{i,t} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \backslash \{T\} \tag{4.12}$$

$$SoC_{i,1} = SoC_{i,n\Delta T} \qquad \forall i \in \mathcal{I} \tag{4.13}$$

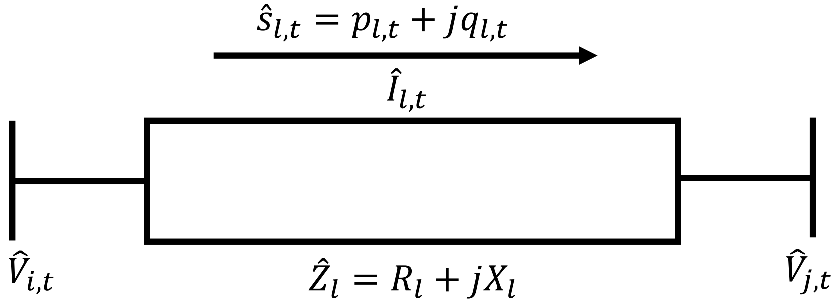

Figure 4.2: Representative scheme to illustrate the power flow modelling.

The DN modeling incorporates a DistFlow, which is the typicall name of AC power flow in distribution networks characterised by the radial network. The modelling approach was proposed in [169], [170], which introduces a convex non-linear formulation. To handle these non-linearities (quadratic functions), the proposal presents an iterative algorithm linearisation studied in [171].

Figure (4.2) is an scheme of a distribution line that illustrates the variable definition. The power flows from the left node to the right node, thus the power departing from left node is $\widehat{s}_{l,t} = p_{l,t} + jq_{l,t}$. The distribution line has an impedance given by $\widehat{Z}_l = R_l + jX_l$. The nodes have a voltage $\widehat{V}_{i,t}$ which is the phasor representation. Finally, $\widehat{I}_{l,t}$ is the phasor of the current flowing from the left to the right to the scheme.

The initial procedure of the DistFlow method involves working with the squares of voltages and currents. Therefore, for voltage, it is assumed that $v_{n,t} = |\widehat{V}_{n,t}|^2$ and for currents is considered that $i_{l,t} = |\widehat{I}_{l,t}|^2$.

Thus equations (4.14) and (4.15) show the nodal aggregated demand for active and reactive power respectively. Note that $N_{i,n}$ contains the connection node of every user (i.e., consumer and prosumer) of the distribution network.

Nodal aggregated demand

$$d^A_{n,t} = \sum_{i \in \mathcal{I}} (e^w_{i,t} - e^{in}_{i,t}) N_{i,n} \quad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{4.14}$$

$$d^R_{n,t} = \sum_{i \in \mathcal{I}} (r^w_{i,t} - r^{in}_{i,t}) N_{i,n} \quad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{4.15}$$

The equations (4.16) y (4.17) sets limits for voltage and current respectively. Typically, the voltage limits are related with the standard allowed by the regulation [2].

Voltage and current limits

[2]For instance the standard in UK can be found in [172], which is between -6% and +10%. Meanwhile the Chilean standard is in [173], which in some cases can be +10% and -10%.

$$\underline{v_n} \leqslant v_{n,t} \leqslant \overline{v_n} \quad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{4.16}$$

$$i_{l,t} \leqslant \overline{i_l} \quad \forall l \in \mathcal{L}, t \in \mathcal{T} \tag{4.17}$$

Equations (4.18) and (4.19) show the active and reactive power nodal balance, respectively. The left-hand side of the equation represents the sum of all power departures through the distribution line plus the nodal aggregated demand. Meanwhile, the right-hand side represents the sum of all power arrivals minus the power lost through the distribution lines.

Nodal balance

$$\sum_{l \in \mathcal{L}} p_{l,t} O_{n,l} + d^{A}_{n,t} = \sum_{l \in \mathcal{L}} (p_{l,t} - R_l i_{l,t}) I_{n,l} \quad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{4.18}$$

$$\sum_{l \in \mathcal{L}} q_{l,t} O_{n,l} + d^{R}_{n,t} = \sum_{l \in \mathcal{L}} (q_{l,t} - X_l i_{l,t}) I_{n,l} \quad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{4.19}$$

Equation (4.20) shows the DistFlow version of Ohm's law. The left-hand side of equation represent the voltage difference between the voltage of two nodes connected by a line l. Meanwhile, the right-hand side of the equation relates the impedance of the line with the current.

Ohm's law

$$\sum_{n \in \mathcal{N}} v_{n,t}(O_{n,l} - I_{n,l}) = 2R_l p_{l,t} + 2X_l q_{l,t} - (R_l^2 + X_l^2) i_{l,t} \quad \forall l \in \mathcal{L}, t \in \mathcal{T} \tag{4.20}$$

The equations (4.21) and (4.22) reveals the power exchange at the primary substation. The active power is in (4.21) and reactive power in (4.22). Note that in both cases, the left-side refrain to the lines l connected with node 0, which is the number associated with the primary substation.

Primary substation power balance

$$\sum_{l \in \mathcal{L}} p_{l,t} O_{0,l} = p^{w}_{t} - p^{in}_{t} \quad \forall t \in \mathcal{T} \tag{4.21}$$

$$\sum_{l \in \mathcal{L}} q_{l,t} O_{0,l} = q^{w}_{t} - q^{in}_{t} \quad \forall t \in \mathcal{T} \tag{4.22}$$

Equations (4.23) to (4.25) present the linearised version of the equations proposed in [171]. Equations (4.23) and (4.24) define the operational limits of the distribution line, specifying the boundaries for active and reactive power flow through the lines. In general terms, a power line can be represented as a circumference centred at the pair $(p, q) = (0, 0)$ and radius

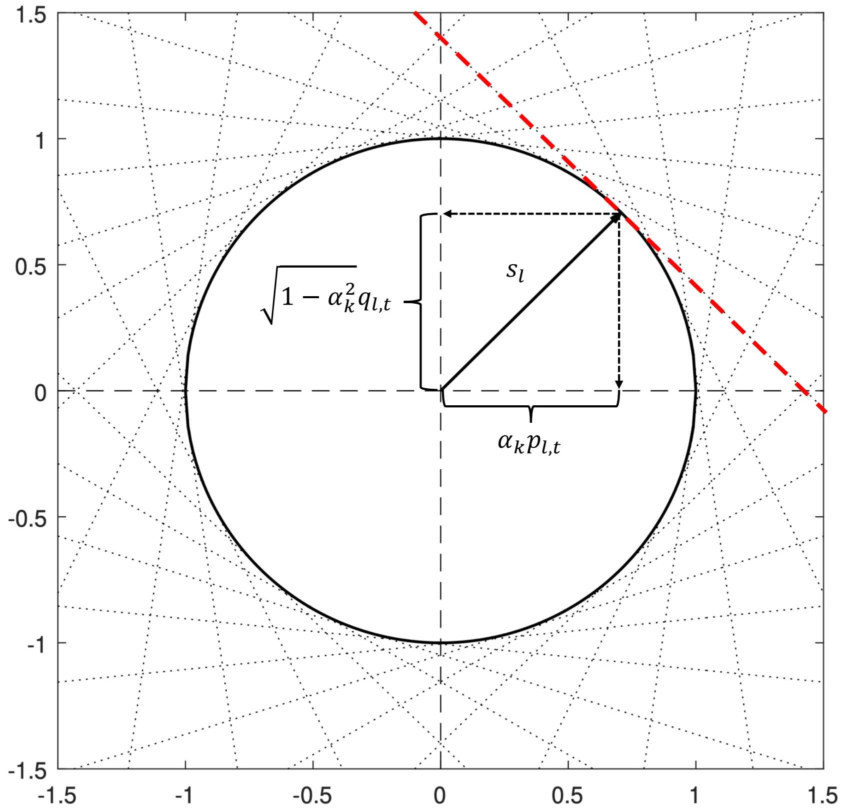

Figure 4.3: Linearisation scheme for equations 4.23 and 4.24. The scheme represents the P-Q diagram of a distribution line, whose capacity is s_l. The x-axis is the active power represented by $p_{l,t}$, meanwhile the y-axis is the reactive power represented by $q_{l,t}$.

s_l [174], [175]. To maintain the model's simplicity, the circumference is approximated by a set of tangent lines. This is illustrated in Figure (4.3), where each α_i represents a tangent cut.Equation (4.23) covers the upper half of the P-Q diagram, while (4.24) represents the lower half.

Distribution line capacity

$$q_{l,t} \leqslant \frac{-\alpha_k p_{l,t} + s_l}{\sqrt{1-a_k^2}} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}, k \in \mathcal{A} \tag{4.23}$$

$$-\frac{-\alpha_k p_{l,t} + s_l}{\sqrt{1-a_k^2}} \leqslant q_{l,t} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}, k \in \mathcal{A} \tag{4.24}$$

Equation (4.25) imposes restrictions on apparent power through a line. The left-hand side encapsulates apparent power in relation to voltage $v_{n,t}$ and current $i_{l,t}$. Meanwhile, the right-hand side represents the operational boundary $p_{l,t}^2 + q_{l,t}^2$ in the P-Q plane. These terms are linearised using an iterative approach explored in [171]. It is important to highlight that equation have a superscript h to denote each iteration, in the same line, $\sim$ symbol on the top shows the value of the previous iteration of the value (for instance $\widetilde{v}_{n,t}^h$ is the value of the $v_{n,t}$ in the iteration $h-1$.

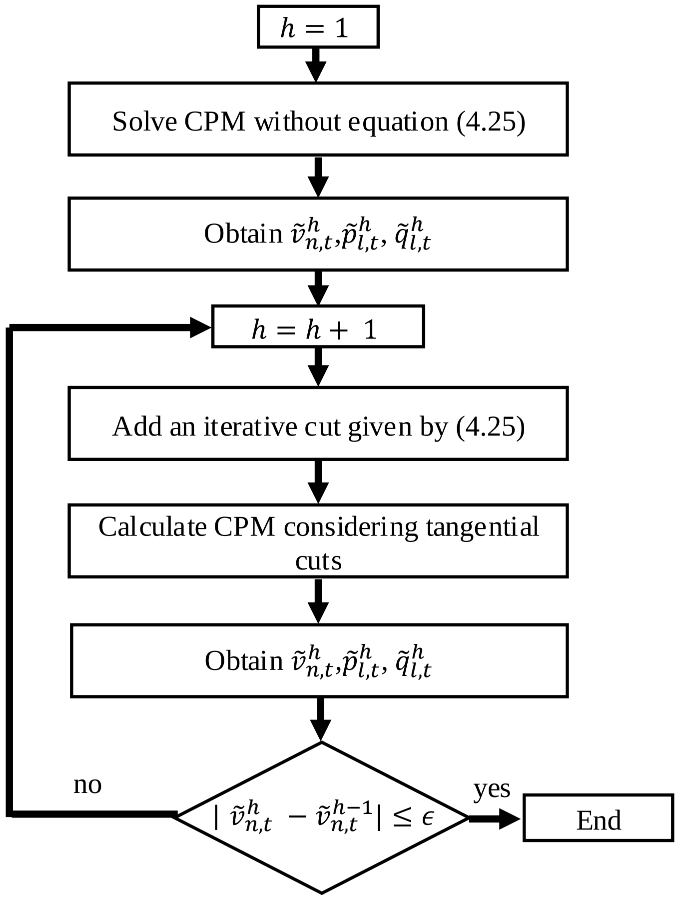

Figure 4.4: Scheme of LP AC-OPF iterative algorithm

Iterative cuts

$$(\sum_{n\in\mathcal{N}} \widetilde{v}^h_{n,t} O_{n,l}) i_{l,t} \geqslant$$

$$(\widetilde{p}^h_{l,t})^2 + 2\widetilde{p}^h_{l,t}(p_{l,t} - \widetilde{p}^h_{l,t}) + (\widetilde{q}^h_{l,t})^2 + 2\widetilde{q}^h_{l,t}(q_{l,t} - \widetilde{q}^h_{l,t}) \quad \forall l \in \mathcal{L}, t \in \mathcal{T} \tag{4.25}$$

Figure (4.4) illustrates the iterative process for the CPM, considering an AC-OPF. Since the iteration process requires the initialisation of the parameters $\widetilde{v}^h_{n,t}$, $\widetilde{p}^h_{l,t}$, and $\widetilde{q}^h_{l,t}$, it begins with results obtained without enforcing constraint (4.25) (or equivalently, setting its value to 0). This initial result is known as the lossless AC-OPF, as equation (4.25) serves as a lower limit for the distribution line current $i_{l,t}$. In the first iteration ($h = 1$), this limit is set to 0. Consequently, considering the nodal balance equations (4.18) and (4.19), the CPM, acting as a cost minimiser, will set the distribution line current $i_{l,t}$ to 0 to avoid losses.

Following this initialisation, the algorithm proceeds by adding cuts imposed by (4.25). Convergence is achieved when the current variation falls within a predefined tolerance ε, which can be reached after a finite number of iterations.

In summary, the CPM formulated between equations (4.1) and (4.25), minimises the total electricity system cost. As a result, the investments associated with DER deployment are made with the objective of minimising system costs. Consequently, depending on the tariff schemes (both for energy and distribution), these DER installation decisions may be suboptimal from the perspective of prosumers' electricity costs. Therefore, the optimal system cost does not necessarily represent an equilibrium.

4.4 Decentralised investment model

The decentralised investment model (DIM) assumes that every prosumer invests in DER following purely economic rationality, and therefore minimise their own electricity bill considering tariffs. In doing so, prosumers do not consider their peers investments.

At the same time, distribution system operator behaves as a proactive distribution planner. Which means that the distribution system operator make investment in the capacity of the distribution power lines proactively anticipating the prosumers decisions in the DER investments. The resulting cost of the network is passed through to prosumers and customers, then the DER investment also serves to diminish the network charges.

The previous relation between prosumers and distribution system operator describes a game situation, where prosumers compete to avoid network charges by installing DER. Consequently, the DIM is formulated as a Stackelberg game between a distribution system operator (leader) and prosumers (followers). Mathematically, the Stackelberg game is a bilevel optimisation problem. Figure (4.5) illustrates the flow of information between the distribution network planner and prosumers within the grid.

Figure (4.5) illustrates the information flow among the different agents. As mentioned earlier, the distribution system operator (upper level), represented by the large rectangle at the top, determines the distribution network costs, and consequently, the values of the distribution tariffs. Simultaneously, each prosumer (lower level) minimises their own electricity costs, leading to their equilibrium investment decisions in DER.

Additionally, in this thesis, tariffs will consider two components: energy and distribution network tariffs. Energy tariff is an exogenous variable because is determined upstream in the supply chain (in the generation or retail sector). Instead, distribution network tariff is determined endogenously following the regulatory rules. The sum of distribution network charges across every prosumer must account the total distribution network.

This section outlines the various components of the DIM. The lower level focuses on the prosumer investment model, while the upper level addresses the distribution system operator's role. Following this, the solution method is presented, which involves the iterative Gauss-Seidel algorithm. This algorithm reformulates the problem into a single optimisation level using Mathematical Programming with Equilibrium Constraints (MPEC).

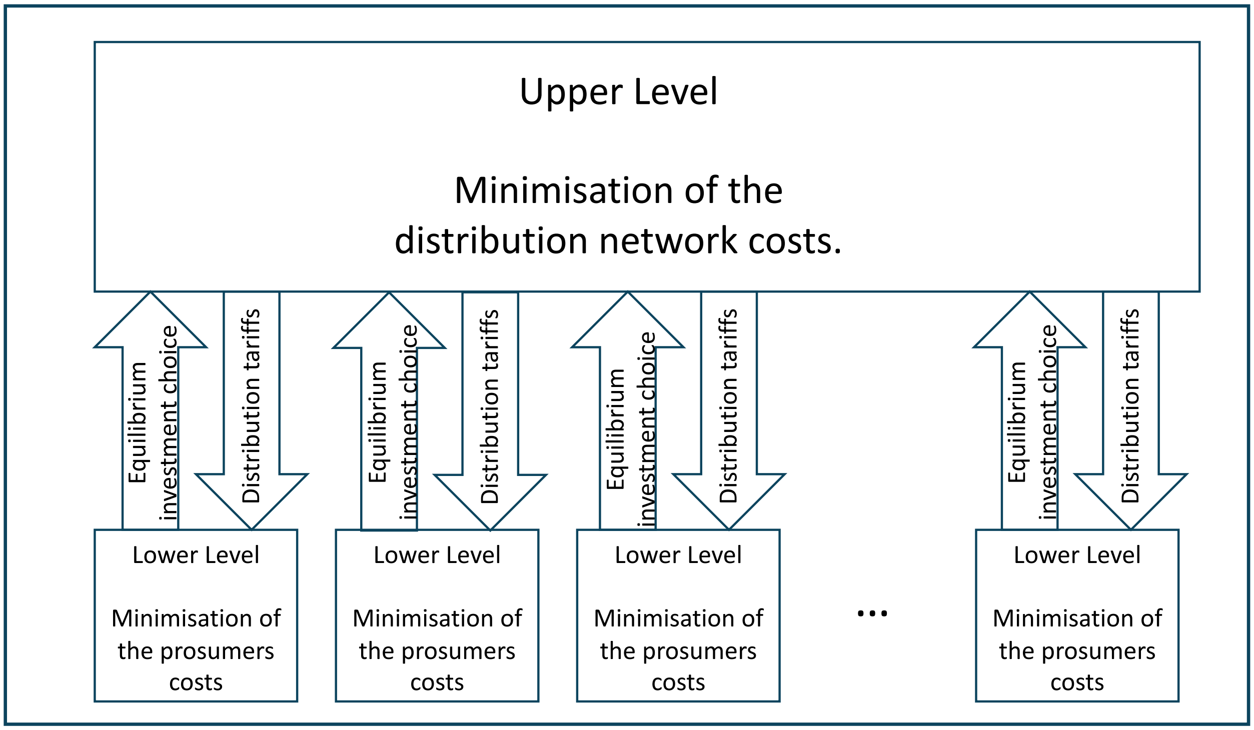

Figure 4.5: Bilevel scheme

4.4.1 Prosumer investment model (lower level)

The prosumer investment model (PIM) represents the lower level, wherein there is one optimisation model per prosumer i, and their outcomes include the investments in solar pv and BESS given by p_i^s and p_i^B respectively. Likewise, the operational variables related with the withdrawals and injection power from the distribution network $e_{i,t}^{w}$, $e_{i,t}^{in}$, the charging and discharging of the BESS $e_{i,t}^{ch}$, $e_{i,t}^{ds}$, and the reative power withdrawals and injections from the network $r_{i,t}^{w}$, and $r_{i,t}^{in}$.

The tariff schemes are represented in three arrays: $\tau_{i,t}^{E}$, $\tau_{i,t}^{D}$, and $\tau_{i,t}^{R}$, denoting the energy, distribution, and reactive energy tariffs, respectively. Their detailed definitions depend on the specific regulatory framework and are explained in details in Section (4.5).

The objective function is defined by Equation (4.26). The first two terms account for the investment in DER, specifically in solar PV and BESS, respectively. The third term represents the costs of energy withdrawals, which are valued at the sum of the energy and distribution tariffs. The fourth term reflects the earnings from energy injections, where the injections are valued at the sum of the distribution tariff and the energy tariff, reduced by a factor of κ and φ respectively. Finally, the objective function includes the reactive energy balance, which is valued according to the reactive energy tariff.

Note that parameters κ and φ are two parameters to adapt the injection tariff to specific regulation. For instance, when $\kappa = 1$ and $\varphi = 1$ the regulation is the well-known net-metering [176]. When $\kappa = 0$ and $\varphi = 1$ is known as a net-billing [79], [177].

The set of constraints are equations between (4.2) and (4.8), which are the power balance, solar PV, non-negativeness and the budget equations. The BESS operation is replaced by the (4.27), which considers a fixed power profile $\psi^B_{i,t}$ which is described in the following subsection. The objective of this formulation is to reduce the number of variables in constraint of the problem. Finally, notate that Equation (4.27) has a dual variable.

It is noteworthy that tariffs vary for every user and time, thus they can be adjusted to a specific tariff definition. Therefore, in general, distribution tariffs $\tau^D_{i,t}$ are non-linear functions (usually defined in several regimes that originate non-linearities). Additionally, when equilibrium is reached, $\tau^D_{i,t}$ becomes a function of all prosumers' decisions, capturing economic relations among agents. Consequently, the prosumer model is a non-linear programming (NLP) model.

$$\textbf{Objective function for prosumer } i$$

$$\min A^s_i p^s_i + A^B_i p^B_i + \sum_{t\in\mathcal{T}}(\tau^D_{i,t} + \tau^E_{i,t})e^w_{i,t}\Delta t - \sum_{t\in\mathcal{T}}(\kappa\tau^D_{i,t} + \varphi\tau^E_{i,t})e^{in}_{i,t}\Delta t + \sum_{t\in\mathcal{T}}\tau^R_{i,t}(r^w_{i,t} - r^{in}_{i,t})\Delta t \tag{4.26}$$

$$\textbf{Constraints} : (4.2) \text{ to } (4.8)$$

$$\textbf{Prosumer BESS Operation}$$

$$e^{ch}_{i,t} - e^{ds}_{i,t} = p^B_i \psi^B_{i,t} \quad : \phi^B_{i,t} \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.27}$$

Initialisation of BESS operation profile

To initialise the power profile $\psi^B_{i,t}$ for the BESS operation, is executed a prosumer operation model (POM). Unlike the PIM, the objective function (4.28) does not consider the investment costs, therefore only consider the tariff charges. The POM consider the solar PV and BESS capacity obtained in the PIM model.

$$\textbf{Objective function for prosumer } i$$

$$\min \sum_{t\in\mathcal{T}}(\tau^D_{i,t} + \tau^E_{i,t})e^w_{i,t}\Delta t - \sum_{t\in\mathcal{T}}(\kappa\tau^D_{i,t} + \varphi\tau^E_{i,t})e^{in}_{i,t}\Delta t + \sum_{t\in\mathcal{T}}\tau^R_{i,t}(r^w_{i,t} - r^{in}_{i,t})\Delta t \tag{4.28}$$

$$\textbf{Constraints} : (4.2) \text{ to } (4.13)$$

In the same vein, the BESS operation is given by the Equations (4.9) to (4.13). This way, the POM model defines optimally the BESS usage profile. Thus, the battery profile $\psi^B_{i,t}$ is defined by Equation (4.29).

$$\psi^B_{i,t} = \frac{e^{ch}_{i,t} - e^{ds}_{i,t}}{p^B_i} \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{4.29}$$

4.4.2 Distribution system operator (upper level)

This subsection presents the distribution system operator model, which behaves as a proactive distribution network planner. Thus, the aim is to minimise the total system cost as Equation (4.1), with the key difference that optimal prosumer decisions from PIM are considered. Accordingly, the final model is a bilevel NLP due to constraint (4.30), which considers the equilibrium decisions of prosumers. The bilevel formulation is called the distributed investment model (DIM).

Note that, unlike the CPM, the DIM represents the case where prosumers respond to tariffs in a selfish manner (i.e., minimising their own costs regardless of the system-level cost). In the same line, the same line the prosumers have any type of coordination among them, therefore the model describes a non-cooperative game. Finally, prosumers follow an economic rational behaviour, other practical motivations are not considered under this scheme and represent a future work

$$\textbf{Objective:}(4.1)$$
$$\textbf{Constraints}: (4.14) \text{ to } (4.25)$$

$$p_i^s, p_i^B, e_{i,t}^w, e_{i,t}^s, e_{i,t}^{in}, e_{i,t}^{ch}, e_{i,t}^{ds}, r_{i,t}^w, r_{i,t}^{in} \in \arg\min(\text{PIM}) \tag{4.30}$$

4.4.3 Iterative Gauss-Seidel algorithm

The bilevel DIM can be approached using heuristic methods, which do not provide theoretical guarantees of optimality [178], and scalability issues may arise due to the presence of non-linearities. To address these challenges, this work proposes an iterative Gauss-Seidel method [179], also known as the Liebmann method, which is widely applied in power systems for solving load flow problems [180]. This algorithm solves the NLP problem by iteratively addressing a MILP problem, where non-linearities are replaced with constants that are updated in each iteration (a similar approach is developed in [181]).

For this purpose, it is initially assumed that $\tau_{i,t}^D$ is constant, allowing the PIM to be replaced with the Mathematical Constrained Equilibrium Constraint equations [182], which are defined by the first-order conditions (Equations (4.31) to (4.39)), and the complementary slackness conditions associated with Equations (4.2) to (4.8), as well as Equation (4.27).

The complementary slackness is linearised using the Fortuny-Amat and McCarl linearisation method [183], applying the big M technique (see Equations (4.40) to (4.51)). This transforms the problem into a single-level MILP.

Thus, the MILP formulation is given by the the objective function (4.1), and constrained by (4.2) to (4.8), (4.14) to (4.25) and (4.31) to (4.51).

$$
\begin{aligned}
&\textbf{Objective function:}(4.1)\\
&\textbf{Constraints:}(4.2)\text{ to }(4.8),(4.14)\text{ to }(4.25)\\
&\textbf{First order conditions}\\
&A_i^s + A_i^s\beta_i - \sum_{t\in\mathcal{T}} \psi_{i,t}^s\phi_{i,t}^s - \sigma_i^s = 0 \qquad \forall i\in\mathcal{I} && (4.31)\\
&A_i^B + A_i^B\beta_i - \sum_{t\in\mathcal{T}} \psi_{i,t}^B\phi_{i,t}^B - \sigma_i^B = 0 \qquad \forall i\in\mathcal{I} && (4.32)\\
&\tau_{i,t}^E + \tau_{i,t}^D - \lambda_{i,t}^A - \sigma_{i,t}^{e^w} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.33)\\
&-\varphi\tau_{i,t}^E - \kappa\tau_{i,t}^D + \lambda_{i,t}^A - \sigma_{i,t}^{e^{in}} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.34)\\
&\phi_{i,t}^s - \lambda_{i,t}^A - \sigma_{i,t}^{e^s} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.35)\\
&\phi_{i,t}^B - \lambda_{i,t}^A - \sigma_{i,t}^{e^{ds}} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.36)\\
&-\phi_{i,t}^B + \lambda_{i,t}^A - \sigma_{i,t}^{e^{ch}} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.37)\\
&\tau_{i,t}^R - \lambda_{i,t}^R - \sigma_{i,t}^{r^w} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.38)\\
&-\tau_{i,t}^R + \lambda_{i,t}^R - \sigma_{i,t}^{r^{in}} = 0 \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.39)\\
&\textbf{Linearized complementary slackness}\\
&A_i^s p_i^s + A_i^B p_i^B - K_i \geqslant M u_i^\beta \qquad \forall i\in\mathcal{I} && (4.40)\\
&\beta_i \leqslant M(1-u_i^\beta) \qquad \forall i\in\mathcal{I} && (4.41)\\
&e_{i,t}^s - p_i^s\psi_{i,t}^s \geqslant M u_{i,t}^{\phi^s} \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.42)\\
&\phi_{i,t}^s \leqslant M(1-u_{i,t}^{\phi^s}) \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.43)\\
&e_{i,t}^w, e_{i,t}^{in}, r_{i,t}^w, r_{i,t}^{in}, e_{i,t}^s, e_{i,t}^{ch}, e_{i,t}^{ds} \leqslant M u_{i,t}^{\sigma*} \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.44)\\
&\sigma_{i,t}^* \leqslant M(1-u_{i,t}^{\sigma*}) \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.45)\\
&p_i^s \leqslant M u_i^{\sigma^s} \qquad \forall i\in\mathcal{I} && (4.46)\\
&\sigma_i^s \leqslant M(1-u_i^{\sigma^s}) \qquad \forall i\in\mathcal{I} && (4.47)\\
&p_i^B \leqslant M u_i^{\sigma^B} \qquad \forall i\in\mathcal{I} && (4.48)\\
&\sigma_i^B \leqslant M(1-u_i^{\sigma^B}) \qquad \forall i\in\mathcal{I} && (4.49)\\
&u_i^\beta, u_i^{\sigma^s}, u_i^{\sigma^B} \in \{0,1\} \qquad \forall i\in\mathcal{I} && (4.50)\\
&u_{i,t}^{\phi^s}, u_{i,t}^{\sigma*} \in \{0,1\} \quad \forall i\in\mathcal{I}, t\in\mathcal{T} && (4.51)
\end{aligned}
$$

Figure 4.6 presents a schematic representation of the algorithm used to find the economic equilibrium within the system. The process is structured into several iterative steps to ensure that equilibrium is achieved, particularly focusing on the interactions between DER, the distribution network, and the associated tariffs.

The first step involves the initialisation of the network model, where the system determines the set of cuts required to model the distribution network, as outlined in equation (4.25). To do this, the CPM is executed, which identifies the optimal size of the distribution network and the operations of the BESS under the initial conditions.

In the second step, the algorithm calculates the initial distribution tariff, denoted as $\hat{\tau}^D i, t$, and the BESS power profile, $\psi^B i, t$. These values are derived from the CPM results, which not only determine the optimal structure and operation of the distribution network but also provide the optimal operation of the BESS under the current system configuration.

The third step involves executing the single-level Distributed Investment Model (DIM) while assuming the distribution tariff $\hat{\tau}^D_{i,t}$ remains fixed. This step simulates the decision-making process of prosumers, who adapt their DER investments based on the current tariff structure. The DIM then provides a new estimate of the equilibrium investment in DERs, alongside the adjusted operation of the distribution network.

In the fourth step, the distribution tariff is recalculated, resulting in a new value, $\tau^D_{i,t}$, which reflects the updated size and requirements of the distribution network based on the results from the DIM model. This recalculated tariff takes into account the changes in DER deployment and the network's capacity needs.

The fifth step involves comparing the initial distribution tariff, $\hat{\tau}^D i, t$, with the recalculated tariff, $\tau^D i, t$. If the difference between these two tariffs is negligible, it suggests that the initial tariff has successfully guided prosumer investments in DERs and the corresponding investments in the distribution network, confirming that equilibrium has been reached. In this case, the system has achieved a balance where both network and DER capacities are optimally aligned with the tariff structure.

If equilibrium is not found, the process moves to the sixth step, where the initial distribution tariff is reinitialised. Specifically, $\hat{\tau}^D i, t$ is updated to match the recalculated value, $\tau^D i, t$, to adjust the tariff in line with the current state of the network and DER investments.

In the seventh step, with the newly updated distribution tariff in place, the power profile of the BESS, $\psi^B_{i,t}$, is recalculated using the POM. This ensures that the BESS operation is optimised according to the new conditions.

Once these recalculations are complete, the algorithm loops back to the third step, where the DIM model is executed again, using the updated tariff and power profile. This iterative process continues until the system converges on an equilibrium, where the distribution network and DER investments are fully aligned, and the tariffs reflect an optimal cost allocation for both prosumers and the network. This iterative loop follows the principles of the Gauss-Seidel algorithm, ensuring that each element of the system—network size, DER investments, and tariffs—gradually adjusts toward a balanced and stable configuration.

4.5 Studied tariffs arranges

Through this model it is considered energy and distribution tariff. In general, energy tariff derives from a competitive business in the supply chain such as the retail and wholesale electricity market. Instead, distribution network tariff derives from the cost of the distribution network, which is a monopolistic business, and therefore, this revenues are regulated.

In both cases, specific tariff structures are determined and serves as a economic signal to

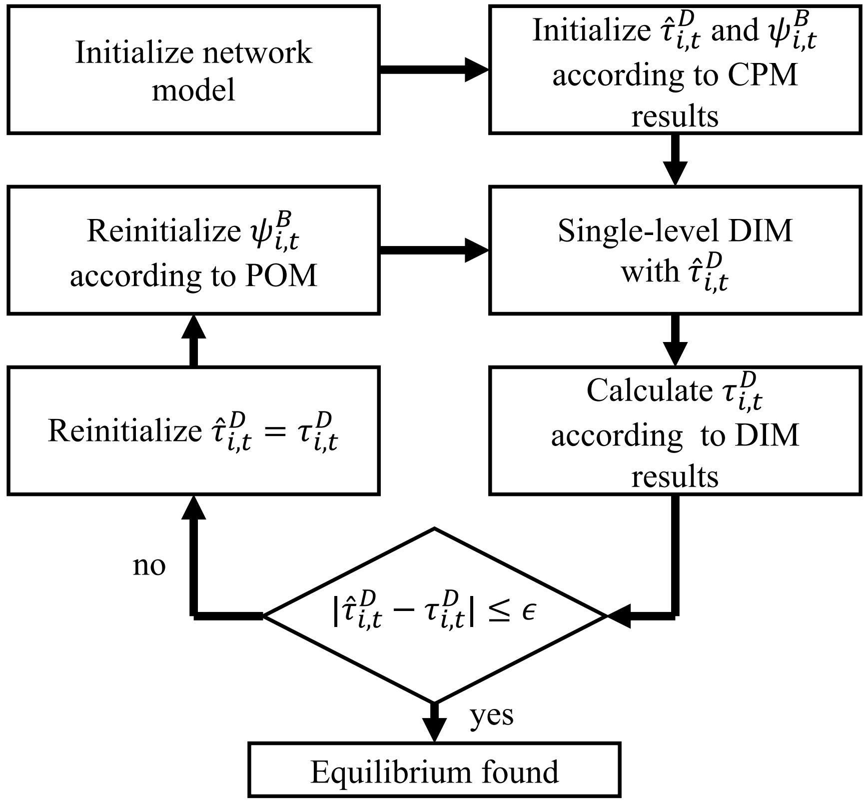

Figure 4.6: Gauss-Seidel algorithm flowchart

guide the prosumers investments. In this subsection, the different tariff structures will be shown.

4.5.1 Energy tariff

As mentioned before, the energy exchange with the bulk power system is valued at marginal costs C^A_t, which is understood as the real costs of electricity, regardless the energy tariff.

However, in practice users are charged according specific tariffs defined by the retailer or the regulator when this segment is bundled with the distribution system [184]. In this work, three energy tariff $\tau^E_{i,t}$ schemes are explored. The Figure 4.7 illustrates the three tariffs.

- Flat tariff, which have the same value during 24 hours per day. In the Figure 4.7 is illustrated on blue.
- 2-blocks tariffs, which has two values across the day.In the Figure 4.7 is illustrated on green.
- Marginal Cost pricing, where the charges are exactly the C^A_t. In the Figure 4.7 is illustrated on red.

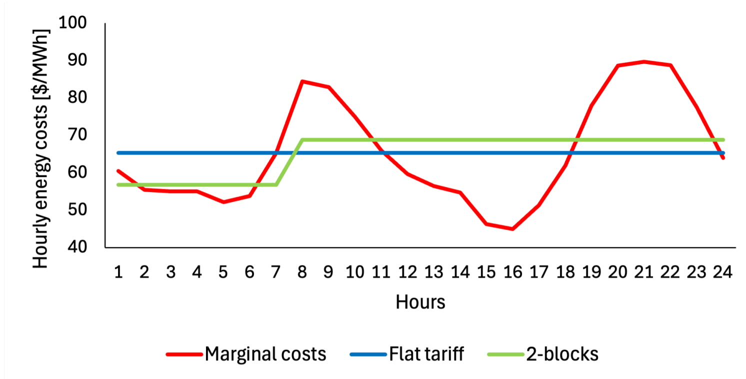

Figure 4.7: Illustration about the different energy tariff explored in this work

4.5.2 Distribution tariff

Distribution tariffs primarily aim to collect the costs associated with the distribution network and allocate them appropriately among the users (adequacy allocation). In this study, two types of distribution tariffs are considered: the Volumetric tariff and the Peak tariff.

The Volumetric tariff allocates the distribution network costs by dividing the total cost of the distribution network by the net electricity demand of the system, as shown in equation 4.52. In this context, the numerator represents the total costs associated with the infrastructure of the distribution network. The denominator, on the other hand, corresponds to the net energy consumption drawn from the bulk power system by all users. Essentially, this tariff structure charges consumers based on the amount of energy they consume. This approach reflects a relatively straightforward method for recovering network costs from users according to their overall demand on the system.

$$Vol_{i,t} = \frac{\sum_{l \in \mathcal{L}} A_l s_l}{\sum_{t'} p^w_{t'} - p^{in}_{t'}} \tag{4.52}$$

Instead, the peak tariff divides the cost of the DN by the sum of the net electricity demand over an threshold P. (i.e., when $p^w_t - p^{in}_t \geqslant P$, Equation 4.53). Therefore, during those times when net demand is lower than a threshold P, the peak demand is 0. Practical applications require that the threshold P defines a high percentile to distinguish peak energy consumption.

$$Peak_{i,t} = \begin{cases} 0 & \text{if } p^w_t - p^{in}_t \leqslant P \\ \dfrac{\sum_{l \in \mathcal{L}} A_l s_l}{\sum_{t' \in \mathcal{T}^P} p^w_{t'} - p^{in}_{t'}} & \text{otherwise} \end{cases} \tag{4.53}$$

Additionally, in this work the linear combination of peak and volumetric distribution tariff. Thus δ denotes the share of volumetric tariff.

$$\tau_{i,t}^{D} = \delta Vol_{i,t} + (1-\delta)Peak_{i,t} \tag{4.54}$$

In this work, the distribution network is planned from scratch (greenfield planning). Theoretically, greenfield planning assumes a long-term horizon where the current assets have reached the end of their useful life. This methodology is currently applied in Chile [185]. However, including an initial network as a starting condition does not fundamentally challenge the formulation, as it would only introduce additional constraints in the upper-level model.

Chapter 5

The impact of time-of-use tariffs on DER deployment across different socioeconomic groups

5.1 Chapter overview

This chapter satisfies the objective 5 of section 1.4.2. Thus, this chapter studies how different socioeconomic groups adapt their electricity consumption using DER technologies.

In doing so, it is necessarily to characterise different socioeconomic groups in their capabilities to adapt their consumption by utilising DER. In this work, socioeconomic groups are classified according their budgets for investing in DER (Distributed Energy Resources) assets, such as solar photovoltaic (solar PV) and Battery Energy Storage Devices (BESS). Thus, the basic assumption is that wealthier groups are more likely to have higher budgets for DER as it offers the possibility to generate energy and manage the energy consumption to reduce the electricity costs. However, residential customers have to face high upfront costs to deploy DER technologies, therefore the capability to invest in DER is directly linked with the customer' wealthy conditions.

In this chapter is studied the prosumers deployment of DER when they act following a rational economic behaviour exclusively, given by the distributed investment model (DIM). Likewise, a central planning model (CPM) is analysed as a benchmark of the DIM. Consequently, the models of chapter 4 are applied for a test feeder. Prosumers have the possibility to supply their consumption from the grid, to install solar PV or manage their net electricity consumption through a BESS. The equilibrium selection will depends on the tariff scheme and the cost effectiveness of DER technologies.

The net benefit of solar PV technology is closely related to the marginal cost of energy, which for this modelling is a exogenous variable. Currently, in some countries, marginal prices are still driven by thermal generation, making solar PV technology attractive due to high energy prices. However, in other contexts, high solar PV integration lowers the marginal cost of energy during daylight hours, which may reduce the attractiveness of solar PV installations from a systemic perspective. Nonetheless, under certain tariff schemes (e.g., flat energy tariffs), users might still find it beneficial to install this technology.

Analogously with BESS, which allows to prosumers to manage their electricity demand profile, giving them the possibility to arbitrage between different net tariffs (i.e. the sum of energy and distribution tariff). Thus, the cost-effectiveness of BESS depends on the variability of the tariff (for instance, in a flat tariff is expected no deployment of BESS as the variability of tariff is null).

Likewise, this chapter examines the impact of different tariff arrangements on system efficiency and cost allocation among various socioeconomic classes, with a focus on equity. The tariff definition is given in the Section 4.5.

The chapter is organised as follows: Section 5.2 describes the case study. Section 5.3 shows the analyisis performed in this chapter. Section 5.4 presents results from a systemic perspective, analysing the role of tariffs in the system's cost efficiency. Section 5.5 examines how tariffs impact cost allocation among customers. Section 5.6 provides a comparison of results among different studied tariffs. Finally, Section 5.7 concludes the chapter.

5.2 Case study

The case study is defined by the set of parameters needed in the model presented in Chapter 4. Thus, in this section is presented the parameters of distribution network, the budgets, electricity consumption patterns, marginal costs, and the features of DER.

Among general considerations is worthing to mention that the case study considers three typical days representing summer, winter and a peak day. The reason behind this selection is the first two days represents the seasonally of energy consumption that drives the energy costs. Instead, the peak day drives the network investments due to the capacity size depend of the peak demand.

5.2.1 Distribution network parameters

The network utilised in this work is the IEEE 37-bus feeder. Authors in [186] provide specific parameters such as the length of the lines, impedance, and resistance.Thus, the structure of the network is shown in Figure 5.1, highlighting the radial structure compatible with DistFlow equations.

It is worth mentioning that the power capacity of the network results from the DIM and CPM models defined in Chapter 4. A single investment cost of A_l=90 \$/MW-km-yr is assumed for each section of the distribution network. It is worth noting that, in practice, these costs will vary across different parts of the network due to the size of the wires, type (e.g., overhead or underground), geographical conditions [187]–[189].

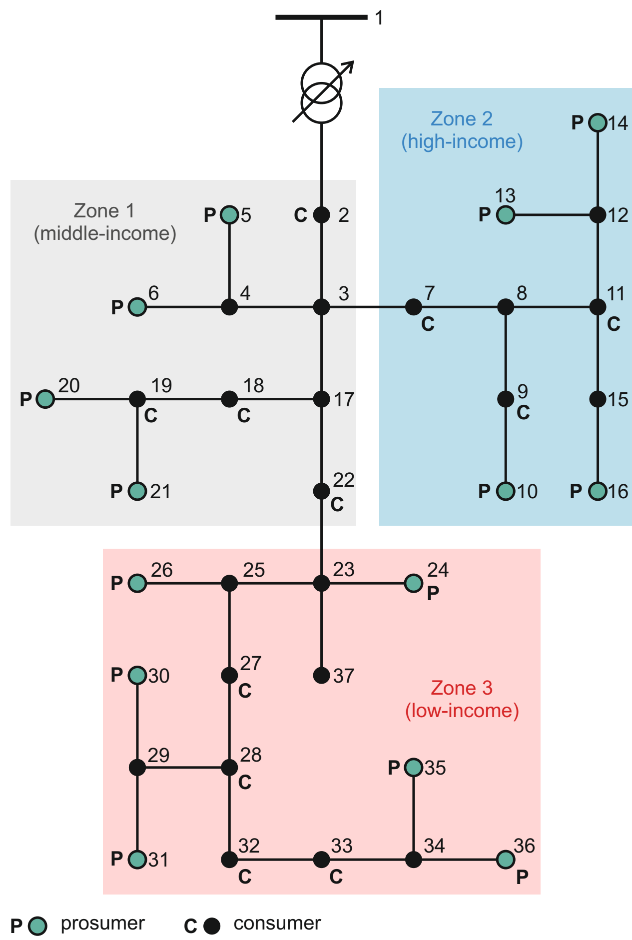

Figure 5.1: IEEE 37-bus feeder scheme. Four classes of prosumers/users, high-budget prosumers (blue), middle-budget prosumers (gray) and low-income (red). Finally, in every zone are consumers denoted by a ”C”, those are users with no budget.

Finally, note that there are three different zones across the distribution feeder (see 5.1). This give an account of three neighbourhood with different socioeconomic backgrounds given by Zone 1, 2 and 3.

5.2.2 Budget parameters

Users are characterised by different budgets for acquiring DER devices, which in this work serves as a proxy for their socioeconomic backgrounds.

Four user classes are defined in this study (see Table 5.1): no-budget (consumers), low-budget, middle-budget, and high-budget users. As mentioned earlier, users are distributed across three zones based on their socioeconomic background. Neighbourhoods in zone 1 represent middle-budget users, zone 2 represents high-budget users, and zone 3 represents low-budget users. It is important to note that consumers (those with no-budget) are present in all neighbourhoods.

Note the budget allocation corresponds to annuities. But in practice, prosumers needs to

Table 5.1: Location of network users and their budget per zone

User	Annuitised budget	Tag
Consumers	$0	No budget
Prosumers zone 1	$50	Middle-budget
Prosumers zone 2	$100	High-budget
Prosumers zone 3	$25	Low-budget

afford the upfront costs to deploy DER technologies. Therefore, the real costs of DER devices depends on the useful life and the cost of opportunity of capital invested.

5.2.3 Electricity consumption parameters

The main purpose of this work is to determine the impact of socioeconomic features (i.e., the budget) on DER deployment. To isolate the effects specifically related to DER deployment, all prosumers and consumers are assumed to have identical hourly electricity demands. Therefore, the only differentiation between prosumers is based on their budget and location within the distribution system.

Additionally, electricity demand is considered for three representative days throughout the year: a typical summer day, a typical winter day, and a peak demand day. The first two days represent 182 days each, with the objective of capturing different electricity consumption profiles over the year. These two days are used to estimate annual energy consumption. In contrast, the third day represents the peak demand, which drives the capacity requirements in the distribution system. Peak demand is influenced by several factors such as the type of technological devices used (e.g., air conditioning), their quantity, and the insulation quality of dwellings [190]. Some systems, like those in Chile [191] and the UK [192], experience peak demand in winter, while others, such as many subsystems in Australia [193], see peak demand in summer. In this thesis, the peak day follows the same pattern as a typical winter day.

The electricity demand profiles are generated using a model developed by the Centre for Renewable Energy Systems Technology (CREST) [194], which is a bottom-up model that simulates electricity usage patterns based on various household devices and demographic characteristics. As a result, the CREST model provides electricity demand for a household across different seasons. Figure 5.2 illustrates the active demand. Each user is assumed to have a power factor of 0.95 inductive.

5.2.4 Marginal costs parameters

The energy exchanges between distribution energy system and bulk power system are valued at marginal costs. Therefore are direct costs for distribution system operator or a central planner, and an indirect cost for customers as the marginal costs impact the energy tariff. In this work a representative day of marginal costs of energy is considered. In this regard, two sensitivities are considered.

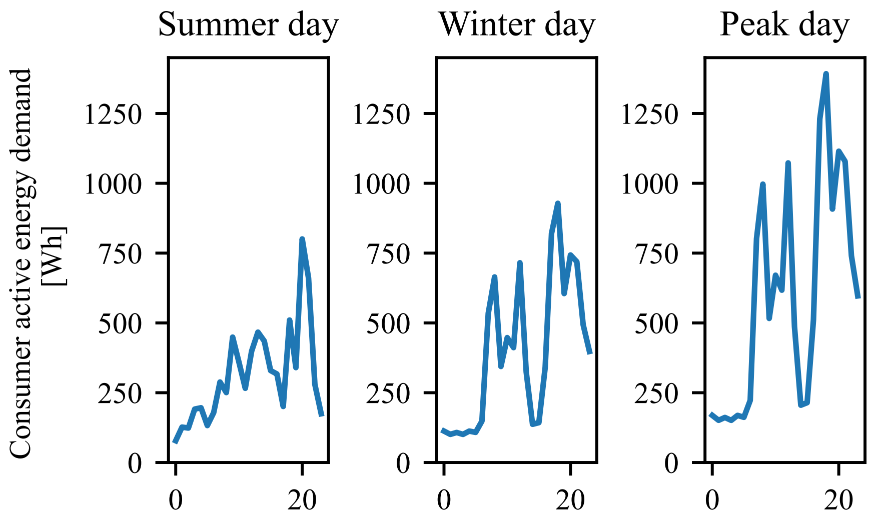

Figure 5.2: Demand per user of the three representative days.

First, a marginal cost profile emulates thermal generation, showing less volatile economic signal moving between 50 \$/MWh and 90 \$/MWh. Second, another marginal cost profile emulates a high penetration of solar PV generation. Consequently, the economic signal is more volatile and the marginal cost of energy varies between is 0 \$/MWh and 150 \$/MWh during daylight hours. Both profiles are synthetic, and their average, weighted by the net energy demand, is equal to 71 \$/MWh.

Figure 5.3 depicts the marginal costs in the two sensitivities above mentioned. On the top is shown the marginal cost driven by thermal generation, meanwhile on the bottom is the marginal cost driven by renewable generation.

The energy tariff is strongly related with marginal cost of energy. In general, the difference depend on the structure of the retail market, the competition conditions and the risk of the industry. In spite of that, in this work the energy tariff will have the same weighted average with electricity demand. Specifically, the definition is given by.

- Flat tariff, which have the same value during 24 hours per day, and it is equal to the marginal average cost, averaged by the net demand. This is the most utilised scheme.
- 2-blocks tariffs, which has two values across the day: a low value between midnight and 6:59h, and a high value between 7:00h and 23:59h. This scheme is based on the UK's economy seven tariffs [195]).
- Marginal Cost pricing, where the charges are exactly the C_t^A.

On the other hand, the distribution tariffs definition are discussed in Section 4.5.2.

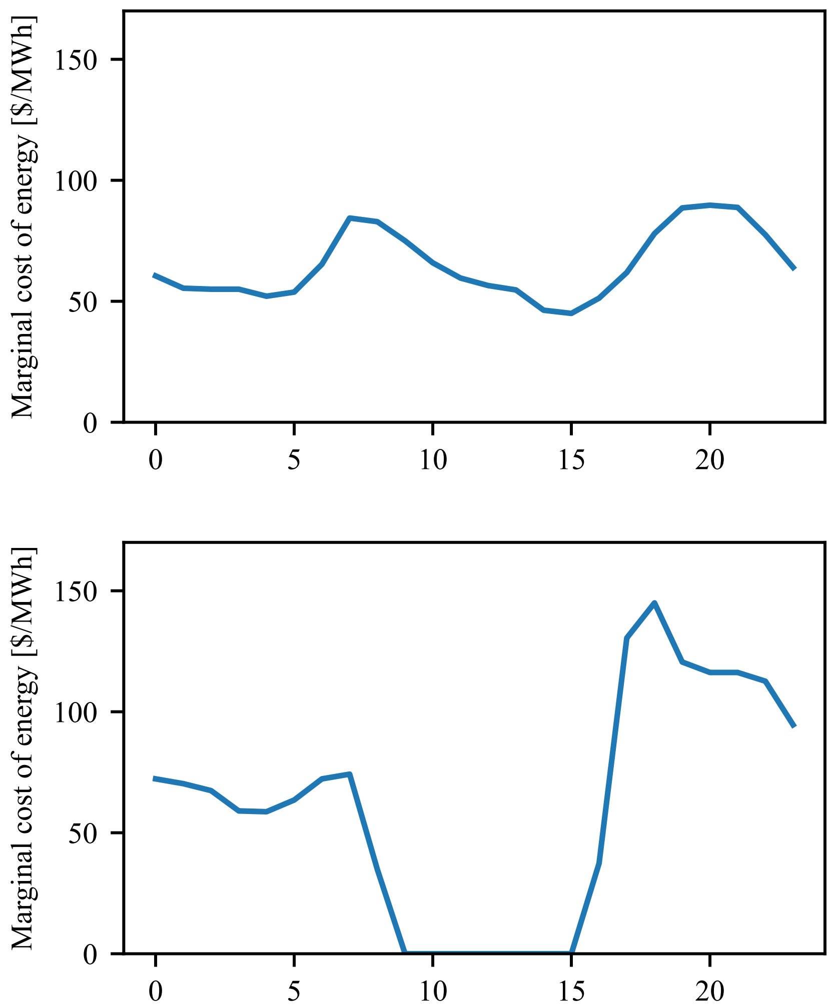

Figure 5.3: Marginal cost profile. Two sensitivities are displayed. First, a profile based on thermal generation, and second, a profile based on renewable generation.

5.2.5 DER parameters

In this work, prosumers have the option to deploy Solar PV and BESS. These two technologies are particularly suitable for residential deployment due to their technological maturity, cost-effectiveness, and current market trends [196]. However, future deployments could also consider other DER technologies, such as demand response.

Regarding Solar PV, the annuitised investment cost is A_i^S = 150 k$/MW-yr, based on a useful life of 10 years and a standard rate of return of 10%. This investment level aligns with optimistic market expectations [197]. Figure 5.4 illustrates the solar generation rate, with the power factor of Solar PV set at 40%. While this power factor is achievable in highly favourable conditions, such as the Atacama Desert [198], it may not be realistic for typical residential deployments. Future studies with specific local conditions should adjust these parameters accordingly.

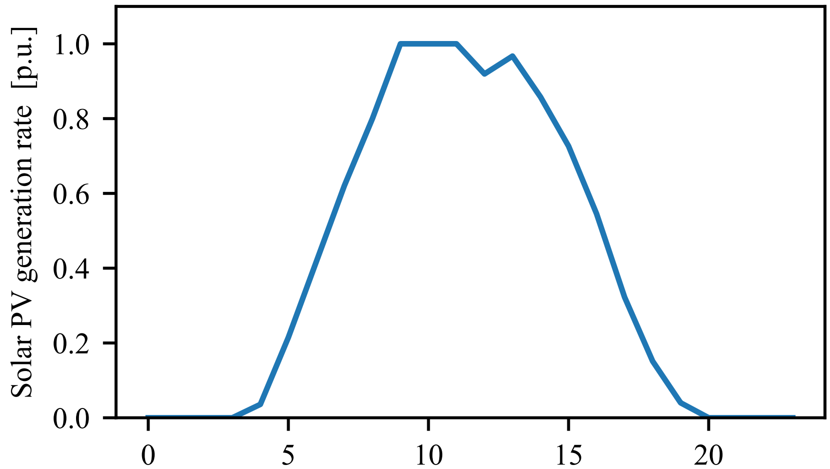

Figure 5.4: Solar availability

The battery energy storage systems (BESS) have an investment cost of $A_i^B = 120$ k\$/MW-yr. This cost is considered optimistic given current market trends [199], and more realistic studies would require a review of these values. The discharge time at maximum power is $H_i = 4$ hours, and the round-trip efficiency is $\eta_i^B = 0.85$. These values align with the observed range of capabilities for BESS [200].

5.3 Analyses performed

The analysis performed in this chapter can be divided into those related to *system-level* analyses and those related to *user-level* analyses. Then a global comparison among tariffs is performed, highlighting efficiency and fairness as two dimensions to evaluate the tariffs. Finally, the computational efficiency associated with the Gauss-Seidel algorithm (see Section 4.4.3) is examined.

The system-level analysis focuses on the total costs, including energy, distribution network infrastructure, and DER investment costs at the system level, which are impacted by DER integration. This is because DER not only influences the energy mix but also affects network infrastructure and energy exchanges, depending on the degree of DER deployment. Given that tariffs are the main economic incentive for DER deployment by prosumers, the analysis quantifies the impact of tariffs on efficiency.

Moreover, system-level costs are not necessarily distributed evenly among users. At the *user-level*, some users may benefit (when comparing their costs to a scenario without DER installation), while others bear higher costs due to inefficiencies (sub-optimal solutions) or the benefits gained by other users. Therefore, the allocation of costs, as driven by tariffs, is characterised in detail.

This work studies two distribution network tariffs and three energy tariffs, with the mathematical descriptions provided in Section 4.5 (see Table 5.2). The rationale for incorporating

Table 5.2: Types of tariffs analysed in this Chapter

Case	
Vol 100 Peak 0	Flat
	2-blocks
	MgC
Vol 10 Peak 90	Flat
	2-blocks
	MgC

these distribution tariffs is that they represent two extremes in the principles of distribution network pricing.

In the same line, the reason for the three different energy prices schemes are because the flat tariff and marginal costs represents two opposite principles for energy pricing. Likewise, the 2-blocks (or more blocks) tariffs are becoming popular in real applications.

System-Level analyses

The results of the equilibrium conditions for different tariff arrangements are compared against two benchmarks:

1. The "No DER installation" scenario: This scenario represents the current situation in many countries where DER deployment by residential prosumers is either in its very early stages or non-existent (e.g., Sub-Saharan African countries [201]). Comparing the long-term equilibrium with this scenario helps determine whether widespread DER deployment leads to a general reduction in system costs.
2. The CPM scenario: This scenario represents the system's optimal costs as determined by a central planner. Comparing the long-term equilibrium with this benchmark allows an assessment of how efficient the equilibrium is under different tariff schemes. Formally, the differences between the long-term equilibrium (i.e., Stackelberg equilibrium) and CPM costs are referred to as Stackelberg inefficiencies.

User-Level analyses

For each long-term equilibrium computed with the six tariffs, the resulting costs for each socioeconomic group are analysed through two approaches:

- Comparison among socioeconomic groups: By comparing the costs between no-budget users and high-budget users, the maximum cost difference within the studied population is analysed. A smaller difference in costs implies a more equitable distribution. This metric is aligned with the equality principle of fairness. See section 2.3.

- Comparison of cost allocation against the No DER scenario: By comparing the total charges to no-budget consumers in the long-term equilibrium with those in the No DER scenario, the analysis examines whether DER deployment has resulted in benefits or additional costs for consumers. This analysis focuses on the Min-Max fairness (or John Rawls) principle, which aims to maximise the position of the least advantaged socioeconomic groups. See section 2.3

Comparison among tariffs

The previous analyses at the system level and user level provide insights into the impact of tariffs on both efficiency and fairness in the system. These two principles are just part of the multiple objectives that a tariff structure must balance.

In this subsection, the aim is to provide a graphical representation offering a comprehensive view of the performance of each tariff scheme with respect to these two principles. The efficiency and fairness of the six tariffs are plotted on a two-axis chart, illustrating the trade-offs between the different tariff schemes.

5.4 System-level analysis

This section analyses the overall results of the long-term equilibrium between the distribution network and DER deployment by prosumers (referred to as "equilibrium" for simplicity). The section is divided into two parts: the impact of tariffs on the efficiency of the equilibrium and the impact of tariffs on the equilibrium portfolio.

5.4.1 Tariffs and their impact on efficiency

This section compares the system costs of the long-term equilibrium with the costs of the CPM and No DER scenarios for the six different tariffs, alongside two sensitivities regarding marginal costs.

Efficiency in this chapter is understood as the cost increase of the equilibrium compared to the CPM solution, referred to as Stackelberg efficiency. Similarly, the system costs are compared with the No DER installation scenario to assess whether DER integration has resulted in economic savings for the system, despite the Stackelberg inefficiencies.

The results are presented for two sensitivities related to marginal costs, as described in Section 5.2.5. It is worth noting that the scenario with marginal costs driven by thermal generation shows values around 70 \$/MWh during the day. In contrast, marginal costs driven by renewable generation are equal to 0 \$/MWh. This is due to the system having an excess of solar generation, sending a signal to the distribution system to avoid further solar PV installation. However, this signal is distorted by tariffs, leading to inefficiencies that will be quantified.

The total costs for the six tariff structures are shown in Figures 5.5 and 5.6 for marginal costs driven by thermal and renewable generation, respectively. All the charts display the CPM system costs (red dashed line), representing the optimal system costs, and the No DER costs (green dashed line). The charts on the left-hand side show the case with a purely volumetric distribution tariff (Vol 100 Peak 0), while those on the right-hand side depict the case with a Vol 10 Peak 90 tariff. Each box illustrates the three studied energy tariffs: MgC, 2-block (2-b), and Flat energy tariffs.

Considering the case of marginal costs driven by thermal generation (Figure 5.5), the CPM cost is 10.2 k$-yr (red dashed line). Meanwhile, for the case of marginal costs driven by renewable generation (Figure 5.6), the CPM costs are 9.3 k$-yr. The lower costs in the latter case are attributable to the higher volatility of marginal costs driven by renewable generation compared to those driven by thermal generation (as seen in Figure 5.3, where the bottom chart shows higher volatility compared to the top chart). Consequently, the BESS technology has greater potential to exploit energy arbitrage by charging energy during the day and discharging during the night, leading to lower costs in the case of marginal costs driven by renewable generation.

In both sensitivities of marginal costs, the No DER installation scenario has a cost around 10.8 k$-yr. This means that CPM costs have the potential to save 4.5% compared with the case of No DER installations when marginal costs are driven by thermal generation. Instead, the savings could reach 12.2% for those marginal costs driven by renewable generation.

If the energy transition is towards a future with more renewable generation, it is expected that more volatile economic signals (e.g., marginal price of energy) will emerge. Consequently, the economic potential of DER is higher in systems with a greater share of renewable generation.

The previous discussion focuses on the economic potential of DER technologies in different market contexts. However, tariff distortions deviate from the efficient solution[1]. Thus, the role of tariffs in efficiency depends on:

- **Distribution network tariff:** In this case, distribution tariffs play a partial role in determining efficiency depending on the cost-reflective features of the tariff. Firstly, it is worth noting that demand (Figure 5.2) is not correlated with solar generation (Figure 5.4), meaning that solar PV installations have a limited impact on the distribution network capacity. Given this, a purely volumetric tariff (Vol 100 Peak 0) sets a constant price for energy exchanges, which might be higher than the LCOE of solar PV[2], encouraging an overinstallation of solar PV from the perspective of prosumers. Consequently, under a volumetric distribution tariff, the total system costs do not depend on the energy tariff (see left-hand charts in Figures 5.5 and 5.6).

  In contrast, when the distribution tariff includes a high peak component (Vol 10 Peak 90), consumers are incentivised to avoid energy consumption during peak hours. Since solar PV generation is not correlated with demand, solar installations do not alleviate

[1] this distortion may be justified for simpler economic signals to consumers, and for risk hedging to consumers, protecting customers from energy price spikes

[2] This will be analysed in depth in the next subsection

distribution charges. As a result, the total system costs depend on the energy tariff. Finally, a peak-based tariff is cost-reflective, encouraging efficient prosumer investment, whereas a volumetric tariff does not, promoting inefficient investments. Thus, efficiency losses are partially explained by the nature of each tariff.

- **Energy tariff:** The energy tariff has a partial impact into the energy efficiency. In this case, the effects of the energy tariff are observable when the distribution tariff is cost-reflective (Vol 10 Peak 90, see right-hand charts in Figures 5.5 and 5.6).

  In this regard, Flat and 2-block tariffs are two distorted tariffs in terms of the efficiency due to those are two are different than the real cost of energy (marginal costs of energy C_t^A). Evidently, the marginal costs of energy is a cost-reflective tariff.

  Flat and 2-block have a stronger distorting effect depending on how volatile is the marginal costs. In the first sensitivity given my marginal costs driven by thermal generation, the marginal costs moves in a narrow gap, then those energy tariffs do not deviate too much from the marginal costs. As a consequence the total system cost are not too different from the marginal cost energy tariff. Those results are shown in the right hand of Figure 5.5.

  Instead, in the second sensitivity, when the marginal costs are driven by renewable generation the marginal costs are more volatile. As a consequence, Flat and 2-blocks tariffs may significantly deviate in certain hours from the marginal costs (For instance, during the mid-day, the marginal cost is 0 $/MWh and the Flat tariff is 71$/MWh). Thus, Flat and 2-blocks tariffs have a significant higher costs compared with the marginal costs energy tariff.

- **Marginal price of energy:** As demonstrated in the previous case, the volatility of the marginal energy price has a partial impact on the efficiency of the equilibrium. Conceptually, lower prices during certain hours of the day indicate an excess supply of energy, signalling to prosumers to avoid generation during those times. Thus, lower volatility in marginal costs may result in a reduced disturbance from the energy tariff, having a lesser impact on the overall efficiency of the system.

  But higher volatility, as in the second case when marginal costs are driven by renewable generation, may have a significant impact on the system's efficiency. In this scenario, the inefficiency could mean that the total system costs are higher than the cost with No DER deployment, implying that the deployment of DER may not provide any benefit to the system (see Figure 5.6 showing that the blue bars may have a higher value than the green dashed line).

Considering the previous analysis, in the first sensitivity, when the marginal costs of energy are driven by thermal generation, the inefficiencies are approximately 2% of the CPM cost (the optimal system cost) on average, and 1.4% when the tariff is cost-reflective in both the energy and distribution network components (i.e., MgC energy tariff and Vol 10 Peak 90 distribution tariff). Similarly, inefficiencies are higher when marginal costs are driven by renewable generation. In this case, inefficiencies can reach up to 17.5% compared to the CPM costs. As a counterfactual, when the tariff scheme is cost-reflective, the inefficiencies reduce to 2.8%. As a summary of the previous analysis, the Table 5.3 show the cost increase of the equilibrium induced by the tariffs compared with the CPM cost (optimal cost) of the system.

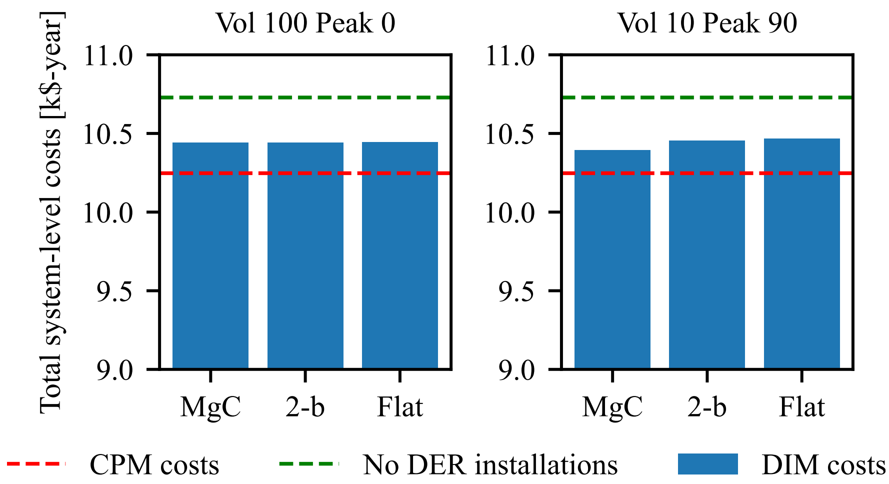

Figure 5.5: The figure illustrates the total system-level costs when marginal costs are driven by thermal power plants cost. The distribution tariff is specified at the top of each chart. The x-axis represents the energy tariff. The red dashed line indicates the CPM cost, while the green dashed line represents the system-level cost in the absence of DER investments.

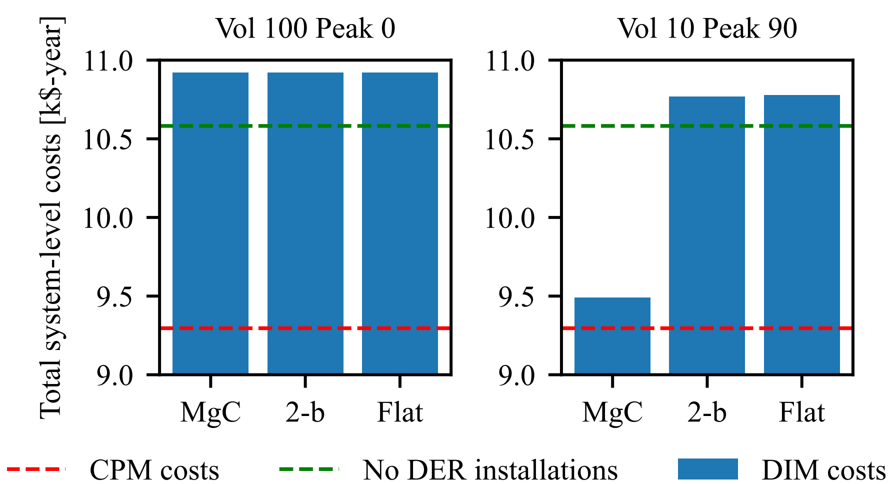

Figure 5.6: The figure illustrates the total system-level costs when marginal costs are driven by renewable power plants cost. The distribution tariff is specified at the top of each chart. The x-axis represents the energy tariff. The red dashed line indicates the CPM cost, while the green dashed line represents the system-level cost in the absence of DER investments.

These facts highlight that updating the electricity tariff (i.e., network and energy tariffs) requires a comprehensive analysis of each component that constitutes the tariff. Partial updates, whether in energy or distribution tariffs, may have a limited impact on reducing system inefficiencies. A clear example is the volumetric tariff (Vol 100 Peak 0), where the energy tariff has a negligible effect on total system costs (see the left-hand side of Figure 5.5 and Figure 5.6).

Moreover, beyond tariffs, market conditions play a crucial role in influencing efficiency. In

Table 5.3: Cost increase of the equilibrium compared with the CPM (optimal) solution. Thus, lower values represent more cost efficient solutions

Case		Marginal cost driven by thermal generation	Marginal cost driven by renewable generation
Vol 100 Peak 0	Cmg	2%	17%
	2-b	2%	17%
	Flat	2%	17%
Vol 10 Peak 90	Cmg	1%	2%
	2-b	2%	16%
	Flat	2%	16%

this study, market conditions are defined by the marginal costs in two sensitivities. When marginal costs are less volatile (as in the case driven by thermal generation), the inefficiencies caused by energy tariffs (such as Flat or 2-block tariffs) are lower compared to when marginal costs are more volatile (as driven by renewable generation).

5.4.2 Tariffs and DER deployment

In this subsection, the interdependencies between the equilibrium DER portfolio and the tariff schemes are analysed. Similar to the previous case, the results are presented for two sensitivities of energy marginal costs, driven by thermal and renewable energy, as shown in Figure 5.3. In the same vein, the equilibrium portfolio is presented for the two distribution tariffs and the three energy tariffs. Additionally, the optimal portfolio obtained with the CPM model is also displayed.

Considering the budget information available in Table 5.1, the total annuitised budget for each prosumer sums to 750 \$-yr. The equilibrium investment per prosumer is obtained using the DIM model, where investment is allocated to minimise electricity costs. Notably, in this study, the budget is fully utilised for any combination of tariff and marginal cost sensitivity.

The analysis in this section is divided into two parts. First, the results for the scenario where marginal costs are driven by thermal generation, followed by the sensitivity analysis for the scenario where marginal costs are driven by renewable generation. As explained earlier, the main difference between these two sensitivities lies in the marginal price during the day: in the case of thermal marginal costs, the price is around 70 \$/MWh, while for renewable marginal costs, the price is approximately 0 \$/MWh, reflecting an excess of solar energy.

The initial analysis examines the results from the CPM model, which shows the DER portfolio that minimises costs for each sensitivity. The portfolio for marginal energy costs driven by thermal generation is illustrated in Figure 5.7, in the chart on the left-hand side. The first result, shown at the left of the chart, represents the CPM investments (i.e., the optimal DER mix). In this case, the portfolio consists of \$606 per year in storage investments, equivalent to 5 MW across all prosumers, represented by the orange bar. Meanwhile, the optimal solar PV investment totals \$144 per year, equating to approximately 1 MW across all prosumers, represented by the blue bar.

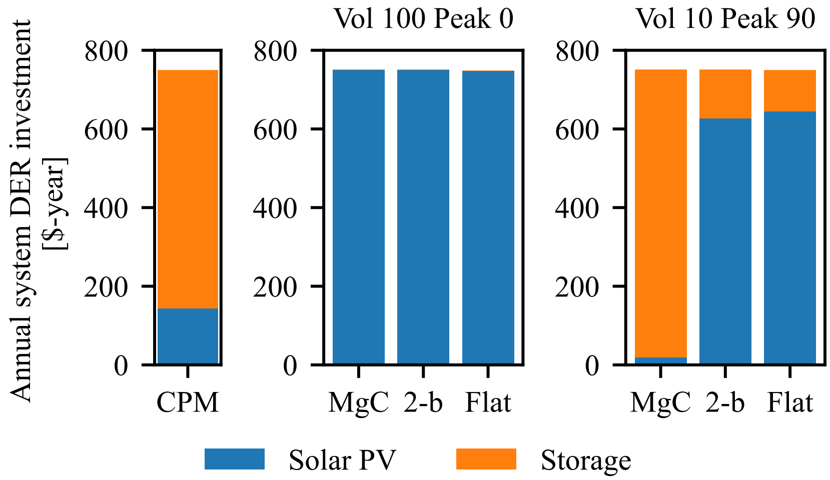

Figure 5.7: The figure illustrates investment in DER in stacked bars when marginal costs are driven by thermal power plants cost. The analysed cases are the CPM investments (left), the equilibrium investment for Vol 100 Peak 0 distribution tariff (middle), and Vol 10 Peak 90 distribution tariff (right).

Similarly, the case for marginal energy costs driven by renewable generation is shown in Figure 5.8, in the chart on the left-hand side. In this scenario, the CPM model only considers storage in the optimal portfolio (6.3 MW), while solar PV is not included, as marginal costs during daylight hours are 0 $/MWh.

These investment portfolios represent the optimal perspective of a CPM, where a central entity makes investments on behalf of prosumers to minimise system costs. However, this solution does not correspond to an economic equilibrium under any of the analysed tariff arrangements. As a result, prosumers may be incentivised to pursue a different DER portfolio that minimises their individual electricity bills, considering both energy and network tariffs.

The decisions made by prosumers under each tariff arrangement (Figures 5.7 and 5.8) can be explained by the electricity tariffs (the sum of energy and distribution network tariffs), which are shown in Figures 5.9 and 5.10 for the two sensitivities: marginal costs driven by thermal generation and renewable generation, respectively. These figures display the LCOE as a red dashed line, the total electricity consumption for net energy consumption as a continuous line, and the net energy injection as dashed lines. This allows for a comparison of the total tariff with the LCOE during solar generation hours and reveals three cases:

- The solar PV LCOE is lower than the injection tariff ($\varphi\tau^E_{i,t} + \kappa\tau^D_{i,t}$): In this case, the deployment of solar PV is efficient from the prosumers' perspective, as their injections are valued higher than their costs. Consequently, prosumers are incentivised to install as much solar PV as their budget allows.

- The solar PV LCOE is between the injection tariff ($\varphi\tau^E_{i,t} + \kappa\tau^D_{i,t}$) and the withdrawal tariff ($\tau^E_{i,t} + \tau^D_{i,t}$): In this case, it is not cost-efficient for prosumers to inject energy into the system, as the value of injection is lower than the LCOE. As a result, prosumers are encouraged to install solar PV up to the limit of their self-consumption.

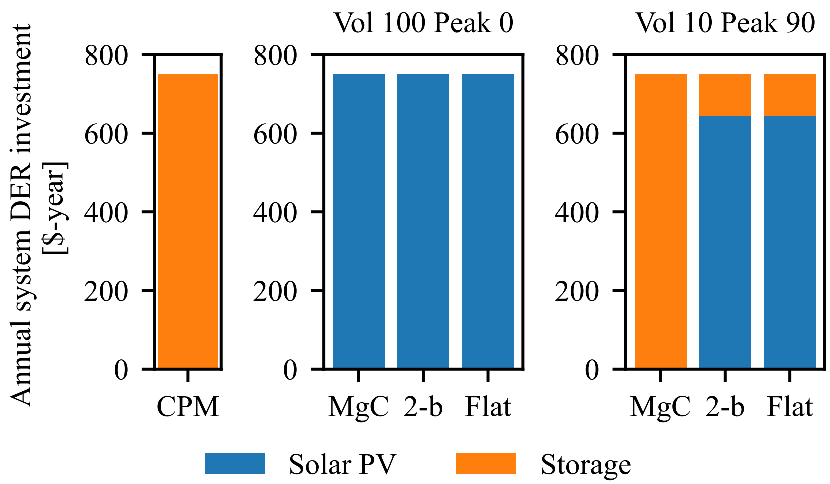

Figure 5.8: The figure illustrates investment in DER in stacked bars when marginal costs are driven by renewable power plants cost. The analyzed cases are the CPM investments (left), the equilibrium investment for Vol 100 Peak 0 distribution tariff (middle), and Vol 10 Peak 90 distribution tariff (right).

- The solar PV LCOE is greater than the withdrawal tariff ($\tau_{i,t}^{E} + \tau_{i,t}^{D}$): In this case, solar generation is no longer advantageous for prosumers, as the value of the generation is lower than the LCOE, making solar PV installations uneconomical.

Following the previous explanation, when the distribution network tariff is purely volumetric (Vol 100 Peak 0), the LCOE is lower than the injection tariff (dashed lines) for both marginal cost sensitivities (marginal costs driven by thermal and renewable generation, as seen in Figures 5.9 and 5.10, respectively, in the central chart). As a result, prosumers invest their entire budget in solar PV, regardless of the energy tariff. Consequently, BESS deployment is not attractive from the prosumers' perspective, which can be explained by two factors:

First, the volatility of tariffs is insufficient to incentivise BESS deployment (for instance, under a flat tariff, BESS cannot provide effective arbitrage). Second, the cost-effectiveness of solar PV is superior to that of BESS. Therefore, even though marginal cost energy tariffs could enable energy arbitrage, solar PV remains the preferred option for prosumers due to its better financial return.

When the distribution network is Vol 10 and Peak 90, the LCOE of solar PV is greater than the injection tariff $\varphi\tau_{i,t}^{E} + \kappa\tau_{i,t}^{D}$ for both marginal sensitivities (marginal cosst driven by thermal and renewable generation, as depicted in Figures 5.9 and 5.10 respectively). In addition, depending on the energy tariff, the solar generation is lower than the electricity tariff or higher. Thus in the case of Flat and 2-block tariff, the LCOE is lower than the electricity tariff, and therefore the solar generation is encouraged until the self-consumption limit. Thus, for Flat and 2-block energy tariffs, the investment in BESS ranges between 105-120 $-yr (equivalent to 0.9-1 MW of total installation), while the investment in solar PV ranges between 630-645 $-yr (equivalent to 4.2-4.3 MW of total installation). It is worth noting that for Flat and 2-b energy tariffs, the potential to apply energy arbitrage is limited.

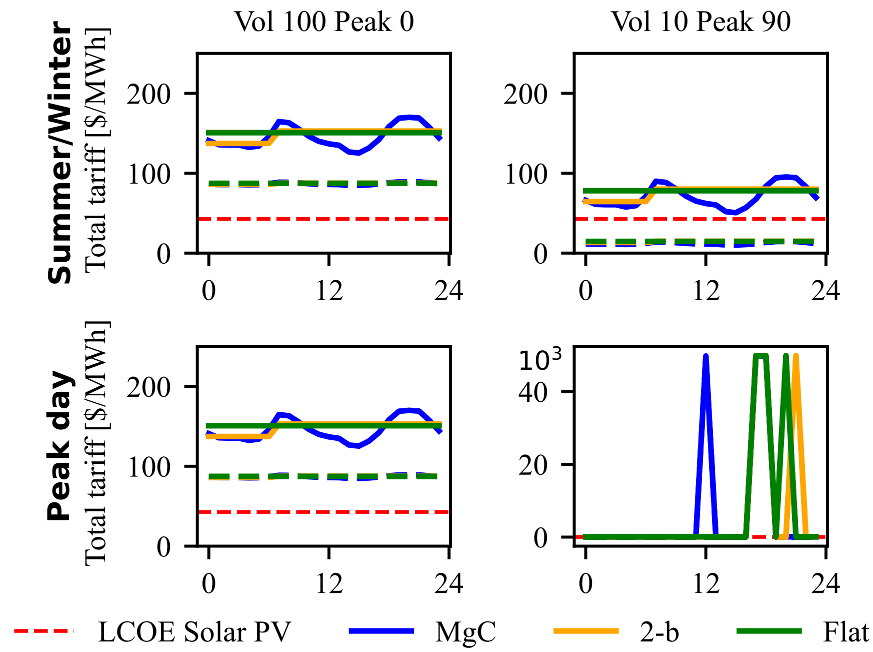

Figure 5.9: The charts depict the obtained tariffs after solving the DIM model (Stackelberg's equilibrium) when marginal costs are driven by thermal power plants cost. The first row column the Vol 100 Peak 0 distribution tariff, and the second column shows the Vol 10 Peak 90 distribution tariff. The top row indicates the summer/winter period, and the bottom shows the peak day. Each chart displays the LCOE of Solar PV (red dashed line). For each energy tariff, the total tariff for imports is shown with a continuous line, and the export tariff with a dashed line. Exports are valued at $\varphi\tau^E_{i,t} + \kappa\tau^D_{i,t}$.

Thus, the main incentive for storage deployment is the savings in distribution network charges.

Conversely, the MgC energy tariff offers the highest incentives to install storage systems due to the energy tariff volatility and the arbitrage capabilities of the storage systems. Therefore, in this case, the storage investment is 731 $-yr (6 MW) when the marginal costs of energy are driven by thermal generation, and 750 $-yr (6.3 MW) when the marginal cost of energy is driven by renewable energy. Consequently, the main incentive for storage deployment is an electricity tariff that allows for energy arbitrage. As result, the resulting in BESS installations six times higher compared to the case with a Vol 10 Peak 90 distribution network tariff and Flat or 2-block energy tariffs.

5.5 Results from prosumers point of view

This section analyses the cost allocation among different prosumers, differentiated by their budget to invest in DER, which is understood as a proxy of socioeconomic background. Similar to the previous subsection, the results are presented for cases with marginal costs driven by thermal and renewable generation as shown in the Figure 5.3.

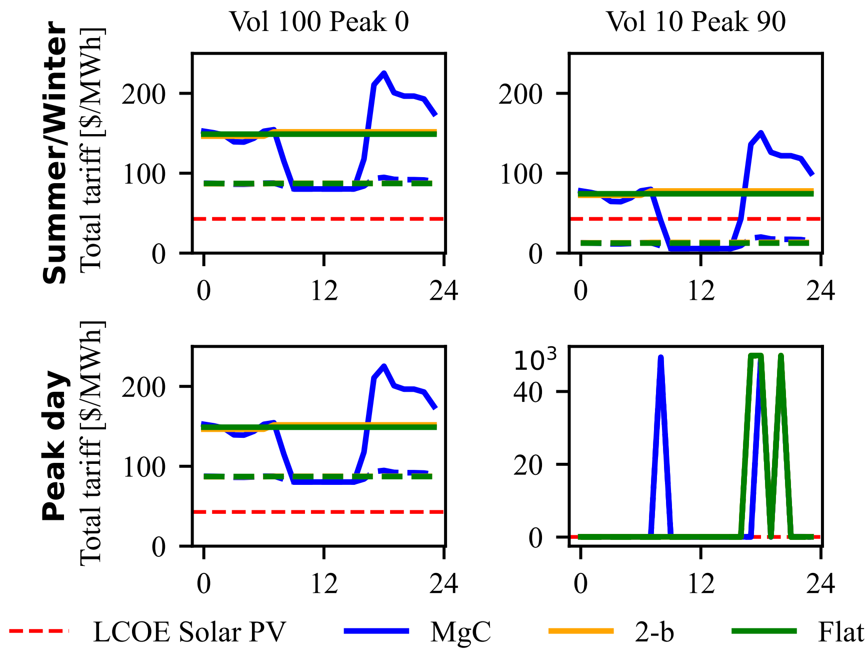

Figure 5.10: The charts depict the obtained tariffs after solving the DIM model (Stackelberg's equilibrium)when marginal costs are driven by renewable power plants cost. The first column shows the Vol 100 Peak 0 distribution tariff, and the second column shows the Vol 10 Peak 90 distribution tariff. The top row indicates the summer/winter period, and the bottom shows the peak day. Each chart displays the LCOE of Solar PV (red dashed line). For each energy tariff, the total tariff for imports is shown with a continuous line, and the export tariff with a dashed line. Exports are valued at $\varphi\tau^E_{i,t} + \kappa\tau^D_{i,t}$.

This section is divided into two main parts. Firstly, it analyses the total cost allocation (i.e., DER investment, energy, and distribution network charges). Secondly, given that the distribution network has features aligned with a public good, the cost allocation of distribution network costs is examined specifically.

The results of this section highlight that, beyond the impact on efficiency in terms of cost, analysed in the previous subsection, tariffs significantly affect cost allocation equity among users, and therefore, it rises concerns about the fairness in the energy system.

5.5.1 Tariffs and total costs allocation for different budgets

This section analyses the total cost allocation among different prosumers, grouped according to their budget, as shown in Table 5.1. There are four types of customers: no-budget, low-budget, medium-budget, and high-budget. As mentioned earlier, total costs include energy charges, distribution charges, and DER investments that each prosumer may undertake. This analysis examines how different prosumers adapt their consumption based on the technological landscape, represented by DER technologies (solar PV and BESS in this case) and their associated investment costs, and how this adaptation is influenced by their budget constraints.

The total cost allocation for different socioeconomic groups is presented in Figures 5.11 and 5.12, for marginal costs driven by thermal and renewable generation, respectively. The charts display the cost allocation for the two distribution tariffs (Vol 100 Peak 0 on the left-hand side, and Vol 10 Peak 90 on the right-hand side) and for three energy tariffs (Marginal Costs, 2-block, and Flat tariff). Additionally, the scenario with no DER installations is highlighted with a red dashed line. It is important to note that in the No DER scenario, all prosumers consume the same amount of electricity, as explained in Section 5.2.3, leading to uniform cost allocation across all socioeconomic groups.

Analysis of the gap between high-budget and no budget prosumers.

A first analysis is calculate the gap between the cost that pays high-budget prosumers and those with no budget (i.e., the difference of electricity costs between no budget and high budget). As expected, those with higher budget have the capability to deploy DER in order to reduce the electricity charges, meanwhile those without budget relies in the consumption from the distribution network.

The results in Figures 5.11 and 5.12 show that the largest disparity in equilibrium occurs when the distribution tariff is purely volumetric (Vol 100 Peak 0). In this case, higher-budget prosumers bear electricity costs that are 34-37% lower than those of no-budget users when marginal costs are driven by thermal generation (Figure 5.11, left-hand side). Conversely, when the marginal cost of energy is driven by renewable generation, this gap ranges between 22-37% (Figure 5.12, left-hand side). The 22% gap occurs when the energy tariff is MgC.

As shown in Figure 5.10, the blue line indicates that during hours of solar generation, the marginal costs are equal to 0 $/MWh, leaving only the energy tariff to be paid. Consequently, solar generation is less attractive compared to the scenario where marginal costs are driven by thermal generation, with values around 70 $/MWh. This reduction in solar attractiveness narrows the gap between high-budget and no-budget prosumers, leading to a more equitable distribution of costs.

When the distribution tariff is Vol 10 Peak 90, the cost gap between high- and no budget users is reduced. With the 2-b or flat energy tariffs, the gap is around 14% when the marginal costs of energy are driven by thermal generation (Figure 5.11). The highest inequality is found in the case of the MgC energy tariff, where the gap reaches 16%. This difference is due to the extra revenue high-budget users earn through energy arbitrage using batteries.

Similarly, for the Vol 10 Peak 90 distribution network tariff, when the marginal cost is driven by renewable generation (Figure 5.12), the gap between high- and no-budget prosumers is still 14% for Flat and 2-b energy tariffs. However, for the case of the MgC energy tariff, the gap reaches 43%, explained by the higher savings from storage systems that high-budget prosumers achieve.

As a result, the distribution tariff Vol 10 Peak 90 tends to reduce the gap in electricity costs between high-budget and low-budget prosumers. There are no significant differences between the Flat and 2-block tariffs in terms of cost distribution. Finally, marginal costs can either widen or narrow the gap depending on the context of the marginal cost structure.

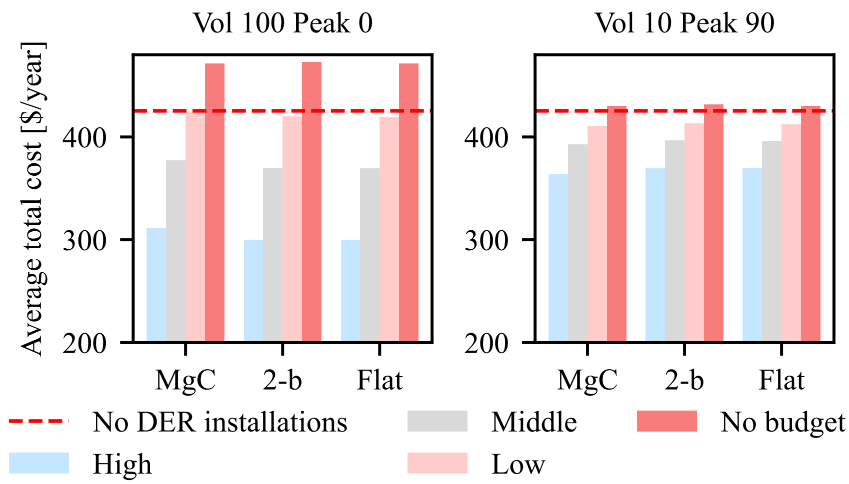

Figure 5.11: The figure depicts the average total cost per user with different budgets to invest in DER when the marginal costs are driven by thermal generation. The distribution tariff is specified at the top of each chart, and the energy tariff is shown at the bottom. The red dashed line represents the cost when there is no DER deployment, and therefore, all users face the same cost.

The size of the gap depends on both the tariffs and the capabilities of DERs to avoid certain charges.

In this context, when tariffs are high, solar PV provides an opportunity to reduce charges by generating energy during daylight hours. On the other hand, when tariffs exhibit volatility, BESS offers the ability to reduce charges by arbitraging across different periods. The greater the potential of DERs to reduce charges, the larger the gap between prosumers with varying budget capacities.

Analysis of total electricity cost for no budget users compared to No DER scenario

The second analysis focuses on the most vulnerable socioeconomic group, those with no budget to deploy DER. This approach aligns with the principle of energy fairness, based on the min-max criterion (Section 2.3), where a fairer distribution is one in which the most vulnerable prosumers bear lower energy costs.

In this context, the analysis compares the total electricity costs of no-budget users with the No DER scenario, assessing whether the absence of DER deployment leads to disproportionate costs for these users and how tariff structures influence their relative position in comparison with the electricity cost of No DER scenario.

No-budget prosumers may observe an increase in their bills due to DER adoption under equilibrium conditions compared to the case when there is no DER deployment whatsoever. For instance, considering the Vol 100 Peak 0 distribution network tariff, no-budget prosumers exhibit an increase of 10-11% when comparing equilibrium costs with the case of no DER installation. This result is common for marginal costs driven by thermal or renewable

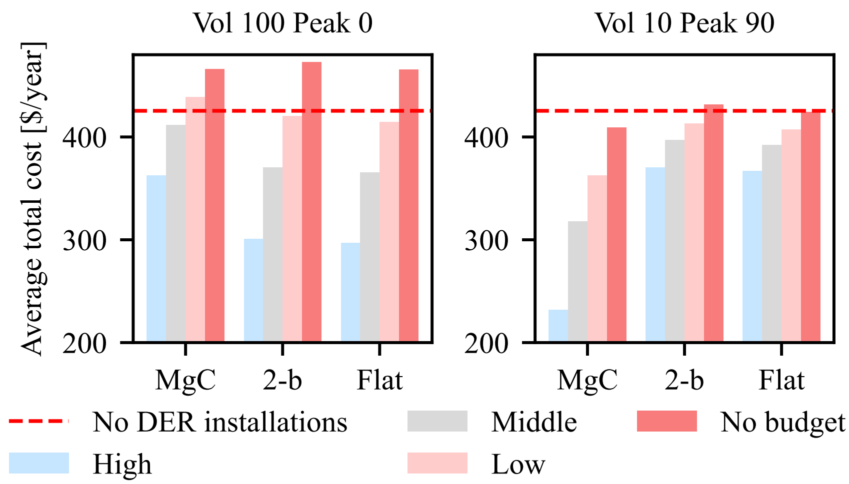

Figure 5.12: The figure depicts the average total cost per user with different budgets to invest in DER when the marginal costs are driven by renewable generation. The distribution tariff is specified at the top of each chart, and the energy tariff is shown at the bottom. The red dashed line represents the cost when there is no DER deployment, and therefore, all users face the same cost.

generation (Figure 5.11 and 5.12 left-hand).

Similarly, when the Vol 10 Peak 90 distribution network tariff is applied, no-budget consumers see an increase in their costs of up to 1.4% (Figure 5.11 and 5.12 right-hand). The exception is when the MgC energy tariff is applied, and the marginal costs are driven by renewable sources. In this case, no-budget consumers reduce their costs by 4% compared to the no DER costs (Figure 5.12 right-hand). This can be attributed to the savings at the system level (around 16%), and how a portion of those savings benefits those who do not invest.

Once again, the Vol 10 Peak 90 distribution tariff places vulnerable customers in a better position compared to the Vol 100 Peak 0 tariff. Similarly, the Flat and 2-block energy tariffs do not show significant differences in terms of the economic position of no-budget prosumers. Lastly, the impact of the marginal cost energy tariff depends on market conditions, whether driven by thermal or renewable generation. Specifically, in the case of a highly volatile energy market (as seen with renewable generation), the inclusion of BESS provides general benefits to the system, leading to reduced electricity charges for no-budget prosumers (Figures . It's important to note that while this is a positive effect for no-budget users, in the analysis of the cost gap among prosumers, it represents a negative effect, as it increases the disparity.

Therefore, the min-max and equality principles have practical implications in the design of tariff schemes, underscoring the importance of the ongoing debate regarding how energy fairness is conceptualised and implemented.

Table 5.4 summarises various measurements of cost allocation equity discussed in the previous paragraphs. The general conclusion is that the Vol 100 Peak 0 distribution network tariff results in unequal cost allocation, with no-budget prosumers facing higher costs. This

Table 5.4: Inequality measurements for total costs payed by type prosumers

Case		Marginal cost driven by thermal generation		Marginal cost driven by renewable generation	
Index		Rate of cost of high and no budget prosumers	Overcost of no budget prosumers	Rate of cost of high and no budget prosumers	Overcost of no budget prosumers
Vol 100 Peak 0	Cmg	34%	11%	22%	10%
	2-b	37%	11%	36%	11%
	Flat	36%	11%	36%	10%
Vol 10 Peak 90	Cmg	16%	1%	43%	-4%
	2-b	14%	1%	14%	1%
	Flat	14%	1%	13%	0%

inequality is generally mitigated by the Vol 10 Peak 90 distribution network tariff. However, when the MgC energy tariff is applied, high-budget prosumers increase their savings relative to no-budget prosumers, leading to a more unequal cost distribution. At the same time, under certain circumstances, the marginal cost tariff can result in lower costs for no-budget prosumers.

These contradictory effects on energy fairness, depending on the specific measure used, highlight the complexities in defining and evaluating fairness in energy cost allocation. This raises important questions about how energy fairness should be understood and measured, emphasising the importance of the criteria used to assess it

5.5.2 Tariffs and distribution network cost allocation for different budgets

As discussed in the previous section, one of the explanations for the higher inequities in electricity cost distribution is the tariff scheme and the greater potential for certain prosumers to save costs under that scheme. Therefore, the distribution network tariffs play a critical role in determining equity outcomes.

The distribution network tariff is responsible for collecting the distribution network costs (i.e., the infrastructure costs). Thus, this section focuses on analysing the allocation of distribution network costs, concluding with an assessment of the significance of this tariff structure in relation to energy fairness principles.

Figures 5.13 and 5.14 illustrate the average distribution network costs when marginal energy costs are driven by thermal and renewable generation, respectively. The overall trends align with the total costs analysed in previous sections.

Fucusing the analyisis according tho the gap in the distribution charges between high- and no budget prosuemr. The highest gap are observed when the distribution tariff is Vol 100 Peak 0 (see the left-hand columns of Figures 5.13 and 5.14). Conversely, the distribution network tariff Vol 10 Peak 90 helps reduce the gap. Consequently, the Vol 10 Peak 90 is coherent with an equalitarian sense of energy justice.

Focusing the analysis on no-budget prosumers (i.e., the most vulnerable prosumers), they experience higher costs compared to the scenario without DER installations, and this

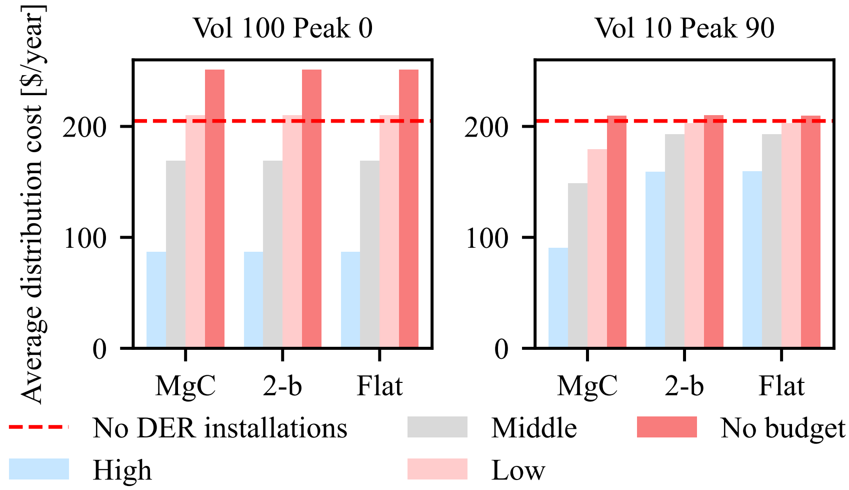

Figure 5.13: The figure depicts the average total cost of distribution network per user with different budgets to invest in DER when the marginal costs are driven by thermal generation. The distribution tariff is specified at the top of each chart, and the energy tariff is shown at the bottom. The red dashed line represents the cost when there is no DER deployment, and therefore, all users face the same cost.

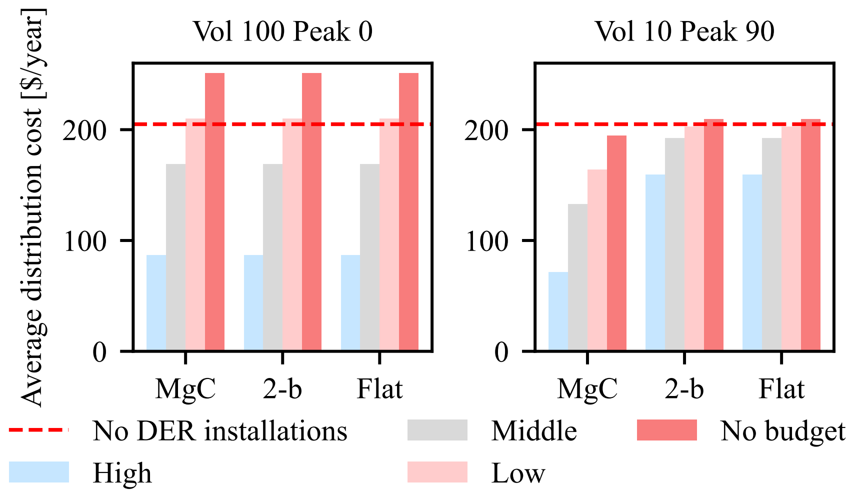

Figure 5.14: The figure depicts the average total cost of the distribution newtork per user with different budgets to invest in DER when the marginal costs are driven by renewable generation. The distribution tariff is specified at the top of each chart, and the energy tariff is shown at the bottom. The red dashed line represents the cost when there is no DER deployment, and therefore, all users face the same cost.

additional cost is more pronounced under the Vol 100 Peak 0 distribution tariff. However, when the tariff is Vol 10 Peak 90, this over-cost is significantly reduced. In the case where marginal energy costs are driven by renewable generation and the energy tariff is MgC, no-budget prosumers even see savings compared to the no DER scenario (as shown on the right-hand side of Figure 5.14).

Table 5.5: Difference of total costs and distribution network costs for no budget prosumers when the marginal costs are driven by thermal generation

Budget		No		
Measure		Total cost [$-yr]	DN cost [$-yr]	DN cost/Total cost [%]
Vol 100 Peak 0	Cmg	46.3	46.3	100%
	2-b	47.4	46.3	98%
	Flat	46.3	46.3	100%
Vol 10 Peak 90	Cmg	4.5	4.5	100%
	2-b	6.1	5.0	82%
	Flat	4.8	4.8	100%

Table 5.6: Difference of total costs and distribution network costs for no budget prosumers when the marginal costs are driven by renewable generation

Budget		No		
Measure		Total cost [$-yr]	DN cost [$-yr]	DN cost/Total cost [%]
Vol 100 Peak 0	Cmg	40.5	46.3	114%
	2-b	47.7	46.3	97%
	Flat	40.5	46.3	114%
Vol 10 Peak 90	Cmg	-16.2	-10.4	64%
	2-b	6.1	4.6	76%
	Flat	-1.2	4.6	-397%

The primary reason for the additional cost for no-budget prosumers is attributed to the distribution network charges. Table 5.5 compares the over-cost of total electricity faced by no-budget prosumers with the over-cost of distribution network charges for the scenario where the marginal cost of energy is driven by thermal generation. In both cases, the over-costs are compared to the no DER solution. The results show that the majority of the over-cost is driven exclusively by increased distribution charges. In most instances, the distribution network accounts for 100% of the cost increases.

For the scenario where marginal energy costs are driven by renewable generation, Table 5.6 shows that the distribution network still represents a significant portion of the total distribution costs. However, the total cost savings involve other components of greater importance, such as reduced energy costs and general savings. As a result, there is not a perfect correlation between the over-cost of the distribution network and the total costs in this scenario.

Similar to Table 5.4, Table 5.7 presents various indices to analyse the distribution network cost allocation. It is clear that these indices are significantly influenced by the distribution tariff structure. When the tariff is Vol 100 Peak 0, there is a marked inequality in cost allocation, with high-budget prosumers paying only 65% of what no-budget prosumers pay for the distribution network. Additionally, no-budget prosumers pay 23% more for the network compared to the no DER solution.

Table 5.7: Inequality measurements for distribution network costs payed by type prosumers

Case		Marginal cost driven by thermal generation		Marginal cost driven by renewable generation	
Index		Rate of cost high and no budget prosumers	Over-cost of no budget prosumers	Rate of cost high and no budget prosumers	Over-cost of no budget prosumers
Vol 100 Peak 0	Cmg	65%	23%	65%	23%
	2-b	65%	23%	65%	23%
	Flat	65%	23%	65%	23%
Vol 10 Peak 90	Cmg	57%	2%	63%	-5%
	2-b	26%	2%	24%	2%
	Flat	24%	2%	24%	2%

Equity concerns are generally mitigated with the Vol 10 Peak 90 tariff, where high-budget prosumers save about 25% on distribution network charges compared to no-budget users. However, when the MgC energy tariff is applied, high-budget prosumers can save as much as 60% on distribution network charges, further exacerbating inequity. This demonstrates how cost-effective tariffs can sometimes lead to unintended consequences in terms of fairness in cost allocation.

In terms of the min-max principle, or Rawls' principle, it is crucial to examine the costs incurred by no-budget prosumers. The increase in distribution network costs compared with the No DER scenario is highly dependent on the distribution network tariff. Under the Vol 100 Peak 0 tariff, no-budget prosumers experience a 23% increase in costs. In contrast, with the Vol 10 Peak 90 tariff, the increase is reduced to only 2%, and when the MgC energy tariff is applied, no-budget prosumers actually save 5%.

As with the previous case, this analysis raises concerns about how energy fairness is defined. Depending on whether the evaluation is based on the equity principle or the min-max principle, the performance of the tariff in terms of fairness may vary significantly. This highlights the importance of carefully considering the definition and measurement of energy fairness when designing tariff structures.

5.6 Comparison among tariffs

In the previous sections, it was discussed the role of tariffs in achieving equilibrium efficiency and in addressing energy fairness, as framed by both equality and Rawls' principles. This subsection offers a comprehensive comparison of different tariffs, highlighting the trade-offs between various tariff structures and the criteria used to evaluate their efficiency and fairness.

Figure 5.15 presents an analysis based on the total cost allocation from Table 5.4, while Figure 5.16 is constructed using the distribution network cost allocation from Table 5.7. Efficiency data for both cases is drawn from Table 5.3.

The charts displayed in Figures 5.15 and 5.16 are structured as follows: The left-hand column of charts illustrates cases where marginal costs are driven by thermal generation, while the right-hand column focuses on cases where marginal costs are driven by renewable generation. The x-axis represents the over-cost of the system compared to the CPM (optimal) cost, serving as a measure of system efficiency (refer to Table 5.3).

For the top charts, the y-axis shows the savings rate of high-budget prosumers compared to the charges of no-budget prosumers, illustrating the equity gap. For the bottom charts, the y-axis represents the over-costs incurred by no-budget prosumers compared to the no DER charges, reflecting the burden on the most vulnerable prosumers in line with the Rawls' principle.

Each chart plots the performance of the six analysed tariffs. In blue, we see the results for the Vol 100 Peak 0 distribution tariff, and in red, the Vol 10 Peak 90 distribution tariff. The shapes on the charts represent different energy tariffs: circles indicate the marginal cost energy tariff, squares represent the 2-block tariff, and diamonds denote the flat tariff. This visualisation allows for a clear comparison of how different tariff structures perform in terms of both efficiency and fairness, under varying market conditions.

Note that the three measures involved in these charts can be described as follow:

- **Over-cost of equilibrium compared with CPM cost (x-axis):** Over-cost of equilibrium compared with CPM cost (x-axis): This measure reflects the additional cost incurred compared to the optimal system cost (obtained with CPM). A lower value indicates a more efficient solution, where the system operates closer to its optimal state.
- **Savings of high-budget compared to no-budget prosumers in terms of cost:** This measure represents the relative savings enjoyed by high-budget prosumers compared to no-budget prosumers in distribution network costs. A lower value reflects a more equitable cost allocation among different consumer types, aligning with the equity principle by reducing the disparity in costs.
- **Over costs paid by no-budget prosumers compared with the no DER costs** This measure indicates the extra burden on no-budget prosumers (those unable to invest in DER) relative to a scenario without DER deployment. A lower value here suggests a reduced burden on disadvantaged consumers, consistent with Rawls' principle, which prioritises the welfare of the most vulnerable.

These visualisations enable a graphical analysis of the different tariff schemes, allowing us to easily identify the strengths and weaknesses of each. In the charts, a tariff positioned further to the left represents a more efficient equilibrium, meaning the system operates closer to its optimal cost. Similarly, a tariff positioned further down reflects a more equitable cost allocation, where the financial burden on more vulnerable prosumers is reduced, indicating a fairer distribution of costs across socioeconomic backgrounds.

By comparing the relative positions of different tariffs, it becomes possible to determine which tariff structures achieve the best balance between efficiency and fairness, and where trade-offs may occur between these two objectives. This visual approach provides a clear, intuitive framework for understanding how various tariff designs impact both system performance and equity, offering valuable insights into the trade-offs and synergies inherent in different pricing strategies.

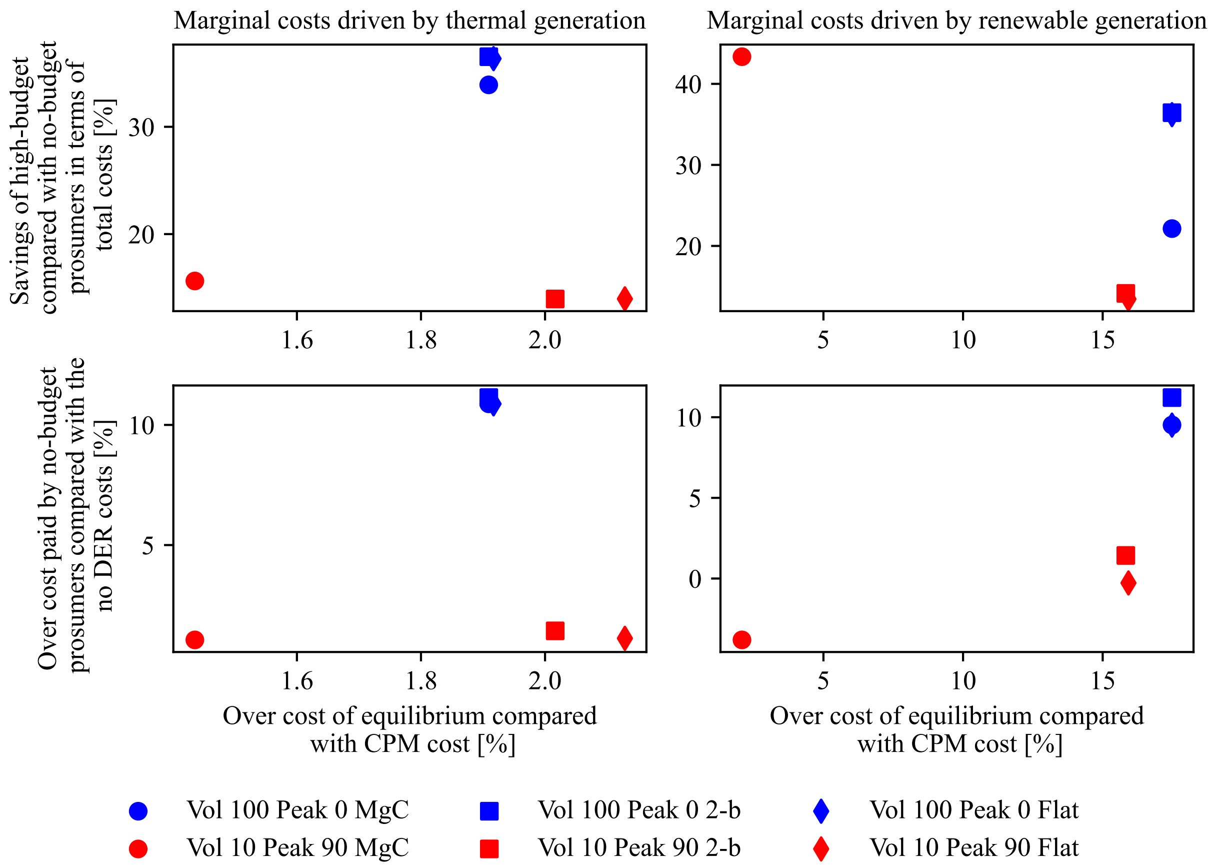

Figure 5.15: The figure illustrates four charts. Every chart contains six points showing the efficiency and fairness notions (equity and Rawls' principle) associated with the equilibrium tariffs. This figure is made using the data distribution network cost allocation of Table 5.4 and efficiency of Table 5.3.

Figure 5.15 illustrates that no single tariff outperforms all others in balancing efficiency and fairness in terms of both equality and Rawls' principles. Focusing first on the case where marginal costs are driven by thermal generation (i.e., left column), the red markers (representing the Vol 10 Peak 90 tariff) are positioned below the blue ones, indicating that Vol 10 Peak 90 has a notably positive effect on fairness. This outcome is more equitable (as shown in the top chart) and fairer in terms of Rawls' principle (as shown in the bottom chart).

In terms of efficiency, the MgC energy tariff (among the red markers) shows a significant impact, but it does not clearly perform better in terms of fairness. In fact, the 2-block tariff (2-b) is slightly more equitable, as seen in the top chart, where the gap between high-budget and no-budget prosumers is smaller.

In the case where marginal costs are driven by renewable generation (i.e., right column), there is no clear superiority of the Vol 10 Peak 90 tariff over the Vol 100 Peak 0 distribution tariff. In fact, when considering the savings of high-budget prosumers compared to no-budget prosumers in terms of total cost (top chart), the Vol 10 Peak 90 tariff with the MgC energy tariff results in the most unequal distribution (the red circle, positioned around 43% savings for high-budget prosumers compared to no-budget prosumers).

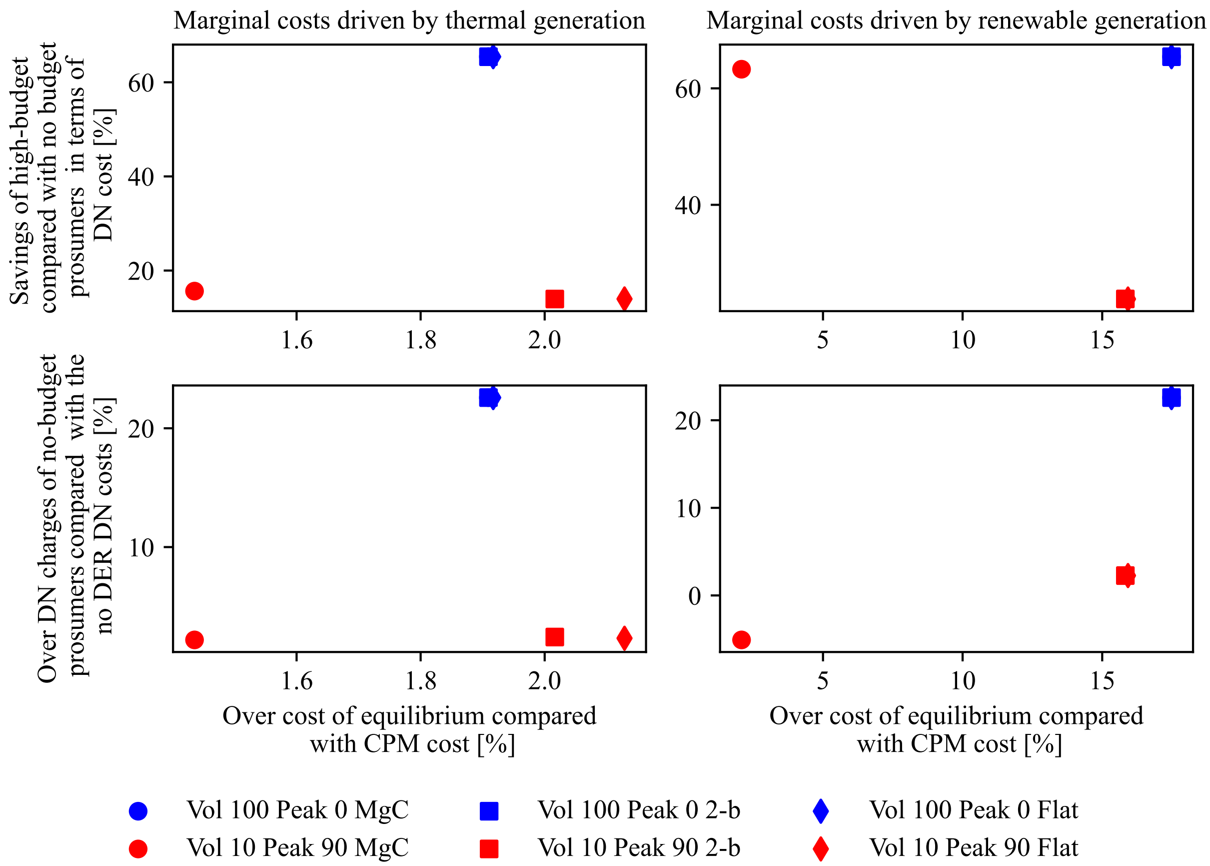

Figure 5.16: The figure illustrates four charts. Every chart contains six points showing the efficiency and fairness notions (equity and Rawls' principles) associated with the equilibrium tariffs. This figure is made using the data distribution network cost allocation of Table 5.7 and efficiency of Table 5.3.

However, when analysing the over-costs paid by no-budget prosumers (following Rawls' principle) compared to the no DER solution (bottom chart), the combination of the Vol 10 Peak 90 and MgC tariffs performs best in terms of both efficiency and fairness (the red dot positioned farthest left and lowest on the chart, indicating both lower over-costs and higher efficiency relative to other tariffs). This highlights the complex trade-offs between fairness and efficiency, which vary based on the tariff structure and market conditions.

Figure 5.16 displays results that are nearly symmetrical to those in Figure 5.14, underscoring the critical role of distribution networks in equity considerations. For no-budget prosumers, distribution network costs make up a substantial portion of their annual electricity expenses, highlighting the importance of carefully designing distribution tariffs to ensure a fair allocation of costs across different socioeconomic groups. This symmetry further emphasises that distribution network tariff structures can significantly influence overall fairness, particularly for the most vulnerable consumers.

5.7 Summary

The efficiency and fairness of the allocation are studied through six different tariffs.

The following conclusions can be drawn from the analysis:

1. **The context of the market has a strong impact on equilibrium features**: In this work, the context is modelled as the marginal cost of energy, reflecting the composition of the generation market. This variable significantly affects the equilibrium's efficiency and equity:

   - **Efficiency**: Flat, 2-b energy tariffs, and Vol 100 Peak 0 distribution tariffs are distorting tariffs that lead to sub-optimal equilibrium. The extent of distortion strongly depends on the market context. For instance, in a market with a surplus of solar energy, a flat tariff implies more efficiency loss compared with a market driven by expensive thermal generation. The same applies to distribution tariffs; the distortion of a Vol 100 Peak 0 tariff is higher in expensive distribution networks (e.g., low population density areas).
   - **Fairness**: Depending on the Fairness measure, the same tariff can have different performances. For example, the Vol 10 Peak 90 distribution network tariff and MgC energy tariff could produce different outcomes. Considering marginal costs of energy driven by renewable generation can imply a significant difference between the costs for high-budget and low-budget prosumers affecting the egalitarian notion of fairness. This can be explained by the advantages that storage systems bring to high-budget prosumers. Conversely, the same tariff in a context of marginal costs driven by thermal generation results in a more equal distribution of costs.

2. **The need for a holistic tariff review**: In this work, tariffs have energy and distribution network components, where the combination of three energy tariff schemes and two distribution network tariff schemes are studied. The application of a cost-reflective tariff (i.e., Vol 10 Peak 90 and MgC tariff) brings substantial improvements in efficiency. Nevertheless, partial replacement could lead to more inefficient and unfair equilibrium.

3. **Impacts of DER deployment strongly depend on the tariff schemes**. These impacts have different consequences at the system and prosumer levels:

   - **System-level**: Depending on the context (i.e., marginal cost of energy) and tariff arrangements, the system could face an increase in costs compared with the case with no DER whatsoever. This happens when the bulk-power system has an excess of energy at certain hours (i.e., lower marginal cost), and the energy tariff scheme does not capture this event, or the distribution tariff rewards off-peak generation. Conversely, cost-reflective tariffs reduce the total cost of the system.
   - **Prosumer-level**: Tariffs and different socioeconomic backgrounds strongly impact cost allocation across prosumers. Generally, the higher the budget, the greater the savings. However, low- and no-budget prosumers generally see an increase in costs when others deploy DER due to the increase in distribution charges.

4. **Distribution network tariffs play a crucial role in the costs for low- and no-budget prosumers**. Since no-budget prosumers cannot invest in DER, their costs rely on energy and network charges, where the latter vary significantly with DER integration.

5. **The importance of a clear energy fairness definition**. This work analyses two fairness measures: (i) the rate of costs between high- and no-budget costs, related with egalitarian sense of fairness and (ii) the over-cost of no-budget consumers, related with the min-max or Rawls' sense of fairness. Both measures address different aspects of fairness in energy charges and provide useful information for policymakers tariff making processes. The performance of a tariff scheme in terms of fairness is impacted on how the fairness is measured.

Chapter 6

Conclusions

This section is divided into general specific conclusion associated to the impact of socioeconomic factors into the short-term adaptation capabilities for disruptive events, and the impact of socioeconomic factors into the long-term energy transition. Then, the general conclusion extracted from both point of view, short-term and long-term.

6.1 Conclusion from the impact of socioeconomic factors in the short-term adaptation capabilities for disruptive events

This research analysed how residential customers adapted their electricity consumption during the disruptive event of the COVID-19 pandemic. The study focused on 230,000 customers located in Santiago, Chile, whose electricity consumption was measured by smart meters from January 2019 to September 2020.

Residential consumers showed an increase in demand following the implementation of the first lockdowns at the beginning of the pandemic. The sharpest increase occurred between June and August 2020, coinciding with the lowest temperatures and the most restrictive mobility measures. Notably, the maximum increase was observed in the week of 22 June 2020, when demand was, on average, 91% higher than in the first week of March. This surge was the result of both the pandemic and lower temperatures. It is estimated that the pandemic accounted for up to a 17% increase in demand in June compared to the same month in 2019. It is important to note that this effect varied significantly across different zones. In fact, zones with higher demand increases were typically those with higher incomes. Likewise, the results showed considerable variation in demand changes within each commune.

These results can be partially explained by the varying degrees of adherence to lockdown measures among different socioeconomic groups. In wealthier areas, consumers were more likely to stay at home and continue their work activities remotely, while those in less affluent zones were more likely to need to travel to their workplaces. Both conditions had an impact on electricity consumption. However, while both wealthier and less wealthy populations were affected by the pandemic, the extent of the impact differed. Less affluent populations had fewer options available, as many could not afford to stay at home for the duration of the lock downs mandated by authorities.

This narrative demonstrates how customers have different capacities to adapt their consumption during disruptive events. The causes of these differences may stem from structural aspects of energy systems (such as the quantity and quality of electric devices in different homes) as well as behavioural patterns that affect electricity consumption. Thus, the varied adaptation capabilities among customers can be explained by both structural and behavioural factors.

6.2 Conclusion from the impact of socioeconomic factors in the long-term energy transition

This research develops a model to assess the long-term economic equilibrium between distribution networks and DERs deployed by prosumers. The novel feature of this model is its long-term perspective on DER deployment and distribution networks, with both capacities being results of the equilibrium assessment. The distribution network is modelled using an AC power flow suitable for low-voltage networks. Similarly, the DER investment driven by prosumers is constrained by a budget to illustrate the different purchasing powers of various socioeconomic groups.

The equilibrium conditions assume that every agent in the model (i.e., prosumers and proactive distribution planners) behaves rationally in the economic sense. Thus, given the definition of energy and distribution network tariffs, prosumers choose a DER capacity that minimises their electricity costs.

The analysis presents several important conclusions about the impact of market context, tariff structures, and DER deployment on the efficiency, equity, and cost dynamics in energy markets. Firstly, the study emphasises that the market context, modelled through the marginal cost of energy at the primary substation level, plays a significant role in shaping the equilibrium's efficiency and equity. Energy tariffs such as flat rates, two-block energy tariffs, and volumetric distribution tariffs can lead to sub-optimal equilibriums, with varying degrees of distortion depending on market conditions. For example, in markets with an abundance of solar energy (and therefore, low marginal costs during daylight hours), flat tariffs can result in greater efficiency losses compared to those driven by costly thermal generation (where marginal costs are high during most parts of the day). Equity outcomes also vary significantly based on the type of tariff and the marginal cost context, indicating a need for a deep understanding of tariff impacts on different consumer segments.

Secondly, the findings highlight the importance of a holistic review of tariff structures. The combination of energy and distribution network components in tariffs requires careful consideration to enhance both efficiency and equity. The study shows that adopting a cost-reflective tariff structure, such as a Vol 10 Peak 90 tariff for the distribution network or an

MgC tariff for energy, can significantly improve efficiency. However, partial replacements of these tariffs (i.e., replacing either the energy or distribution tariff, but not both) could lead to outcomes that are both less efficient and more unequal. This underlines the complexity of tariff design, suggesting that policymakers should consider comprehensive reviews rather than partial adjustments to avoid unintended consequences.

Thirdly, the deployment of DERs has varying impacts at the system and prosumer levels, which are closely linked to the prevailing tariff schemes. At the system level, costs can increase if tariff structures do not accurately capture the dynamics of energy supply, particularly in scenarios where there is an excess of renewable energy during certain hours. Conversely, cost-reflective tariffs can help reduce overall system costs. At the prosumer level, the analysis indicates that DER deployment tends to favour high-budget prosumers, who are more capable of leveraging storage systems and other benefits, while low- and no-budget prosumers may face increased costs, particularly through higher distribution charges. This points to a disparity that needs to be addressed through targeted policy measures.

Lastly, the study underscores the crucial role of distribution network tariffs in influencing costs for low- and no-budget prosumers, who lack the financial capacity to invest in DERs and are more reliant on energy and network charges. The variation in these charges with DER integration can disproportionately affect them, highlighting the need for better measures of inequality in the energy sector. The study discusses two equity measures—cost rate differentials between high- and no-budget consumers and the over-cost for no-budget consumers—as useful tools for understanding these disparities. However, it also calls for the development of a more comprehensive equality index to guide future tariff design and policy interventions, suggesting that current measures may not fully capture the complexity of equity in energy markets. In this vein, equality measures need to be aligned with the fairness principles adopted by policymakers.

6.3 General conclusions

Socioeconomic factors have a profound impact on the distribution of benefits and costs among residential customers, with significant consequences for energy poverty and energy fairness. These impacts can be explained by dividing them into issues derived from the economic rationality of agents and those that are not.

The long-term equilibrium model presented in Chapters 4 and 5 addresses the issues arising from economic rationality. In these chapters, the case is illustrated where each prosumer behaves as a rational economic agent in a "selfish" manner (i.e., without considering the costs incurred by other users). Under this assumption, the total costs of the electricity system are minimised (or, analogously, social welfare is maximised).

However, in practice, electricity consumers are often motivated by factors beyond economic rationality. As a result, their behaviour impacts may have positive or negative consequences in the total cost of the system (or social welfare) and, consequently, in the distributional aspects of energy benefits and costs. The interplay between economic rationality and non-economic rationality is explored in Chapter 4.

The findings of this thesis underscore the importance of adopting a comprehensive view of the drivers behind the unequal distribution of benefits and costs in the energy system. The risk of considering only economic rationality (or non-economic rationality) is that it may lead to limited or unintended impacts on the fairness of the energy system.

6.4 Future work

The future work is structured considering the main limitation in the short-term analysis, the long-term analysis, and finally, general future work.

6.4.1 Future work for the analysis in short-term adaptation capabilities for disruptive events.

The future work associated with the short-term analysis developed in Chapter 3 is summarised by the following points:

First, the separation of the effects of a disruptive event, such as the COVID-19 pandemic, from other factors like weather conditions is an area for improvement. In this work, the analysis was based on the evolution of electricity consumption among customers considered non-sensitive to temperature variations. This was done by comparing the increase in electricity consumption with a predefined threshold (for instance, customers who increased their consumption by a factor of two or more during cold weeks were classified as temperature-sensitive). Future studies could enhance this approach by incorporating more detailed customer characterisation through surveys that identify the population's heating preferences.

Additionally, the classification of consumers based on their electricity usage variation with temperature changes could be refined using clustering methods, such as decision trees, which may provide better performance and more accurate groupings. This would allow for a more nuanced understanding of the impacts of both disruptive events and external factors on electricity demand.

Second, the set of 230,000 customers could be further characterised according to their electricity consumption patterns. It is well-known that certain neighbourhoods share specific sociodemographic characteristics; for example, some areas are predominantly occupied by students, elderly people, or young families with children. The key question is whether these neighbourhoods exhibit distinct electricity consumption behaviours that can be characterised.

If these patterns can be identified, a more detailed analysis could be conducted to understand the varied responses of different customer groups during a disruptive event. This would potentially lead to a clearer, more quantifiable understanding of how specific demographic factors influence electricity consumption. By identifying and characterising these patterns, future research could offer more targeted insights into the energy usage behaviours of different socioeconomic groups during crises, thereby enabling more effective policy-making and intervention strategies.

6.4.2 Future work for the analysis of the impact of socioeconomic factors in the long-term energy transition

The future work related to the long-term analysis developed in Chapter 4 and Chapter 5 can be expanded upon as follows:

First, the modelling presented in these chapters is based on a simple feeder with approximately 25 prosumers. While this simplified approach provides useful insights and allows for general conclusions to be drawn, it would be highly valuable to explore larger models that consider more complex distribution networks with significantly higher numbers of prosumers. Such an expansion would make the analysis more applicable to real-world distribution systems, providing a more detailed understanding of network behaviours. One method for managing the increased complexity of larger models is to apply clustering techniques to group customers based on their locations within different zones of the distribution network. This approach would reduce the dimensionality of the problem, with the decisions of individual prosumers representing those of an aggregated group, thereby making the problem more manageable while maintaining accuracy.

In addition, this broader modelling framework opens up the possibility of analysing the roles of additional agents and technologies. For example, the role of an aggregator could be an interesting focus of future research. An aggregator, acting as an intermediary, could coordinate DER investments across a group of prosumers, potentially leading to lower overall costs by optimising investment decisions. A key research question in this context would be to investigate whether an aggregator managing a coalition of customers could achieve lower costs compared to a traditional Stackelberg equilibrium, where prosumers make decisions independently and without coordination.

From a technological perspective, the case study presented in this work primarily focused on the energy market. However, there is ample opportunity to explore the impact of flexible services in the context of long-term equilibrium. Flexible services, such as demand response and flexibility trading, could introduce new revenue streams, but these may also exacerbate existing fairness issues. For instance, a low-budget customer who is unable to afford DER deployment may have to bear the cost of flexibility, while a wealthier prosumer could benefit by trading flexibility products, thereby increasing economic disparities between different customer groups.

Moreover, technologies related to active network management, such as distribution network reconfiguration, could significantly contribute to reducing investment costs within the network. However, such technologies challenge the traditional DistFlow model, which assumes a radial network configuration. Active network management technologies, which allow for more dynamic and flexible control of the network, could lead to a more efficient and cost-effective system. Exploring the long-term equilibrium consequences of these technologies, as well as their implications for fairness and equitable access, represents a promising area for future research that could reshape how distribution networks and DER integrations are modelled and managed.

By pursuing these lines of inquiry, future research can provide a more nuanced and comprehensive understanding of how different market structures, technologies, and socioeconomic factors interact in the evolving energy landscape.

6.4.3 General future work

General future work, considering the motivations and objectives of this research, can be described as follows:

First, future research could focus on developing more integrated models that combine both economic rationality and non-economic behavioural factors to better represent consumer behaviour. This would involve incorporating insights from behavioural economics and social sciences into traditional economic models to capture a broader range of consumer motivations, such as environmental concerns, social norms, and varying levels of risk aversion. In terms of mathematical modelling, these behavioural impacts could be integrated by using agent-based models, where prosumers' decisions are governed by a combination of economic rationality and non-economic behaviours. This approach would provide a more realistic representation of how different types of consumers make decisions in energy markets, particularly in response to tariffs, incentives, and disruptions.

Second, future research could include fairness metrics in equilibrium models. For instance, applying Rawls' criteria, which incorporate the "min-max" rule, would allow models to focus on maximising the benefits for the most disadvantaged members of society. By integrating such fairness considerations, the tariff-making process could endogenously balance potential trade-offs between economic efficiency and energy fairness. This would enable policymakers to assess not only how tariffs promote system-wide efficiency but also how they affect vulnerable populations, thereby supporting more equitable outcomes in energy distribution.

Third, future research could extend the analysis towards policy recommendations by exploring a wider range of regulatory options, such as targeted subsidies and taxes for specific socioeconomic segments. By incorporating these regulatory tools into the modelling, researchers could perform comparative analyses to evaluate the efficiency and equity of various policy interventions. This approach would provide a more comprehensive understanding of how different policies influence both the economic and social dimensions of energy systems, allowing for informed recommendations that align with broader policy goals of fairness, sustainability, and accessibility.

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Appendix A

Number of smart metering devices by type and commune

Table A.1 shows the amount of smart metering equipment distributed in the Metropolitan Region. Initially, 326 thousand devices were counted, however, for data reliability reasons, 230 thousand were finally considered.

Table A.1: Number of smart metering devices by type of consumer and commune.

Commune	**Residential**	**Small business**
Cerro Navia	6581	195
Lo Espejo	1713	20
San Ramón	3080	129
Lo Prado	7128	180
Conchalí	11917	530
Pudahuel	5097	74
La Granja	2301	70
Renca	3510	130
Peñalolén	5050	221
Cerrillos	6334	197
Pedro Aguirre Cerda	2709	56
Quinta Normal	9833	520
San Joaquín	5649	167
Maipú	9468	193
Independencia	6622	480
Recoleta	11769	806
Estación Central	12144	508
La Cisterna	6960	891
Quilicura	3645	83
La Florida	9936	260
Lo Barnechea	484	26

Lampa	1385	96
Colina	1008	95
Macul	5641	264
Santiago	26686	3033
San Miguel	8262	351
Huechuraba	1070	88
Ñuñoa	10633	682
Las Condes	12510	380
La Reina	5768	135
Providencia	9860	1112
Vitacura	3522	107
Total	**218275**	**12079**