UNIVERSITY OF LIÈGE

DOCTORAL THESIS

Smart Regulation for Distribution Networks – Modelling New Local Electricity Markets and Regulatory Frameworks for the Integration of Distributed Electricity Generation Resources

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"If I have seen further than others, it is by standing upon the shoulders of giants."

Sir Isaac Newton

Abstract

Growing awareness of the effects of man-made global warming is leading societies worldwide to re-evaluate our seemingly ever-increasing energy requirements. The need to understand and mitigate the issues brought about by our current use of the world's resources has thus become a pivotal element in the political agendas of most regions. Accordingly, curbing anthropogenic greenhouse gas emissions has been the goal of many of the political decisions of the past decade. In this context, the electricity sector is undergoing deep structural changes to accommodate intermittent renewable electricity generation resources into a system originally designed to rely on dispatchable power plants to supply our energy needs. One of the main changes consists of a decentralisation of the sector, bringing the generation assets closer to the place of final consumption. This creates regulatory challenges that may jeopardise the integration of distributed renewable energy resources (DER). This PhD dissertation presents several research contributions dealing with these challenges.

In the first part of our work, we have created a simulation-based approach to study the effects of different regulatory frameworks on the deployment of DER installations. DER deployment, in turn, is shown to have a notable impact on the revenue of the distribution system operator (DSO), which is also assessed with our simulator. Our approach is designed so as to offer a tool for policy makers and regulators to discriminate between different regulatory frameworks depending on their impact on the distribution network, before implementing them in real life.

The second part of our dissertation models different decentralised electricity markets where consumers may exchange electricity, focusing on the concept of renewable energy communities (REC). We have designed a model of interaction that simulates an REC where its members can offer flexibility services by means of a centralised agent such as the REC manager. In addition, we analyse the allocation of local electricity generation among the REC members, and propose an algorithm based on *repartition keys* to minimise the total electricity costs of the REC.

The modelling tools developed in this thesis highlight a trade-off between promoting the integration of DER and containing their impact on the DSO revenue. In addition, they show that creating RECs may help maximise the use of local production and, therefore, lower the electricity costs of these communities.

Despite having been studied for a few decades now, the promotion of DER is still very much in the political agenda in many regions. Unstable policies concerning these technologies, along with an insufficient understanding of the challenges they pose to the traditional electricity system, have hindered their natural integration into the electricity networks. These problems, though deeply studied in this thesis, call for further research to fight man-made global warming.

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DER	**D**istributed **E**lectricity generation **R**esources
DG	**D**istributed **G**eneration
DSO	**D**istribution **S**ystem **O**perator
ECM	**E**nergy **C**ommunity **M**anager
LCOE	**L**evelised **C**ost **O**f **E**lectricity
LVOE	**L**evelised **V**alue **O**f **E**lectricity
LP	**L**inear **P**rogram
MILP	**M**ixed **I**nteger **L**inear **P**rogram
PV	**P**hoto**V**oltaic
REC	**R**enewable **E**nergy **C**ommunity
SCR	**S**elf **C**onsumption **R**ate
SSR	**S**elf-**S**ufficiency **R**ate

Introduction and contributions

Chapter 1

Introduction

Worldwide, the energy sector is undergoing a revolution – in fact, this revolution has been ongoing for over a decade now. Whilst in the past the most worrisome prospect for society was to run out of fossil fuels to power our lives, the threat of climate change, caused by anthropogenic greenhouse gas emissions, has rearranged the priorities. Today, the most worrisome prospect is not gaining independence from fossil fuels fast enough. For this reason, over the past decades, researchers and policy makers all around the globe have been trying to work out solutions to the challenges posed by climate change.

In December 2015, during the United Nations Climate Change Conference, the Paris Agreement was adopted [1]. This agreement aims at holding global warming below 2 degrees Celsius, with the ambition of limiting it to 1.5 degrees Celsius above pre-industrial levels. In compliance with this agreement, signing countries have had to outline their post-2020 climate actions in the form of intended nationally determined contributions. These climate actions, nonetheless, have been deemed insufficient, according to some scientific publications, to curb greenhouse gas emissions to keep global warming below 2 degrees Celsius [2, 3]. Some researchers even questioned, back in 2016, whether the goal of 2 degrees Celsius is enough to attain these targets [4]. Raising a similar concern, the authors in [5] claim that some tipping points (points-of-no-return which if surpassed would lock the world into a new dynamics) have come so close that, even if all man-made greenhouse gas emissions were to stop today (2021), we are already past some of these points-of-no-return. Their results show a sustained melting of the permafrost for hundreds of years after the emissions are halted. In this context, the intergovernmental panel on climate change (IPCC)[1] published in 2018 a report analysing the risks associated to a 1.5 - 2 degrees Celsius global warming with respect to pre-industrial levels [7]. Such risks, reported for numerous areas of human development, provide a grim overview of what might come about, should actions towards climate change mitigation not take place in short order.

In the European context, the European Union (EU) established in 2015 the EU Energy Union [8] to provide EU consumers with secure, sustainable, competitive

[1]The IPCC was established in 1988 with the mission of assessing climate change based on the latest science [6].

and affordable energy. Central to this Energy Union is the Clean Energy for all Europeans Package [9]. This package represents an update of the EU's energy policy framework towards delivering the EU's commitments in the Paris Agreement. One of the directives brought forward by this package is the recast of the 2009 European renewable energy directive, published in 2018 [10, 11]. This document establishes a new binding renewable energy target for the EU for 2030 of, at least, 32% in gross final energy consumption. However, no fixed path exists at the European level, and Member States may use different strategies toward meeting these targets. In this regard, three possible scenarios are analysed in the last ten-year network development plan (TYNDP) of the European network of transmission system operators for electricity (ENTSO-E) and for gas (ENTSOG). These three scenarios are compiled in two documents: [12] and [13]. The first scenario –National Trends– reflects the commitment of each Member State to meet the EU targets for 2030 - 2050, whilst the other two aim to reach the target set by the Paris Agreement (i.e. a warming of 1.5 degrees Celsius below pre-industrial levels). Of the latter two scenarios, the first one –Global Ambition– looks at a possible future that is led by developments in centralised generation, and the other one –Distributed Energy– is specifically designed to embrace a decentralised approach to the energy transition. In this context, the terms centralised and decentralised refer to the manner the electricity is generated: the former indicates that the electricity is generated mostly in central power plants, whereas the latter implies that electricity production partially takes place where it is consumed, by means of smaller generation devices owned sometimes by the consumers. A substantial amount of research has been produced over the last few years on how a decentralised electricity system may work. In this regard, technological advances in electricity generation from renewable sources, notably including solar photovoltaic (PV), have a natural market in private investments –such as households that deploy these technologies on their rooftops– in a decentralised fashion.

This thesis revolves around this decentralisation of the power sector as a way of achieving renewable energy targets such as the Paris Agreement. In particular, this work focuses on some of the regulatory challenges posed by such a decentralisation, proposing a mathematical description to them as well as modelling solutions.

1.1 The decentralisation of the power sector

The idea of decentralising the electricity sector is not new. One of the first works mentioning the possibility of taking a decentralised energy path, as opposed to the business as usual centralised policy, dates back to 1976 [14]. In this work the author argues that this path would lead to social, economic, and geopolitical advantages[2]. Another early work on this topic is the essay "Power Systems '2000': hierarchical control strategies", written in 1978 by Fred C. Schweppe [15]. In his vision,

[2]Geopolitical advantages relate mostly to curbing the nuclear proliferation which, at that time, was a very relevant objective. In our work however, we abstract from this type of arguments.

Schweppe elaborated upon the importance of demand-side procurement of electricity services, mostly combined heat and power, owing to the limitations of the time.

1.1.1 Definition of decentralised generation units

Despite the existence of some pioneers in the field, it was not until many years later that the scientific literature on the decentralisation of the power sector and, in particular, on the integration of distributed generation, gained momentum. Two scientific papers from 1995 and 1996 elaborate, probably for the first time, on the technical aspects of integrating what the author calls *embedded generation* into the distribution networks [16, 17]. In these two papers the author suggests that embedded generation –what is now understood as distributed energy resources (DER)– can provide only energy and not capacity to the electricity system[3]. These two works claim that some institutional arrangements would be needed to integrate great amounts of DER in the system. Back then, however, this type of technology was yet to be formally defined. The first work addressing this definition was published in 2001 [18]. This scientific paper provides the first formal description of distributed generation as electric power generation within distribution networks or on the customer side of the network. Dealing with the same problem, the authors in [19] define distributed generation as small generation units of 30 MW or less which are located at or near customer sites to meet their specific needs. The definition of distributed generation (or embedded or decentralised generation) is further addressed in two other early works describing these technologies and discussing their benefits and issues [20, 21]. These two works list a collection of definitions provided by different authors in the previous literature, highlighting that all the definitions include small-scale generation devices connected to the distribution grid. Some works, however, also include in this definition larger-scale cogeneration units or large wind farms connected to the transmission network. Finally, in the European context, the trends for distributed generation integration are addressed in [22]. In this paper, the authors highlight a gap in the literature to formally agree on what constitutes distributed generation, suggesting the importance of coming up with a universal definition. They, nevertheless, agree on some common characteristics seen across the existing research works: DER are small-scale generation units that are connected to the distribution network. Using this broad definition, one of the first works focusing on the emergent DER technologies was published as a white paper in 2002. In this paper, the authors consider DER as a way to supply, in an efficient fashion, the growing electricity needs of customers, suggesting the concept of microgrids to organise these resources [23]. Finally, the previous definition of DER is used in [24], another early

[3] When talking about procurement of electricity we can distinguish between energy procurement which refers to the ability to meet the overall energy consumption of the system, and capacity procurement which refers to the ability to meet instantaneous loads.

work which proposes a virtual power plant approach where several DER installations are aggregated. This provides the distribution system operator (DSO) with enhanced visibility and control.

In this thesis we adhere to the use of the definition of DER proposed in [22], considering as distributed generation any small scale electricity generation devices located at or near the consumer end at the distribution level. In particular, we focus on solar PV installations deployed by traditional consumers –who therefore turn into prosumers– or by small companies connected to the distribution network.

1.1.2 Drivers for the integration of decentralised generation

A number of drivers can explain the explosion of the adoption of DER technologies such as rooftop solar PV. These drivers are studied in [25], where the authors establish two distinct categories classifying them:

1. **Commercial drivers**, which comprise the uncertainty of electricity markets and the enhanced power quality they provide.

2. **Regulatory drivers**, among which the most relevant are the incentives to diversify energy sources in order to improve energy security, or the support for competition that increase the amount of players in the market by introducing economically beneficial policies for DER. The latter, though, requires that DER owners trade in the electricity markets, which in turns necessitates appropriate frameworks, as it is discussed later in this introduction.

A consistent decrease of technology prices (including solar PV and batteries) can be added to the list of these drivers [26]. In addition to them, the authors in [25] list a series of challenges brought about by the integration of DER. Examples of these challenges are, according to this work, steering clear of over-voltages, ensuring the power quality, the protection of DER equipments, stability issues in the distribution network, and regulatory issues, which are largely discussed in this document. This paper highlights the importance of moving away from the traditional fit-and-forget approach used to manage the distribution networks. Some other works have focused on the integration of DER, pinpointing challenges and benefits, often from a technical standpoint, as seen in [27]. In this line, the report entitled "The Utility of the Future" deals with challenges and opportunities stemming from the integration of DER, focusing on the evolution of the power system for the coming decades [28]. While this report aims to provide a thorough framework for the cost-efficient integration of both centralised and distributed (decentralised) resources, the importance of DER is remarked throughout the whole document. One of its key messages is that the electricity sector is shifting from a paradigm where large power plants, far from the consumption of electricity, are operated according to the plan of a central authority, to a decentralised fashion of electricity generation by which small generators are deployed close to the loads. The drivers for such a paradigm shift are mainly three:

(i) technological advances leading to substantial cost reduction for DER technologies; (ii) policies related to the deployment of renewable energy technologies and the de-carbonisation of the power sector; and (iii) consumer choices and preferences by which passive consumers are able to express their preferences through decisions concerning their provision of electricity services.

This review on the evolution of the power sector is not intended to be exhaustive but rather to provide the reader with an overview of the trends in the electricity sector over the last decades as well as the outlook to the future. Among these trends, a very prominent one consists in the decentralisation of the electricity generation. Such a decentralisation has been heralded by researchers for many decades, but only over the last few years has become a reality. This is why a large body of literature has been devoted to address new challenges and problems brought about by the integration of these technologies.

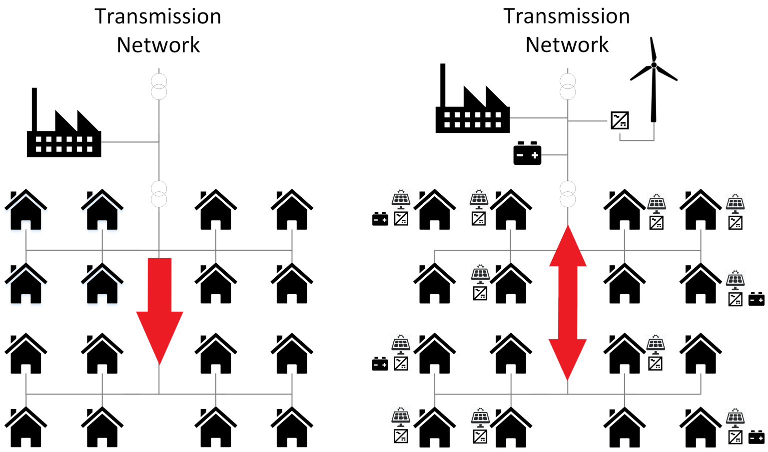
1.2 Challenges posed by integrating decentralised generation

By now, it is clear that the revolution in new generation technologies, in combination with policies and regulations worldwide, have pushed the adoption of distributed generation. This integration of distributed generation has become pivotal to the de-carbonisation of the electricity sector, since a very significant proportion of the new DER installations consist of renewable technologies such as solar photovoltaic (PV). However, this distributed renewable integration does not come free of problems and, albeit it offers promising benefits for the future of the power systems, it may also bring about several problems for this system which must be carefully studied. Accordingly, since the electricity distribution networks were designed decades ago when multi-directional electricity flows were rare, they were not engineered to absorb and re-distribute large amounts of distributed generation. Figure 1.1 presents a schematic of how the electricity flows in a distribution network, before and after the decentralisation of the power sector.

Because of this decentralisation, the integration of renewable electricity generation resources into the electricity distribution networks poses a number of challenges and uncertainties that may jeopardise the adequate operation of the distribution networks. These challenges can be broadly divided, depending on their nature, into technical and regulatory.

1.2.1 Technical challenges

This type of challenges are well known since the beginning of the decentralisation and, therefore, have been studied extensively over the years. They typically range from unbalances on the three phases due to power withdrawals or injections, to under- and over-voltages in the low-voltage distribution networks [25]. A detailed analysis of these problems can be found in [26], where the author proposes several



(A) Before the decentralisation of the electricity generation sector.

(B) After the decentralisation of the electricity generation sector.

FIGURE 1.1: Distribution network set-up.

algorithmic solutions to them. Although more research can be provided to alleviate these challenges, their study falls out of the scope of the present thesis, not being addressed in this document.

1.2.2 Regulatory challenges

The rise in distributed generation resources have prompted a whole different type of challenges, stemming from inadequate regulatory frameworks that cannot provide a stable and level playing field for these new technologies. These regulatory frameworks define the way the power sector is organised. In the particular case of the decentralisation of the sector, they are composed of a number of specific rules that control how distributed generation resources are integrated in the distributed networks. In this context, ill-devised frameworks can cause problems, as they may challenge the correct functioning of the electricity system. Furthermore, in an evolving sector where distributed generation resources are more prominent than they were in the past, these frameworks must be adapted to accommodate new –distributed– generation technologies.

The type of regulatory challenges brought about by the integration of distributed generation energy resources are multifaceted. They span from problems derived from an inadequate design of the distribution network tariff or selection of the metering technology used to an increasing need for establishing the ground rules of new local electricity markets where distributed prosumer[4] can sell their electricity surplus. In this section, these two types of challenges are further elaborated.

[4]The term prosumer is now widely accepted, indicating those consumers who deploy DER installations for their own self-consumption but who can also sell their surplus of electricity, either to their retailers, or to a local electricity market. Note that, in Europe, if the latter is the case, the latest EU directive states that the main activity of these prosumers cannot be to sell their local generation [9].

Distribution network tariff design and metering technology

One of the first works discussing this type of regulatory challenge dates back to 2002, where the authors mention, possibly for the first time, that distribution network tariff structures might need to be revisited in the presence of a significant amount of DER [29]. The authors of this paper highlight that, should distributed generation become widely spread, the distribution network will undergo a long-term transformation where communities and microgrids will naturally emerge. The research on this topic continued over the years in a rather prolific fashion. Consequently, researchers worldwide have been able to pinpoint some of the most prominent challenges stemming from an inadequate design of distribution network tariffs, in the context of an increasing integration of distributed generation into the distribution networks. Two of these challenges stand out: (i) the collapse of the economic sustainability of DSOs, illustrated by the "death spiral" of the utility (see Figure 1.2); and (ii) the cross-subsidies among final customers of the distribution network. These two challenges may be further aggravated depending on the metering technology.

The economic (un)sustainability of DSO: The design of the distribution tariff has a strong impact on the DSO remuneration mechanism. This mechanism works by collecting revenue from final customers connected to the distribution network, and comparing it with the DSO costs. The way revenue are collected depends on the distribution network tariff design and on the metering technology in place. Typically, this tariff may be based on (i) energy charges in € per kWh consumed –commonly known as volumetric charges–, (ii) power charges in € per kWp withdrawn –commonly known as capacity charges–, or (iii) fixed charges in € per connection point. In addition, variations can be introduced to these charges, such as the time-of-use (ToU) fees in which different levels of energy or power charges are applied depending on the time of consumption [30]. Furthermore, the metering technology in place strongly impacts on the way the electricity consumption is measured on the prosumers end. Note that the metering technology is only relevant for prosumers, since it alters the way the electricity exchanges between the prosumers and the grid are measured – for regular consumers the metering is either a mechanical meter that measures energy consumption, or a smart meter that measures power and energy consumption. There are two main metering technologies for prosumers, both addressed in this thesis: net-metering, and net-billing (sometimes referred to as net-purchasing) [30].

- **Net-metering** consists of one single mechanical meter that records imports from the grid by adding units of energy, and exports to the grid by subtracting units of energy. Both types of exchange are assigned with the same monetary value, namely the retail electricity tariff. With this metering system, if the exports exceed the imports, the excess is not remunerated to the prosumer.

- **Net-billing** consists of two independent mechanical meters, or a smart meter that can measure imports and export separately. In this setting, imports are charged at retail price, and exports are compensated at a selling price. No limit exists, in principle, to the amount of exports allowed.

Regarding the costs of the DSO, they typically depend on the physical infrastructure of the distribution network, as well as on the level of use of such an infrastructure. Both costs are known to the DSO [31, 32]. The comparison between costs and revenue may yield an imbalance where either one is greater than the other. In such cases, the DSO must increase or decrease the distribution tariff to ensure a level of revenue that is sufficient to break even[5]. On this basis, a non-negligible proportion of final customers deploying DER installations and turning into prosumers may lead to a drop in the revenue of the DSO, since prosumers consume less electricity from the DSO (be it in the form of energy or power) and, thereby, pay less in distribution fees[6]. This drop in the revenue will be multiplied if a net-metering system is in place, since prosumers will see their imports reduced when they export electricity, heavily eroding the revenue collected by the DSO[7]. Such a revenue drop may, in turn, create a feedback loop leading to an increase in distribution rates. This increase can positively contribute to improve the business case of prosumers, thereby having the potential to spur even more DER deployment, and further erode the DSO revenue [33]. This feedback loop is what some authors have termed the "death spiral" of the utility [34, 35]. Figure 1.2 illustrates this feedback loop.

Cross-subsidisation among final customers: This is one of the most studied challenges arising from an inadequate distribution network tariff design [30, 35, 36, 37, 38, 39, 40, 41]. As with the previous challenge, it all starts with an economic imbalance of the DSO. Then, the DSO, through the remuneration mechanism, adjusts (typically increases) the distribution tariff – be it based on energy or power consumed. In this situation, depending on the distribution tariff design and the metering technology in place, some final customers may be more affected than others by the increase in the distribution tariff. Accordingly, those final customers relying on the DSO to cover the totality of their electricity (i.e. traditional consumers) are more exposed to these changes in tariff than prosumers, who can partially self-consume their electricity needs. In these cases, consumers may wind up bearing most of the costs related to the distribution of electricity, cross-subsidising prosumers. This cross-subsidisation stems from an over compensation to DER owners (i.e. final customers who own a

[5]In this context, a positive imbalance, meaning that the revenues collected by the DSO are greater than the costs, must be met by a reduction of the distribution tariff. Conversely, a negative imbalance, meaning that the revenues collected by the DSO are lower than the costs, will lead to increased rates in the distribution tariff. Note that, depending on the country or region, the increase or decrease in the tariff is computed directly by the DSO, or by the regulatory authority.

[6]This will only occur under volumetric or capacity tariffs, since fixed fees are independent of the level of use of the distribution network.

[7]This will only occur under volumetric fees, since capacity and fixed fees are independent of the energy consumed.

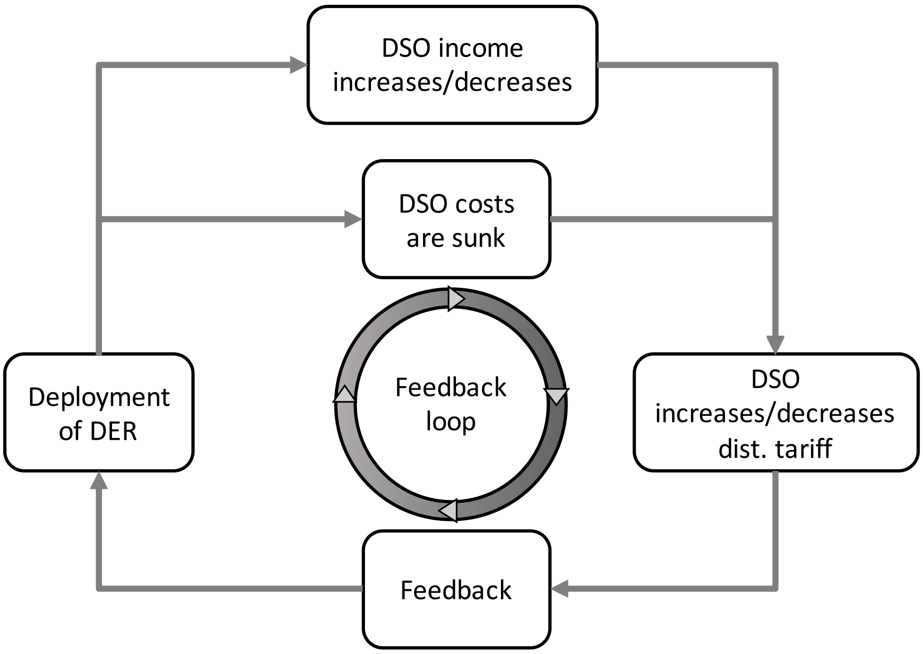


FIGURE 1.2: Feedback loop also known as the "death spiral" of the utility. Prosumers deploying DER installations exert an impact on the level of revenue of the DSO, which, in turn, increases the distribution tariff. A feedback then emerges as higher distribution rates spur further deployment of DER installations.

DER installation, typically in the form of PV and/or batteries) who, sometimes, end up free-riding on the electricity distribution costs [42, 33, 43]. It is worth noting that this effect is highly contingent on the tariff design and on the metering technology. Volumetric and capacity tariffs have the potential to lead to cross-subsidies, whereas this is not true for fixed charges. Likewise, the potential of net-metering to lead to cross-subsidies is higher than such of net-billing [33, 30, 44]

From these challenges it can be pointed up –as many authors have highlighted– that the design of the distribution tariff is of paramount importance for the adequate operation of the distribution network. If these challenges are not tackled in a timely fashion, they may create severe economic strain to the DSO. However, most of these challenges have solely been studied from a qualitative standpoint and, therefore, there is a limited body of literature on their quantitative impact. Furthermore, these challenges present a dynamic aspect that has not been addressed in the prevailing literature, where the impact of prosumers on distribution tariffs and of distribution tariffs on prosumers can be assessed over time, estimating how these two elements evolve and influence each other over time.

In this thesis, the regulatory challenges related to an inadequate distribution tariff design are studied from a modelling standpoint. Thanks to this approach, both a qualitative analysis of the main drivers of these problems and a quantitative evaluation of the dynamics of distribution networks is made possible. The latter provides the action–reaction feedback effect of the relation between prosumers and distribution network prices, allowing for predicting the impact a given distribution network tariff design will have on both the adoption level of prosumers and distribution network rates.

New local electricity markets

The large penetration of DER has also prompted a need to create new frameworks that allow for electricity trading in a decentralised manner. Indeed, despite the empowerment of final customers observed as part of the decentralisation of the power sector, the rules by which these customers interact with the rest of the network are not yet up to date with their capabilities. This means that DER owners have limitations in the way they can use their installations. In fact, to date, usually the only mechanism available for them is to use as much of the energy produced by their installations as possible, exporting the surplus to the distribution network by means of either a net-metering or a net-billing system[8] [33, 43]. To fill this gap in the regulation, some authors have proposed solutions based on central entities managing the communications between several final customers, some of whom are also DER owners, with the goal of maximising the usage of locally generated electricity [45, 46]. Most of the literature, however, has focused on peer-to-peer electricity exchanges, where DER owners trade their electricity surplus without any central entity acting as intermediary [47, 48, 49]. Another popular concept over the last years, concerning the cooperation between final customers, is the renewable energy community (REC). The European Commission, in the 2018 recast of the 2009 European renewable energy directive [11], introduced in Article 22 the RECs as communities of final customers who may also be prosumers (i.e. DER owners) and who may share the renewable energy produced by their generation units or the units owned by the REC. In addition, access to the electricity markets must be ensured in the context of RECs, either directly or through an aggregator. Since this is a rather new concept, the literature on the topic is scarce, and the rules that apply to RECs in some of the existing works [50, 51], are not consistent with new regulations. In the first of these two works, the authors present an energy community where the energy community manager (ECM) acts as the interface between the community members and the market. In addition, the ECM has the ability of computing and offering electricity prices to the REC members. In the second work, a benevolent planner maximises the welfare of the community redistributing revenue and costs among REC members so that all of them are better-off after the REC is established. This problem is cast as a bi-level optimisation where the lower level solves the clearing problem of the REC whereas the upper level shares the profits among the entities. Besides these two works, the practical implementation of RECs is, to date, not well studied.

This thesis aims to fill this gap in the literature, notably by addressing the problem of creating stable frameworks for RECs. This problem is studied from two angles. On the one hand, this thesis analyses the regular operation of an REC with a

[8] Other metering systems exists as, for instance a set-up with three meters sometimes used in Germany, these systems are, however, far less common and are not specifically studied in this work.

unique retailer that must perform the demand provisioning in the day-ahead market, accounting for the local consumption and production from the REC members as well as for flexible load in the form of flexibility bids provided by flexible consumers [46]. On the other hand, the problem of allocation of local production in the REC context is examined, providing a solution based on an *ex-post* settlement where the financial exchanges of an REC are optimised aiming to maximise the self-sufficiency rate of the community, that is, the proportion of REC electricity demand covered by local generation [52].

1.3 Objectives of this thesis

The aforementioned challenges, posed by the integration of decentralised electricity generation units, lead to one broad research question: how to create adequate mechanisms for the integration of DER that do not disrupt the adequate functioning of the distribution networks and facilitate a seamless decentralisation of the power sector? This question can be decomposed in two parts, focusing on particular aspects of the DER integration:

1. what are the **qualitative** as well as the **quantitative** impacts of the deployment of DERs on the economic sustainability of distribution networks, and what roles do the **design of the distribution network** tariff and the **metering technology** play in these dynamics?

2. how should new **consumer-centric electricity markets** be designed and implemented, in particular facing the new regulations concerning RECs?

This thesis sets out to provide answers to these two questions. To that end, different aspects of these questions are addressed in separate chapters which focus on some of the elements described in this introduction: (i) the metering system, (ii) the distribution tariff structure, (iii) the simulation of an REC, and (iv) the allocation of local electricity generation within RECs.

Chapter 2

Contributions

This dissertation is based on different contributions in the domain of regulation for distribution networks, addressing in particular the modelling of new local electricity markets and regulatory frameworks for the integration of distributed electricity generation resources. Each of these contributions deals with one particular aspect of this general topic. Consequently, this document is organised two parts, each of them comprising several chapters.

2.1 Structure of the thesis

After the first part introducing the thesis, consisting of Chapters 1 and 2, the remainder of this manuscript is organised as follows:

The study of the relevance of the regulatory framework fixing the metering technology as well as the distribution network tariff design is addressed in Part I. In particular, the impact of the different metering technologies available is studied in Chapter 3, where the modelling of these technologies is presented, showcasing preliminary results of their effects on final customers and DSO. Then, Chapter 4 introduces the mathematical formalisation of an agent based simulation-based approach in which the final customers of a distribution network are modelled as individual agents who can elect to deploy DER installations composed of PV panels and/or storage devices in the form of batteries. In addition, this simulation-based approach encapsulates several salient characteristics of the distribution network tariff design, enabling the simulation of tariffs based on aggregated energy (volumetric), peak power (capacity), or fixed fees. The feedback loop known as “the death spiral of the utility” is simulated through this approach, where the actions of the final customers (i.e. deploy DER installations) show an impact on the DSO, and the DSO, in turn, reacts by adjusting the distribution networks rates. Finally, the impact of these different metering systems and distribution network tariff designs on the distribution network is shown in Chapter 5. In this chapter, all the previously developed modelling tools are used to simulate a real-life case. Using the most representative features of the distribution networks in Wallonia (southern region of Belgium), a virtual distribution network is simulated, mimicking the real network as accurately as possible. This virtual distribution network permits analysing the impact of using different combinations of metering systems and tariff designs on electricity prices and DER integration.

Part II of this manuscript deals with new models for local electricity markets that may enable a seamless integration of distributed electricity generation resources. This second part consists of three chapters. In Chapter 6, the model of interaction of the members of an REC is presented. This model of interaction mimics the electricity and financial exchanges within an REC, and creates the basis for a complex analysis on the rules regulating its functioning. The advantages of using flexible consumption in this context are evaluated in Chapter 7. In this chapter, flexible consumers offer flexibility bids that increase or decrease their instantaneous consumption, at the expense of a rebound a few time-steps later. The retailer of the community may make use of these flexibility bids to reduce the total costs of performing the demand provisioning in the wholesale electricity markets such as the day-ahead market. Lastly, Chapter 8 presents a novel framework to allocate the local electricity generated within an REC among its members. This framework, based on the concept of repartition keys, allows for different objectives such as the maximisation of the self-sufficiency rates (proportion of demand covered by local electricity) of the REC members or the minimisation of total electricity costs.

Finally, in the last part of this thesis, Chapter 9 presents the overall conclusion and final remarks as well as the outlook and future work.

In addition, two publications are collected in the appendix. Appendix A shows a preliminary study concerning the differences between net-metering and net-billing. Appendix B presents a first approach to introduce fixed fees for the distribution network.

2.2 List of publications

The research papers published in the context of this thesis are:

- Chapter 3 is based on [43]:

  > Manuel de Villena, Miguel; Fonteneau, Raphael; Gautier, Axel; Ernst, Damien. "Evaluating the evolution of distribution networks under different regulatory frameworks with multi-agent modelling". In: *Energies*. 2019; 12(7): 1203.

- Chapter 4 is based on [30]:

  > Manuel de Villena, Miguel; Gautier, Axel; Ernst, Damien; Glavic, Mevludin; Fonteneau, Raphael. "Modelling and assessing the impact of the DSO remuneration strategy on its interaction with electricity users". In: *International Journal of Electrical Power & Energy Systems*. 2021; 126: p. 106585.

- Chapter 5 is based on [44]:

Manuel de Villena, Miguel; Jacqmin, Julien; Fonteneau, Raphael; Gautier, Axel; Ernst, Damien. "Network tariffs and the integration of prosumers: the Case of Wallonia". In: *Energy Policy*. 2021; 150, 112065.

- Chapter 6 is based on [45]:

Mathieu, Sébastien; Manuel de Villena, Miguel; Vermeulen, Eric; Ernst, Damien. "Harnessing the flexibility of energy management systems: a retailer perspective". In: *Proceedings IEEE PowerTech Milan*. 2019.

- Chapter 7 is based on [46]:

Manuel de Villena, Miguel; Boukas, Ioannis; Mathieu, Sébastien; Vermeulen, Eric; Ernst, Damien. "A Framework to Integrate Flexibility Bids into Energy Communities to Improve Self-Consumption". In: *Proceedings IEEE General Meeting Montreal*. 2020.

- Chapter 8 is based on [52]:

Manuel de Villena, Miguel; Mathieu, Sébastien; Vermeulen, Eric; Ernst, Damien. "Allocation of locally generated electricity in renewable energy communities". In: *Submitted for publication*. 2021.

- Appendix A is based on [42]:

Manuel de Villena, Miguel; Gautier, Axel; Fonteneau, Raphael; Ernst, Damien. "A multi-agent system approach to model the interaction between distributed generation deployment and the grid". In: *CIRED Workshop Ljubljana*. 2018.

- Appendix B is based on [53]:

Manuel de Villena, Miguel; Fonteneau, Raphael; Gautier, Axel; Ernst, Damien. "Exploring Regulation Policies in Distribution Networks through a Multi-Agent Simulator". In: *IEEE YRS Benelux*. 2018.

Additionally, research work in the context of this thesis has led to several publications which are not included in this manuscript:

Dumas, Jonathan; Boukas, Ioannis; Manuel de Villena, Miguel; Mathieu, Sébastien; Cornélusse, Bertrand. "Probabilistic Forecasting of Imbalance Prices in the Belgian Context". In: *International Conference on the European Energy Market (EEM)*. 2019.
Shinde, Priyanka; Boukas, Ioannis; Radu, David; Manuel de Villena, Miguel; Amelin, Mikael. "Analyzing Trade in Continuous intra-day Electricity Market: An Agent-based Modeling Approach". In: *Submitted for publication*. 2020.

Part I

Modelling regulatory frameworks for distribution networks

Chapter 3

The impact of the metering technology

This chapter introduces the first elements of a simulation-based approach that models a distribution network and computes, among other variables, the electricity exchanges taking place within it. These exchanges include the energy imported by traditional consumers from the distribution network as well as the energy imported and exported by prosumers from and to the distribution network, respectively. The methodology presented in this chapter is based on a multi-agent discrete-time dynamical system where traditional consumers have the ability to deploy distributed electricity generation resources (DER) composed of solar photovoltaic (PV) panels and (or) batteries. Consequently, the cardinality of traditional consumers and prosumers is not fixed but can rather evolve dynamically over time, and therefore the electricity exchanges computed by our simulation-based approach are not static and their evolution can be determined. From these exchanges, the simulator then calculates the level of revenue of the distribution system operator (DSO), and determines any necessary adjustments to the distribution tariff (part of the overall retail electricity price that finances this entity) to ensure that the DSO breaks even. Those tariff adjustments may impact on the investing decision of traditional consumers, which is reflected in the simulator by means of an investment decision process. This process is further developed in Chapter 4 and, by means of a cost comparison of potential prosumers with and without DER installation, steer the investment decision of consumers. Our simulation-based approach can thereby compute the evolution of the distribution tariff and of the changes in the final customer's composition (cardinality of consumers and prosumers) – these variables show an impact on one another, leading to a dynamically evolving distribution network.

The main idea behind this simulation-based approach is, by taking advantage of its capability to compute the evolution of DER penetration (final customer's composition) and of distribution tariff level, to compute different trajectories of evolutions corresponding to different regulatory frameworks. These frameworks comprise the set of rules, such as the metering technology or the distribution tariff design, that control different aspects of the distribution and have a notable impact on the DSO revenue and the investment decision of consumers. To simulate different frameworks, their salient features (including the metering technology and the design of the distribution tariff) must be modelled and introduced into the simulator. This chapter focuses on the choice of metering technology, modelling two different metering systems, net-metering and net-billing, and integrating them into the different elements of the simulation-based approach. To test these metering systems we assume a tariff design based on volumetric fees is used, in which a gradually increasing proportion of the costs are covered by means of fixed fees.

3.1 Introduction

One of the primary enablers of the energy transition is the widespread growth in the integration of DER into the electricity mix [54]. For this reason, distributed generating technologies as, for example, PV, have been (and are being) globally stimulated by means of policies and directives in order to foster their deployment (see for instance the European Parliament Directive 2009/28/EC [10]). These policies are usually translated into different incentive mechanisms, such as feed-in tariffs (FiT), feed-in premiums (FiP), or other monetary aids which help improve the business models of DER as generating technologies. Along with the incentive mechanisms, there are several indirect key drivers of DER deployment. Two such drivers are the distribution tariff design (which for simplicity will be called tariff design in this chapter), and the technology costs. Regarding the former, they are typically regulated by the incumbent regulatory authority, which can be regional (e.g. in Belgium the tariffs are regulated by three different regulatory authorities depending on the region, namely, Brussels, Flanders, and Wallonia) or national (e.g. in Germany the tariff design is regulated at a national level). As for the technology costs, over the last few years these have been decreasing, and according to the projections, they may still progressively decrease during the coming decade, owing to economy of scales and technological maturity [55]. All these factors combined and, in particular, the widespread use of incentive mechanisms, have contributed to a substantial deployment of DER; however, such a DER integration might conceal the potential to create both technical problems (e.g. under- and over-voltages or increased energy losses) [25] and regulatory challenges (e.g. cross-subsidisation amongst electricity consumers) [33, 37, 56].

These regulatory challenges are multifaceted, and notably comprise, amongst others: (i) cross-subsidies amongst the consumers of the distribution networks created by an unfair allocation of the electricity distribution costs [37]; (ii) the potential failure of the DSOs remuneration mechanisms [33]; or (iii) a generalised increase in the distribution tariff, i.e. the distribution component of the overall retail electricity price, the price end consumers are exposed to, which is composed of energy costs, transmission costs, distribution costs, taxes, and the retailer margin [34].

The scope of this chapter is to quantitatively assess the nature and extent of these regulatory challenges, making use of a simulation environment to evaluate how the deployment of substantial amounts of DER may alter the remuneration mechanisms of DSOs and how this, in turn, may have an impact on the distribution tariffs. In particular, we introduce the first elements of a methodology to compute the impact of different regulatory frameworks on the agents of a distribution network. This methodology allows for dynamically evaluating such impacts, moving beyond the static assessments which are usually performed. In a static analysis, the variables of the system (e.g. deployed DER or distribution tariff level) are computed once (i.e. DER are deployed reacting to increased network tariffs). In a dynamical system approach, each variable evolves over time, rendering different states of the system at every evaluated time-step (i.e. the reaction of DER is evaluated at several points in time). In this context, the complete evolution of the system can be computed by fixing the set of rules (i.e. the regulatory framework) controlling the interactions between the variables. The regulatory framework describes the distribution tariff design (including the metering technology), the remuneration mechanism of the DSO, the incentive mechanisms, and the technology costs. Finally, this methodology enables employing different regulatory frameworks, allowing for testing the short to middle run effects of distinct regulatory practices on the distribution networks and their agents.

For the remainder of this chapter, Section 3.2 documents previous works dealing with the regulatory challenges posed by a large integration of DER. Section 3.3 introduces a high level description of the simulator. Section 3.4 explains how the regulatory framework (including the metering technology) is modelled. Section 3.5 exhibits a case study in which we make use of the developed simulator. Finally, Section 3.6 concludes and exposes the limitations of our approach.

3.2 Related works

Studying the regulatory challenges existing in distribution networks has been the subject of debate over the last decades, as the available literature reveals. In one of the first research papers on this topic [57], the authors identify two main elements to regulate: setting the distribution tariff allocating the total costs among all the users, and establishing an adequate remuneration mechanism for the DSO. Moreover, they propose a remuneration mechanism based on a revenue limitation scheme, as previously described in [58]. The two first documents dealing with the issue of distributed generation (DG) in distribution networks are [59] and [60]. The former focuses on the impact of DG on the power systems, while the latter discusses the effects of regulation on the deployment of DG. The concept of DG as generating technologies, generally of reduced installed capacity, and connected to the distribution networks is introduced in [20], where the authors showcase different DG technologies and their different costs. As mentioned in the introduction, the foremost drivers of DG integration (in which DER are included) are identified. Two of them are the distribution tariff design on the one hand, and the use of incentive mechanisms on the other hand. The existing literature can be divided accordingly.

3.2.1 Distribution tariff design and metering technology

Concerning distribution tariff design, most of the existing literature focuses on exploring how distribution costs should be charged to end consumers. A series of rules for the design of distribution tariffs can be found in [61], as well as in the CEER report [62]. According to these works, the design of a tariff should account for the choice of remuneration mechanisms, the tariff structure, and the allocation of allowed costs. Furthermore, the key regulatory principles to design a tariff are identified, e.g. sustainability, non-discriminatory access, efficiency, transparency, or tariff additivity. These principles are, by and large, shared in [63, 64], where relevant regulatory principles are listed. In [36], the authors recommend that DG (both DER and combined heat and power) pay regulated shallow connection costs in order to facilitate the integration of these generation resources. The discussion shallow vis-à-vis deep connection costs is also addressed in [56, 65, 66, 67, 39, 68], where diverse methodologies are assessed. In short, deep connection costs comprise the connection cost itself as well as the costs derived from reinforcing the network, and shallow connection costs consist only of the connection cost whereas the potential costs of reinforcing the network are socialised via the distribution tariff. Some of the existing works experiment with different distribution tariff designs, looking into their impact on DG and on the DSO ability to recover its costs. In this regard, the authors in [69] explore designs based on the cost-causality principle, claiming that such tariffs function better than average cost distribution tariffs to recover fixed network costs. In [63], the authors suggest a method to assign costs according to the same principle, based on peak demand, overall energy demand, and geographical location. Moreover, in this work it is highlighted that, since consumers may react to the tariffs, setting an adequate tariff might be an iterative process. In [70], the researchers propose a way of taking into consideration the impact of DG on the cost-causality criterion used to design and compute distribution tariffs. In these studies, different metering technologies are mentioned for measuring the energy consumption and production of the DER installation, namely net-metering and net-billing.

- Net-metering (NM): consists of one meter that records imports (DER $\leftarrow$ Grid) by running forwards, and exports (DER to Grid) by running backwards. Therefore, both directions are assigned with the same monetary value, namely the retail electricity tariff. Additionally, if the exports exceed the imports, the excess is not remunerated.

- Net-billing (NB), also called net purchase and sale: consists of two independent meters for imports and exports, in this setting imports are charged at retail price, and exports are compensated at a selling price. There is, in principle, no limit to the amount of exports allowed.

Several authors have discussed the impact of these two systems. In [71], a model to evaluate the impact of NM policies in introduced, concluding that this system is extremely beneficial for consumers owners of a DER installation (prosumers), but may create macroeconomic problems such as the increase of the distribution tariff. Similar analyses are conducted in [33, 72] where the authors compare NM with NB, claiming that NM may lead to both cross-subsidies amongst the users of a distribution network and an uncontrolled increase in distribution prices, also known as the death spiral of the utility [34, 72]. Analogous conclusions are drawn by [37], where the authors state that NM presents a trade-off between incentivising DG and securing the financial stability of the DSO. In [73, 74], NM in the United States is analysed, these papers suggest that NM enhances the value of behind-the-meter devices and claim that the potential feedback created by NM (i.e. the utility death spiral) is rather modest.

Another way of spurring the deployment of DER installations is by introducing changes in the method used to charge consumers and prosumers for their electricity consumption. Various methods have been explored in all the previous works, e.g. capacity or demand tariffs (€/kW), volumetric tariffs (€/kWh), fixed tariffs (€/connection), or time-of-use (ToU) tariffs. In this regard, the analysis in [75] shows that when applying volumetric distribution charges, in a setting where NM is in place, an increase in the distribution tariff leads to household PV deployment. In [35], the author demonstrates that a peak demand capacity tariff is more efficient and cost-reflective than its volumetric counterpart.

3.2.2 Incentive mechanisms

Concerning incentive mechanisms (or support schemes), several authors have examined the effect of FiTs. In [76] FiTs are compared with traditional schemes such as renewable obligations, proposing a two-part FiT with capacity and energy payments which the authors claim to be a more effective framework for fostering the deployment of DER than the existing alternatives. The authors in [77] review the regulatory and policy frameworks of FiT schemes, laying stress on how these have affected the solar PV market. They highlight that, due to generous tariffs the market bloomed in 2008, nevertheless, FiTs have failed to continue supporting PV integration since they tend to distort the electricity prices leading to economic instability. On the same topic, [78] shows that FiTs are likely to work better than quantity-based systems (e.g. quota-obligation) when it comes to fostering DER.

In addition, a few works can be found assessing the use of incentive mechanisms to promote the deployment of DER, for a range of different tariff designs. For example, in [79, 80] the authors analyse the use of FiTs in combination with NM and with NB. However, the results of these studies are inconclusive insofar as they greatly depend on the initial conditions (e.g. level of DER penetration, or distribution prices).

3.2.3 Modelling

To date, the level of modelling in all these analyses is rather limited owing to the complexity of representing abstract regulatory principles in an exact manner. Furthermore, modelling the behaviour of prosumers is complex since they may not act rationally (see for instance [81]). For these reasons, in most of the existing literature, the penetration of DER as well as the distribution prices are considered parameters to study with little or no interaction between them. There are some works, nonetheless, where this is addressed. In [82], the authors highlight the importance of designing efficient distribution charges in the context of increasing DER integration, claiming that the network peak is the main driver of network investment. A model is introduced in this paper in which users can react to distribution charges by deploying fix-sized DER installations in order to overcome high distribution charges. Moreover, in [42], a model of interaction between prosumers and DSO is proposed comparing NM with NB; in this model, prosumers react to distribution prices by deploying optimally sized DER installations, the tariff is then updated by the DSO, responding to a change in energy consumption. In [40] a model including capacity charges and injection fees is proposed, concluding that transitioning to rate structures including capacity charges will not disrupt the adoption of PV and will lower the costs of consumers. Finally, in [31] a game-theoretical model is proposed to assess volumetric and capacity tariffs, their impact on the potential prosumers, and the consequences for the consumers.

3.2.4 Motivation

As we can see, some of the questions proposed in this chapter have been to some extent studied in the previous literature, although from a purely qualitative standpoint. Only a few works exist tackling this issue from a more quantitative perspective, using mathematical tools to simulate the behaviour of end-users in a distribution network and, although with limitations, to estimate the repercussions of such behaviours for the distribution networks and, in particular, for the distribution tariff. This chapter proposes a methodology to quantify the development of distribution networks across time, as a function of the DER deployment and the distribution tariff evolution. Furthermore, an interaction between DER deployment and distribution rates is modelled by which they impact one another and evolve over time, attaining –or not– an equilibrium after the simulation is completed (the horizon is reached). Our work includes notably the analysis of different metering technologies in a simulation environment in which the actors are the residential consumers some of which may become prosumers, and the DSO.

3.3 Simulator

The simulator introduced in this section relies on multi-agent modelling. It allows modelling every consumer/prosumer of the distribution network as a rational agent, who may deploy an optimally sized DER installation if it is cost-efficient compared to the retail prices. Furthermore, the DSO is also modelled as an agent that can adjust the distribution tariff to recover its costs of providing the distribution service. To assess the evolution of the distribution network, we introduce a discrete time dynamical system that enables computing the actions of the agents at every time step. Finally, to compare different regulatory frameworks, we introduce the concept of environment, which includes all of the rules characterising them. In our simulator, the agents interact (perform actions) within a particular environment. By modifying the environment, we also modify the actions of the agents, allowing the assessment of the distribution network evolution under different regulatory frameworks.

3.3.1 Environment representation

Every environment is built with three distinct elements: (i) tariff design, (ii) incentive mechanism, and (iii) technology costs (assumed linearly decreasing over time). Note that in our work, we consider the metering technology as an incentive mechanism.

We introduce distinct tariffs based on different proportions of volumetric fees, paid in €/kWh, and fixed fees, paid in €/connection. Furthermore, we include two different incentive mechanisms for the consumers to deploy DER, NM and NB, which have previously been explained.

3.3.2 Actions of the agents

There are two types of agents:

- Consumers: at the beginning of the simulation they simply draw electricity from the distribution network. However, as the simulation proceeds over the discrete time dynamical system, they take actions to gradually deploy optimally sized DER installations, becoming prosumers. The prosumers may draw (import) and inject (export) electricity to the distribution network. To model the planning and operation of these agents, i.e. the computation of their electricity trades (imports and exports), and the transition consumer to prosumer (DER deployment), we resort to an optimisation framework instantiated as a mixed integer linear program (MILP). This MILP is loosely based on the LP found in [83], and aims at minimising the levelized cost of electricity (LCOE) of the DER installation. The potential investment allowed for the consumers consists of an optimally sized PV installation with or without batteries (depending on the optimisation).

- DSO: the actions of this agent consist in adjusting the distribution tariff according to the environment in place. For example, after collecting revenues, this agent may increase or decrease the distribution tariff, under the assumption that it must break-even (here it is assumed that if the DSO collects the total amount of allowed revenues, it will completely cover its costs). The DSO cannot modify the tariff design, since this is imposed by the environment. Hence, if the tariff design set by the environment consists of a fully volumetric distribution tariff, the DSO will be able to adjust the price per kWh, but it will not be able to recover costs by applying extra charges to the distribution network consumers. The operation of this agent is modelled with its remuneration mechanism.

3.3.3 Discrete time dynamical system

The actions of the agents lead to the evolution of the distribution network. The consumers, by deploying DER, reduce their dependency on the distribution network, lowering their apparent consumption, which refers to the energy recorded by the meter at the end of the billing period. In response to the consumers actions, the DSO will adjust the distribution tariff according to its remuneration mechanism. Thus, we can compute the distribution network evolution as a function of the agents actions, by evaluating them at every time step of a discrete time dynamical system.

Let $n \in \mathcal{N}$ denote the time index of the discrete time dynamical system, with $\mathcal{N} = \{0, \ldots, N-1\}$. At every time step n, our simulator computes the actions of the agents, controlling the transition from n to $n+1$. This computation follows a specific order: (1) the transition from consumer to prosumer is calculated, determining their apparent consumption Ξ_n; (2) the DSO adjusts the distribution tariff $\Pi_n^{(dis)}$. In Figure 3.1, a time-line of the discrete time dynamical system can be found.

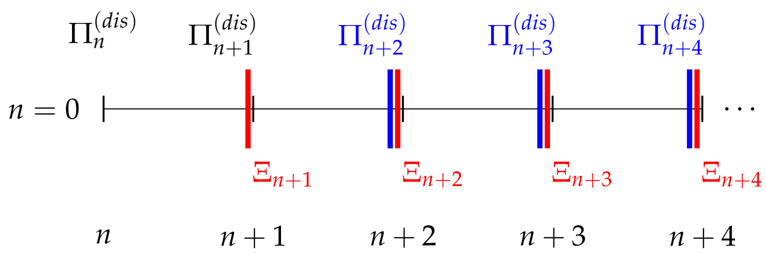


FIGURE 3.1: Time-line of the discrete time dynamical system. The simulation starts by assuming a distribution tariff $\Pi_n^{(dis)}$. Then, at every time step, there is a transition from consumer to prosumer leading to a change in the aggregated apparent consumption Ξ_n. This change induces an adjustment of the distribution tariff $\Pi_n^{(dis)}$.

The first billing period is necessary so that the consumers can observe their electricity bill under the initial conditions. Then, the transition from consumer to prosumer can be computed, and from it, we determine the total apparent consumption Ξ_{n+1} (which corresponds to the period $n+1$ to $n+2$). Since the consumption during the period n to $n+1$ and the consumption under the initial conditions are the same, the distribution tariff does not change ($\Pi_n^{(dis)} \equiv \Pi_{n+1}^{(dis)}$). However, once Ξ_{n+1} is computed, it induces a change in the distribution tariff for the following period $\Pi_{n+2}^{(dis)}$ (after the DSO observation of its revenue during the period $n+1$ to $n+2$). We assume that the consumers can react immediately to this distribution tariff adjustment since they already have knowledge regarding their consumption. Then, the aggregated apparent consumption Ξ_{n+2} can be calculated. The discrete time dynamical system continues in this fashion until no more consumers can turn into prosumers, or until the stopping criteria are met: when reaching the finite time horizon N, or when the DER are not economically profitable .

Every time step of the discrete time dynamical system, except for the first one, is computed with one run of our simulator. Thus, the developed simulator is run recursively to simulate the complete dynamical system. The end of one run will be used as starting point for the next one. The flow diagram representing an outline of one run of the simulator can be found in Figure 3.2.

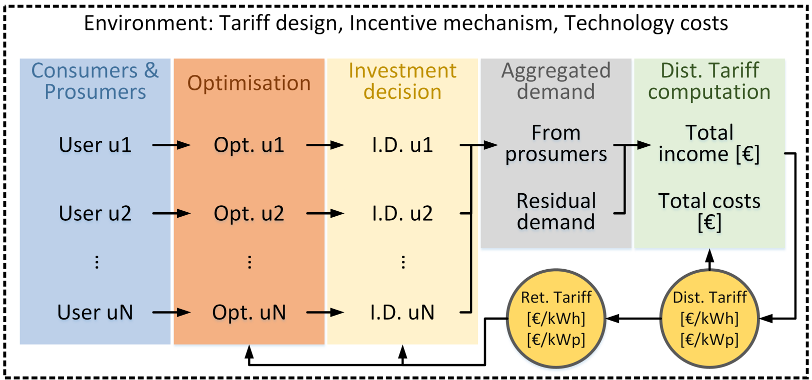


FIGURE 3.2: Flow diagram of the proposed multi-agent simulator. The flow of actions occurs from left to right. The distribution network consumers undergo individual MILP optimisations to minimise their LCOEs. A transition from consumer to prosumer is computed (investment decision tab (yellow) on the Figure), and finally the DSO adjusts the distribution tariff.

The simulation starts with a pool of consumers who may become prosumers at any point of our discrete time dynamical system. These agents, characterised by their load, are modelled through an MILP to plan and operate a DER installation minimising their LCOEs. Such an optimisation requires the retail electricity price at each time step, as well as the demand profile of the consumers. After the optimisation, a transition consumer to prosumer is computed by comparing the costs of the consumers with and without DER installation. The aggregated apparent consumption Ξ_n is then calculated and added to the residual demand of the system (those consumers of the distribution network who cannot deploy DER due to technical or economic constraints). Finally, the DSO revenues are computed, and, assuming constant costs across the discrete time dynamical system, the distribution tariff $\Pi_n^{(dis)}$ for the following time step is determined so as to fully recover those costs.

3.4 Modelling the regulatory framework

In this simulator we introduce the concept of environment as the container of the set of rules that characterise the distribution network, namely the tariff design, the incentive mechanism, and the technology costs. Hence, to model the agents actions, we must take into account the distinct possible environments. Every single agent take individual actions, therefore, we need to introduce the set $\mathcal{I} = \{1, \ldots, I\}$ representing the consumers/prosumers, where I is the number of consumers/prosumers. In the following, we present the differences in the simulator, depending on metering technology and the the tariff design.

3.4.1 Metering technology

We may use net-metering or net-billing. This choice impacts the individual apparent consumption, and as such, the aggregated one.

Net-metering

The individual apparent consumption of the consumers/prosumers is given by:

$$\forall i, n \in \mathcal{I} \times \mathcal{N} \quad \xi_{i,n} = \max\left\{0, \left(\rho_{i,n}^{(-)} - \rho_{i,n}^{(+)}\right)\right\} \tag{3.1}$$

where $\rho_{i,n}^{(-)}$ and $\rho_{i,n}^{(+)}$ are, respectively, the imports and exports of the i^{th} prosumer at the n^{th} time step.

Net-billing

In this case, the exports do not affect the apparent consumption, thus:

$$\forall i, n \in \mathcal{I} \times \mathcal{N} \quad \xi_{i,n} = \rho_{i,n}^{(-)} \tag{3.2}$$

3.4.2 Tariff design

In this chapter we use the most commonly adopted design, based on volumetric charges. In addition, we introduce a gradually increasing fixed term to cover part of the tariff.

Under this setting, the individual electricity costs $\psi_{i,n}$ of the agents in I are calculated as follows:

$$\forall i, n \in \mathcal{I} \times \mathcal{N} \quad \psi_{i,n} = \xi_{i,n} \cdot \left(\Pi_n^{(dis)} + \Pi^{(en)}\right) \tag{3.3}$$

where $\xi_{i,n}$ represents the individual apparent consumption of the i^{th} prosumer at the n^{th} time step, $\Pi_n^{(dis)}$ is the distribution tariff set by the DSO, and $\Pi^{(en)}$ represents the costs of energy, transmission and taxes, held constant across the simulation.

The DSO revenues are calculated as:

$$\forall n \in \mathcal{N} \quad R_n = \Pi_n^{(dis)} \cdot (\Omega + \Xi_n) \tag{3.4}$$

with Ω being the residual demand of the system (held constant), and Ξ_n is the aggregated apparent consumption of the consumers/prosumers, which is calculated as $\Xi_n = \sum_{i=1}^{I} \xi_{i,n}$

To introduce a fixed fee into the tariff, we introduce a fixed term in the calculations. The electricity costs of the consumers/prosumers are calculated as follows:

$$\forall i, n \in \mathcal{I} \times \mathcal{N} \quad \psi_{i,n} = \xi_{i,n} \cdot \left(\Pi_n^{(dis)} + \Pi^{(en)}\right) + c_i \tag{3.5}$$

where the term c_i is set at the beginning of the simulation (see equation (3.8)) and kept constant. As for the DSO, its revenues are computed as follows:

$$\forall n \in \mathcal{N} \quad R_n = \Pi_n^{(dis)} \cdot (\Omega + \Xi_n) + C \tag{3.6}$$

where $C = \sum_{i=1}^{(I+J)} c_i$, with J being the amount of consumers who make up the residual demand Ω.

3.4.3 Distribution tariff update

For every option of tariff design and incentive mechanism, the distribution tariff is updated at every time-step according to the following equation:

$$\forall n \in \mathcal{N} \quad \Pi_{n+1}^{(dis)} = \frac{\Theta + \Delta_n - C}{\Omega + \Xi_n} \tag{3.7}$$

where Θ are the costs of the DSO, which are calculated as the revenues of the first time step R_0, and held constant across the dynamical system. The imbalance from the previous period is introduced with the difference $\Delta_n = \Theta - R_n$. In other words, Θ represents the costs of the DSO, Δ_n represents the "missing money" from the previous period, and C represents the money recovered through fix charges, the sum of these parameters thus represents a quantity in €. Then, Ω represents the residual demand of the system (only consumers), and Ξ_n represents the demand of the prosumers, the sum of these parameters is therefore a quantity in kWh. The mechanism works in a way the the tariff $\Pi_{n+1}^{(dis)}$ is updated according to costs divided by demand.

3.5 Case study

To assess the impact of different environments on the distribution network evolution, we introduce a case study in which we compare nine different environments (regulatory frameworks). The simulator necessitates a set of consumers/prosumers to work. Each consumer/prosumer is characterised by a demand profile and a production profile. Once we have produced the set of consumers/prosumers we evaluate: (i) four distinct designs with decreasing proportions of costs recovered through volumetric charges being replaced by fixed ones (where the incentive mechanism is kept fixed for all of them), and (ii) five different incentive mechanisms (where the proportion of volumetric charges is kept fixed for all of them). The different assessed environments are presented next.

- Different proportions of volumetric and fixed charges:
  - E1: environment with 100% volumetric charges. NB is used as incentive mechanism with a selling price of 0.04€.
  - E2: environment with 75% volumetric charges and 25% fixed charges. NB is used as incentive mechanism with a selling price of 0.04€.
  - E3: environment with 50% volumetric charges and 50% fixed charges. NB is used as incentive mechanism with a selling price of 0.04€.
  - E4: environment with 25% volumetric charges and 75% fixed charges. NB is used as incentive mechanism with a selling price of 0.04€.
- Different incentive mechanisms:
  - E5: environment with NM as incentive mechanism and with 100% volumetric charges.
  - E6: environment with NB as incentive mechanism, a selling price of 0.04€ and with 100% volumetric charges. Note that this is the same as E1, but for the sake of clarity in the plots, it is used with the two names.
  - E7: environment with NB as incentive mechanism, a selling price of 0.04€ and with 100% volumetric charges.
  - E8: environment with NB as incentive mechanism, a selling price of 0.04€ and with 100% volumetric charges.
  - E9: environment with NB as incentive mechanism, a selling price of 0.04€ and with 100% volumetric charges.

For all of the environments we set the value of $\Pi^{(en)}$ to 0.132 €/kWh. Furthermore, we assume an initial distribution tariff $\Pi_n^{(dis)}$ of 0.088 €/kWh (making an equivalent retail price of 0.22 €/kWh). To determine two-part tariffs (E2 - E4), we compute:

$$\forall i \in \mathcal{I} \quad c_i = \frac{(\Omega + \Xi_n) \cdot \left(\Pi_n^{(dis)} \cdot \eta\right)}{I + J} \cdot \gamma_i \tag{3.8}$$

where η is the percentage of volumetric charges, and $\gamma_{i,n}$ is an adjustment factor applied depending on the peak demand of the consumer/prosumer, which is useful to charge users fixed costs depending on their power consumption. In this case study γ_i is assumed equal to 1 for all prosumers.

3.5.1 Results

To represent the distribution network evolution for each environment we rely on four metrics: (i) the evolution of the variable (volumetric) term of the distribution tariff, (ii) the penetration of DER relative to the maximum potential I, (iii) the actual deployed PV and battery capacity (in kWp and kWh), and (iv) the LCOE of the deployed DER installations (in €/kWh).

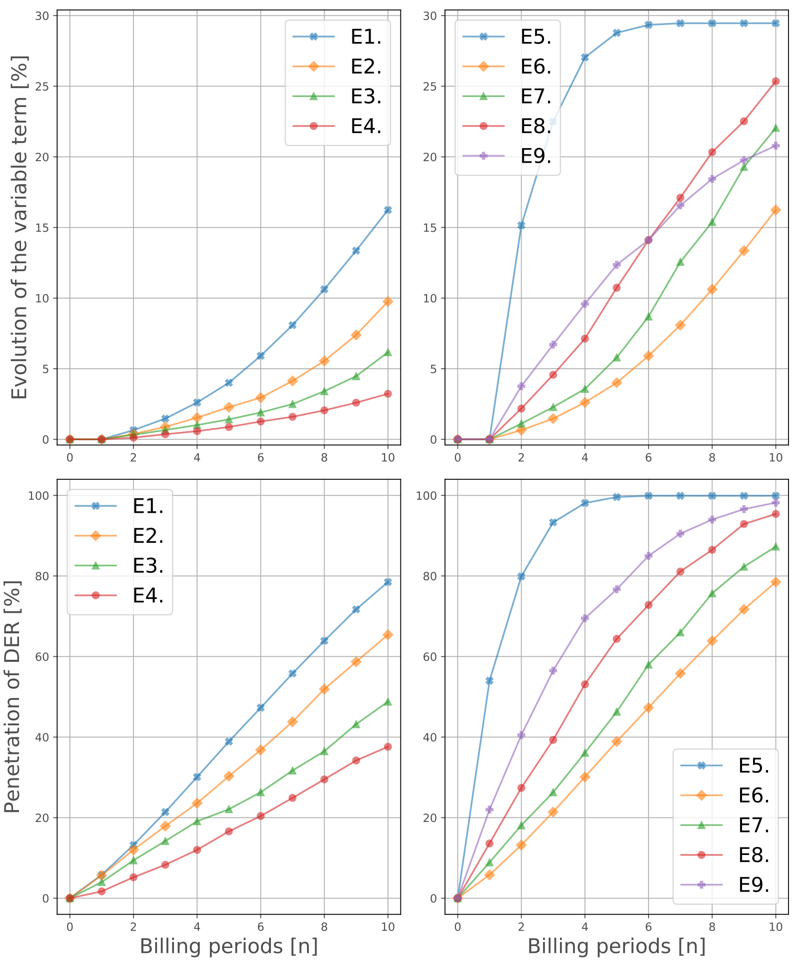


FIGURE 3.3: Evolution of $\Pi_n^{(dis)}$ (upper two figures) and of the DER adoption (lower two figures) across the discrete time dynamical system, for the evaluation of tariff designs E1 - E4 (left hand side figures), and of the incentive mechanisms E5 - E9 (right hand side figures).

Tariff designs (E1 - E4)

According to Figure 3.3, upper-left subfigure, the variable (volumetric) term of the distribution tariff increases in a quicker fashion when the share of this term in the two-part tariff design is large. Likewise, the deployment of DER over time (Figure 3.3, lower-left subfigure), and the actual DER deployed capacity (Figure 3.4, upper subfigure) which represents the counterpart to the growth of the distribution tariff, increase in environments where the variable term in the two-part design is more

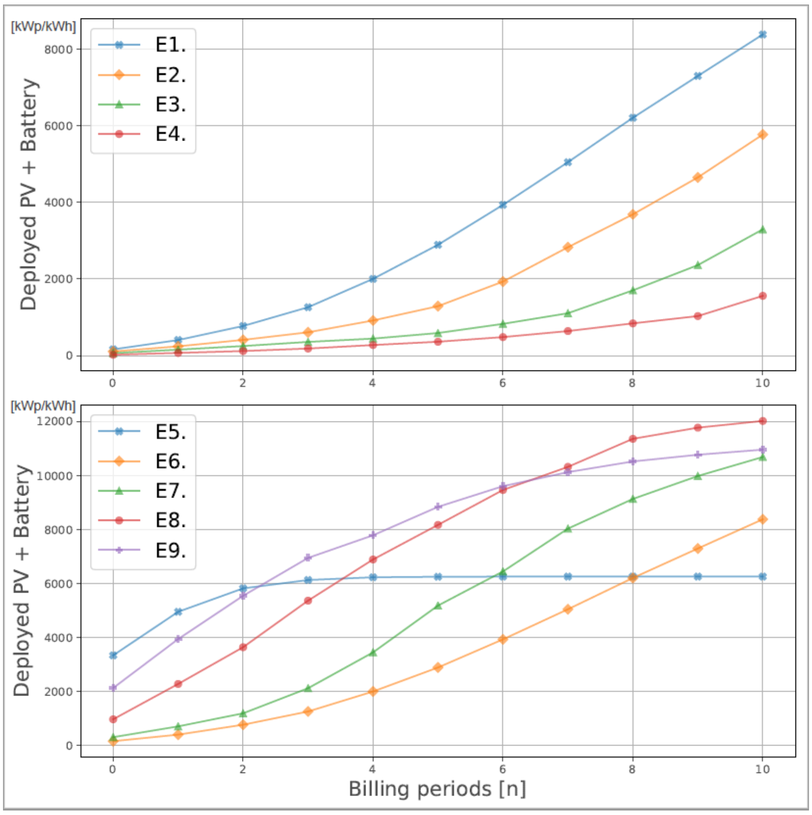


FIGURE 3.4: Cumulative sum of the size of the deployed DER installations (including PV and batteries), over the discrete time dynamical system. The upper figure corresponds to the evaluation of tariff designs, whereas the lower one corresponds to the evaluation of the incentive mechanisms.

prominent. In Figure 3.5, we can observe that the probability density functions of environments E1 - E4 exhibit larger installation sizes for E1 (note that E1 and E6 represent the same environment) than E2, E3, and E4. Finally, regarding the LCOE of the DER installations, the four cases costs are similar to the equivalent retail price. Note that higher volume shares (E1) results in lower LCOEs. Finally, in Figure 3.6 the resulting LCOE of the prosumers is showcased. The red, dotted line indicate the electricity price (at the initialisation conditions) in €/kWh, without DER installation (i.e. for consumers).

Incentive mechanisms (E5 - E9)

Figure 3.3, upper-right subfigure, shows two different trends, one for the NM environment (E5), and another for the rest. E5 variable term outgrows the other four by at least 5%, followed by E8, E7, E9, and E6 at the end (n=10) of the simulation. The same trends are observed in Figure 3.3, lower-right subfigure, which represents the total DER penetration. However, examining the total capacities of deployed DER (Figure 3.4, lower subfigure, and Figure 3.5), it is visible that, despite the larger DER

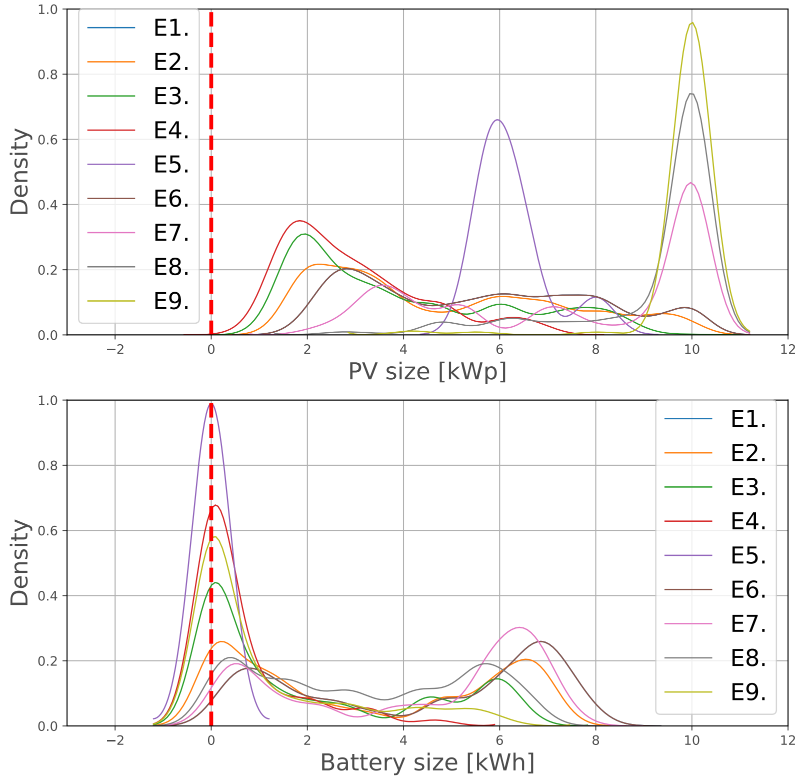


FIGURE 3.5: Gaussian kernel density estimation of the installed capacity of PV (upper plot), and of batteries (lower plot). These figures represent the probability density function for the kernel density estimation of PV and battery capacities, for every environment (E1 - E9). This probability is computed based on the calculated DER installation size of the set $\mathcal{I}$.

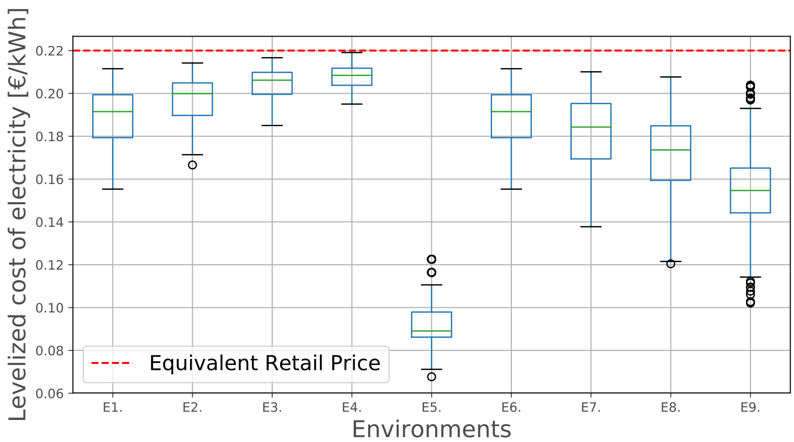


FIGURE 3.6: Levelized cost of electricity of the prosumers in set $\mathcal{I}$, for every environment (E1 - E9).

penetration, E5 results in lower total capacity of deployed PV and batteries. Regarding the LCOE, E5 displays a considerably lower LCOE than the rest of the environments. Figure 3.6 displays the resulting LCOE of the prosumers for scenarios E5 to E9, as well as for the previous ones.

3.5.2 Discussion

Tariff designs (E1 - E4)

We observe that by increasing the share of the variable term in the distribution tariff, the business case to deploy DER installations improves, thus facilitating the transition from consumer to prosumer. This, in turn, causes the distribution tariff to grow further in the environments with higher share of variable term, indicating a larger potential death spiral behaviour for those environments. Hence, introducing a two-part design reduces the instability of the system, as already highlighted in [35]. If we observe the total amount of PV and battery deployed (Figure 3.4), we can deduce that relying on distribution tariffs which are predominantly volumetric results in larger deployed DER capacities. This suggests a trade-off between DER penetration and total capacity installed, and a distribution price spiral. Such a trade-off must be addressed by policy makers in order to decide the desired trend. Finally, since the incentive mechanism in place (NB with a selling price of 0.04 €/kWh) does not significantly improve the DER business case, the four LCOEs are similar to the equivalent retail price, as can be seen in Figure 3.6. The lowest LCOE corresponds to E1, which is consistent with Figures 3.4 and 3.5.

Incentive mechanisms (E5 - E9)

The different trends observed for NM and NB are a consequence of the distinct behaviour of prosumers they induce. With NM there is no incentive to make a business case selling electricity or becoming self-sufficient. NM offers the perfect scenario for the prosumers to adjust their production so that they import and export equivalent amounts of energy ($\xi_{i,n} = 0$). For this reason, the variable term in E5 (Figure 3.3), outgrows the other four environments, since the apparent consumption with E5 is close to zero, and the DSO needs to adjust the distribution tariff in a larger extent. We may also note that, under NM, no batteries are deployed (Figure 3.5). This is compatible with the findings in [33], where the authors observe that, with this system, batteries and imports are perfect substitutes. In Figure 3.6, we can the LCOE of these environments. The low LCOE of E5 is also consequence of the extremely low apparent consumption of the prosumers under NM. In the other four environments, the prosumers tend to deploy more PV and battery capacity to reduce their imports. Interestingly, when the selling price is high (E9), the prosumers rely on selling electricity as a business case, not reducing their apparent consumption in the same extent as E7 or E8. Hence, the increase in the distribution tariff is not so prominent in E9. A new trade-off appears between selling price and a distribution price spiral, where both imply an extra burden for the community.

3.6 Conclusion

In the context of increasing decentralised electricity generation, this chapter has evaluated the effects of different regulatory frameworks and, in particular, different metering technologies, on the evolution of distribution networks. A multi-agent model is used to simulate the behaviour of the agents of a distribution network. The actions of the agents are evaluated at several time-steps, leading to the evolution of the distribution network. Electricity consumers interacting with a single distribution network are modelled as rational agents that may invest in optimally sized distributed energy installations composed of PV and/or batteries. Finally, the distribution tariff is adapted according to the remuneration mechanism of the DSO.

We have designed and simulated several examples based on the metering technology, on the selling price of electricity applied when net-billing is used, and on gradually decreasing the proportion of volumetric charges switching them by fixed ones. The results are presented according to four distinct metrics: (i) the evolution of the volumetric term of the distribution tariff, (ii) the penetration of DER installations, (iii) the amount of deployed PV and batteries, and (iv) the LCOE of the deployed DER installations.

The results show that using net-metering creates a potential spiral of the distribution tariff, with no integration of battery capacity in the system. When net-billing is used instead, the spiral of prices may be more easily contained by controlling the electricity selling prices. Furthermore, replacing volumetric charges with fixed ones impairs the economic business case of the consumers willing to deploy DER in the system. In general, we observe a trade-off between spiralling electricity prices and the desired penetration of PV and batteries. Such trade-off may be tuned by policy makers by adjusting key parameters such as the level of fixed charges, or the selling price of electricity when net-billing is utilised, the latter being possible only depending on the retailers' offers.

Chapter 4

The impact of the distribution network tariff design

This chapter elaborates upon the ideas introduced in Chapter 3, expanding the scope of the previously introduced simulation-based approach, enhancing its capabilities, and accurately formalising its various elements. On the one hand, this chapter provides the mathematical formalisation of all the elements of this simulation-based approach. On the other hand, it completes such an approach by improving the modelling of certain constraints such as the investment costs, and by introducing new elements as, for example, a redesigned investment decision process to control the transition from traditional consumer to prosumer. However, the most relevant feature added in this chapter is the possibility of simulating several types of distribution tariff design. Accordingly, four types of tariff designs are modelled in this chapter, based on: energy consumed (volumetric), power consumed (capacity), fixed connection fees, and time-dependent rates that are contingent on the time of energy or power consumption (time-of-use or ToU fees). Among these four types of tariff design, the capacity and the ToU fees require smart meters to work. Consequently, the methodology presented in this chapter assumes a full roll out of smart meters, in addition to accounting for the uncertainties posed by the integration of distributed electricity generation resources. All these new capabilities enable our simulation-based approach to perform more realistic simulations that take into account different types of metering technologies (as explained in the previous chapter) as well as several types of distribution tariff design.

This redesigned simulation-based approach can simulate the dynamics of the interactions between the different final customers of a distribution network and the distribution system operator (DSO). In this context, traditional consumers have the possibility to deploy distributed electricity generation resources (DER) in the form of solar photovoltaic (PV) and batteries. This is modelled through an optimisation framework and an investment decision process that gradually deploys household PV installations depending on their profitability and the electricity charges, including the distribution rates. The electricity exchanges taking place within the distribution network heavily depend on the proportion of consumers and prosumers, since prosumers are less reliant on the network to cover their electricity needs. Finally, these exchanges dictate the level of revenue of the DSO and, eventually, the need for adjusting the tariff if such a level is not sufficient for this entity to break even. This is measured by an accurate modelling of the remuneration mechanism of the DSO, which can adapt to various distribution tariff designs.

All the previously described dynamics occurring within a distribution network are greatly affected by the regulatory framework in place. For this reason, the presented approach allows for modelling the salient features of a regulatory framework, assessing then their impact on the final customers and the DSO. This assessment is carried out over a discrete-time dynamical system, computing the evolution of different variables, such as the level of penetration of DER or the distribution tariff level. Lastly, since different regulatory frameworks lead to different interactions, several frameworks may be analysed and compared with the presented approach.

Our methodology is illustrated in a broad range of examples of distribution tariffs including traditional –based on energy consumption or on per-connection fixed fees– as well as novel –based on power consumption or time-of use fees– designs. Finally, we provide a comprehensive sensitivity analysis of the proposed simulation environment to the main parameters of the methodology.

Notation

Sets of the MILP

$\mathcal{T}$	Set of time-steps comprising each year of the optimisation with $t \in \{0, \ldots, T-1\}$
$\mathcal{Y}$	Set of years comprising the optimisation horizon with $y \in \{0, \ldots, Y-1\}$

Parameters of the MILP

$Q^{(pv)}$	Deployment costs of PV
$Q^{(bat)}$	Deployment costs of battery
$P^{(pv)}$	Scaling costs of PV per kWp installed
$P^{(bat)}$	Scaling costs of battery per kWh installed
Π^{ot}	Sum of energy and transmission costs, and taxes in €/kWh
Π^{sp}	Selling price of electricity surplus for prosumers €/kWh
Π^{vol}	Volumetric term of the distribution tariff €/kWh
Π^{cap}	Power (capacity) term of the distribution tariff €/kWp
Π^{fix}	Fixed term of the distribution tariff €/consumer
$\eta^{(-)}$	Battery charge efficiency
$\eta^{(+)}$	Battery discharge efficiency
$F^{(-)}$	Battery maximum charge rate
$F^{(+)}$	Battery maximum discharge rate
B	Battery lifetime in years
$U_t^{(c)}$	Time-series of consumption
$U_t^{(p)}$	Time-series of production
$\overline{p}$	Maximum PV potential per prosumer

$\overline{b}$	Maximum battery potential per prosumer
r	Discount rate

Decision variables of the MILP

p	PV capacity deployed in kWp
b	Battery capacity deployed in kWh
χ	Investment costs of a single DER installation
$\rho_t^{(-)}$	Imports of energy of a prosumer
$\rho_t^{(+)}$	Exports of energy of a prosumer
ξ_y	Yearly energy consumption of a prosumer in kWh
γ	Peak demand of a prosumer in kWp
v_y	Yearly distribution costs
ψ_y	Yearly transmission and taxes costs
m_y	Yearly operation and maintenance costs
ϕ_y	Total yearly costs
k_t	PV output of a prosumer in kW
$j_t^{(-)}$	Energy flow into the battery
$j_t^{(+)}$	Energy flow out of the battery
ϖ_t	State of charge of the battery
ζ_y	Revenue of a prosumer from electricity surplus sales

Auxiliary variables of the MILP

$\tau^{(pv)}$	Binary variable enforcing the deployment costs of PV
$\tau^{(bat)}$	Binary variable enforcing the deployment costs of battery
σ_t	Binary variable controlling the status –charging or discharging– of the battery

Additional sets

$\mathcal{I}$	Set of potential prosumers with $i \in \{1, \ldots, I\}$
$\mathcal{N}$	Set of time-steps of the dynamical system with $n \in \{0, \ldots, N-1\}$
$\mathcal{J}_n$	Set potential prosumers at time n where $\mathcal{J}_n \subseteq \mathcal{I}$

Additional parameters

α	Continuous [0,1] bias of Bernoulli distribution
Ω	Residual demand of the system made of consumers

Additional variables

A^*	Optimal sizing configuration of a prosumer
$LVOE$	Levelised value of electricity of a prosumer
Λ	Levelised costs of an actual prosumer as though there was no DER
Γ	Price ratio between LVOE and Λ
Ξ	Aggregated consumption of prosumers in set $\mathcal{I}$
R	Revenue of the DSO

Δ	Economic imbalance of the DSO
Θ	Costs of the DSO

4.1 Introduction

One of the central objectives of the energy transition process is to progressively shift from fossil fuel-based power generation to low-carbon, renewable alternatives [84]. The integration of DER has been deemed a key enabler of a successful energy transition and thereby, DERs are typically promoted by means of various incentive mechanisms, which vary from region to region [85]. These incentive mechanisms, nonetheless, may sometimes have unforeseen and harmful effects on the electricity distribution sector, which are difficult to identify *a priori*. Indeed, since the distribution networks are not technically and administratively designed to absorb large amounts of distributed generation [86], the incorporation of DER may cause both severe technical disruption [25] and regulatory challenges [36]. This paper proposes a methodology to test novel regulatory frameworks promoting the integration of residential DER, usually composed of solar PV panels and/or batteries, evaluate their effectiveness, and identify their shortcomings. More precisely, assuming that a constant part of the DSO costs must be recovered through the distribution charges to distribution network users, we investigate how business models exploiting behind-the-meter devices to reduce electricity bills may impact on the remuneration mechanisms of DSOs.

Previous studies on the topic suggest that the integration of DERs into the distribution networks induce changes in the way in which the distribution network is used, challenging its normal operation. Such changes, according to [87], are region independent, therefore representing a worldwide dilemma, and raise the question of how to distribute the costs in these new distribution systems. The authors of this report review the distribution tariff structures of several countries/regions[1], and simulate their effects through notional households. The authors introduce several notions of fairness, highlighting the importance of finding the right scheme to deter an unfair allocation of distribution costs among final customers, and stressing that the fairness of the scheme depends on the interpretation of this concept. Another report, this time centred in Australia, discusses distribution tariff reforms in Victoria's distribution network [88]. The authors outline different tariff options toward distinct objectives, making use of the principles of simplicity, efficiency, adaptability, affordability, and equity. Similar principles are suggested in other research articles such

[1]This report ([87]) analyses four European Union Member States: Italy, Portugal, Romania, and The Netherlands; one European Economic Area State: Norway, and one state outside European jurisdiction: the State of California in the US. The distribution tariff schemes in each of these examples is different: Italy – energy, power, and fixed components, with an increasing block tariff; Portugal – energy and power components, with a time-of-use basis; Romania – energy component; The Netherlands – power and fixed components; Norway – energy and fixed components; California – energy and fixed components, with an increasing block tariff and a time-of-use basis.

as [89, 82]. The works presented in [37, 33] indicate that, under certain regulatory frameworks designing the DSO remuneration strategies, the deployment of DER, such as household PV units, may be responsible for a non-negligible increase in the distribution component of the overall retail price of electricity (the latter typically including energy generation costs, transmission costs, distribution costs, and taxes). In particular, [37] suggests reviewing tariff designs based on volumetric charges with single metering, arguing that these designs are not cost reflective and potentially lead to cross-subsidies, proposing bi-directional metering as an alternative. To add to the previous, the authors in [33] make the comparison of a single metering mechanism (net-metering) with a dual one (net-purchasing), advocating the use of the latter in order to create more accurate price signals to synchronise consumption and production and to avoid cross-subsidisation from consumers to prosumers. Furthermore, the authors in [75] show, with empirical data, that in a setting where the distribution charges to the consumers are predominantly volumetric (i.e. in €/kWh), an increase in the distribution tariff leads to a corresponding increase in household PV deployment. The combination of these effects can result in a potentially disrupting phenomenon known as the death spiral of the utility.

This concept is introduced in [34], where it is analysed in depth and tentative solutions from the DSO stand point are proposed to mitigate its potentially harming effects (e.g., approval of new rate-making practices or support for new business models). In another work, [35], the author states that an inadequate flat-rate tariff design in Queensland, Australia has led to network price increases of 112% owing to a death-spiral-related problem. The death spiral takes place in two stages: (1) distribution tariffs increase due to the deployment of DER (DSOs struggle to recover their costs and must increase the distribution tariffs), and (2) higher distribution tariffs induce the proliferation of DER installations (or other types of response from final customers to mitigate on their end the tariff increase). Should this phenomenon proceed unchecked for some time, an uncontrolled increase in distribution tariffs may occur, in which the extra financial burden resulting from higher tariffs is mostly met by the users who have not deployed DER, and who are thus more exposed to price fluctuations, as shown in [33, 42]. The latter work proposes a stylised framework assessing the costs for consumers and prosumers after the deployment of DER installations, in a setting where net-metering is employed, quantifying the difference in costs. This difference in costs may result in cross-subsidies from traditional consumers to DER owners, as shown in [37, 41]. In [41], the authors suggest a connection between the self-consumption rate (i.e., the proportion of a prosumer's consumption covered by their own DER installation) and the level of cross-subsidies from consumers to prosumers, in a study focused on France. A similar observation is made across the Atlantic in [90], where different distribution tariff designs in Texas, US, are assessed, reporting on their impact on the distribution network as a function of the level of cross-subsidisation –proxy for unfairness according to the authors– they induce.

To cope with these problems, several DSO remuneration strategies have been proposed and analysed – strategies that better reflect the costs of the electricity distribution, and induce electricity rates that serve as efficient signals for the users of the distribution network, as explained and recommended in [28, 64]. The challenges created by the integration of DER are qualitatively analysed in [67], where the authors recommend regulatory improvements on the remuneration mechanism of DSOs, taking into account the cost-reflectivity principle. In particular, they recommend the use of incentive regulation based on price or revenue caps rather than rate of return regulation, where DSOs are allowed to keep any efficiency gains from efficient DER integration. Other cost-reflective strategies are analysed in [69], where the transition from a distribution tariff based on average costs to a cost-causation tariff that looks into time and location to determine the costs (via e.g., coincident peak) is analysed. The authors ultimately show the importance of breaking down the different effects a change in distribution tariff may induce, to quantitatively understand their foreseeable impacts. Hence, quantitatively assessing the effectiveness and potential pitfalls of novel DSO remuneration strategies is essential, and simulation-based techniques can be invoked to test them in various technological and regulatory settings.

We can find several examples in the literature where the authors have made use of different simulation-based techniques to attain similar goals. The authors in [57] develop an framework to establish the remuneration mechanisms of DSOs. Such a framework lays out a global remuneration scheme to compute the distribution tariff, which is based on a revenue-limitation scheme that considers initial distribution costs, annual market increases, and efficiency gains. Several works have made use of agent-based modelling to analyse this type of problem. For instance, in [91], a simulation approach based on multi-agent modelling is developed to analyse the impact of the integration of renewable resources (wind in this case) on the efficient use of the transmission system in Québec, Canada. Similarly, in [92], a multi-agent-based model is developed and applied to study the integration of distributed generation units where the agents are the DER installations. This tool is employed to help ensure the power system balance control in Hungary. The previous two works focus on control problems but show the suitability of these frameworks to model renewables resources and, in particular, DER integration. In [93], a quantitative approach is presented to assess distribution network performances when presented with incentive-based regulation. These performances are measured with and without DERs, and serve to guide DSO investments as well as to quantify the impact of incentive regulation on these investments. This topic is also dealt with in [94], where a method for regulators to find the right incentive scheme for distributed generation is exposed. The proposed method is based on a multi-objective optimisation problem that provides pareto-optimal solutions to the decision to invest in DERs from the investor (maximisation of the net present value) and the DSO (maximisation of the net present value derived from the provided incentives) perspectives. In [95], an active distribution network is simulated by means of multi-agent system-based modelling, using cooperative agents representing different loading scenarios.

A non-cooperative game is proposed in [31], where different tariff structures are evaluated, and their impacts on the electricity users are studied. This work is further developed in [32], where the authors introduce three types of fee to design the distribution tariff: energy, power and fixed; considering prospective, in additional to sunk costs, to set the tariff level. In [82], the design of cost-reflective distribution tariffs is addressed, introducing a model in which users can react to high distribution charges by deploying fix-sized DER installations in order to reduce their electricity bills. The impact of regulation on the willingness of DSOs to integrate distributed generation is addressed in [96], where a method is proposed and applied to different case studies. Finally, [43] introduces a stylised set-up where two different metering systems (net-metering and net-billing) are analysed in their ability to promote the deployment of DER. In the latter work, the impact of such metering systems on the consumers in the distribution network and on the electricity prices is studied, concluding that the death spiral of the utility might be a potential issue, in particular in the net-metering case which can be considered as an incentive mechanism on its own. All these works deal with simulation-based analysis of the relation between DSO remuneration strategies, DER integration, and impact on distribution networks.

Building upon the existing literature, the presented paper introduces a simulation-based computational tool that enables the modelling and study of the multi-agent system dynamics resulting from interactions between the agents of a distribution network, namely the distribution network users and the DSO. At every time-step, agents may either stay idle or perform a pre-defined action: the distribution network users can deploy optimally sized PV installations with or without batteries aiming at minimising their electricity bills, whereas the DSO can adjust the distribution tariff in order to collect sufficient revenue so as to break even. Hence, the present paper adds to the literature by explicitly modelling the action-reaction dynamics of agents under various tariff structures, thereby allowing to represent the system evolution over time and estimate the short-to-middle-run effects of specific pieces of regulation on aforementioned distribution network attributes.

In the remainder of this paper, Section 4.2 establishes the concrete contributions of our work. Section 4.3 provides an introductory overview of the simulation-based approach. Section 4.4 details the underpinning mathematical models. Section 4.5 illustrates the methodology considering various regulatory frameworks and DSO remuneration strategies, and tests the limits of the simulation-based computational tool by introducing an extensive sensitivity analysis of the main parameters of the model. Finally, Section 4.6 concludes the paper.

4.2 Contributions

Our approach adds to the previous works (notably including [43]) by:

- Mathematically formalising a sizing tool which is used to optimally size DER installations.
- Mathematically formalising an investment decision process for modelling the adoption and deployment of DER installations based on the cost-efficiency and profitability of the installation.
- Modelling, in a realistic fashion, the non-linear investment costs of deploying DER installations by making use of a continuous piecewise approximation which is more accurate than the traditional approach whilst being computationally efficient.
- Mathematically formalising the remuneration mechanism of DSOs that determines the economic balance (or imbalance) of the DSO, which depends on the distribution tariff and the DSO costs – this mechanism must take into account all possible distribution tariff structures (i.e. based on units of energy consumed, units of power consumed, or type of access point to the distribution network).
- Introducing the concept of levelised value of electricity (LVOE) as an extension of the traditional levelised cost of electricity (LCOE) to take into account not only the costs of DER installations, but also potential revenue via electricity sales – the LVOE is then used both as the objective function of a minimisation problem and as a metric on which to report.

The simulation environment presented in our work requires a tariff design as input, which is typically set by the regulator. In previous works (such as [43]), these designs were limited to mechanical meters, therefore only volumetric and fixed fees were possible. In this paper we assume full roll out of smart meters, opening the door to new tariff designs. Thus, in addition to the previous, we expand the current literature by introducing:

- Capacity fees by which the DSO charges the users depending on the power they draw from the distribution network.
- Time-of-use (ToU) fees that are time varying, i.e. the costs for the users depend on the time of the day.

We thus provide one single simulation environment which can assess, in a realistic fashion, the impact of all the different tariff designs (volume, capacity, fixed, ToU) on a detailed investment decision process where prosumers are accurately modelled through an optimisation framework, taking into account a coherent representation of the DSO remuneration mechanism.

4.3 Simulation configuration

The proposed methodology relies on a multi-agent system formalisation in which the agents (i.e. consumers, potential prosumers, actual prosumers, and the DSO) interact with each other within a given set of rules characterising a technical and a regulatory framework. Through the agent's interactions over time, the topology of the distribution network changes, and so does the distribution tariff and, by tracking the actions of agents across a provided simulation horizon, we can determine trajectories of topologies and prices over such a horizon. By using this principle utilising various starting conditions, we may estimate the different topology changes those starting conditions induce.

Each type of agent interacts in a different way:

- **Consumers** are passive agents who simply consume electricity from the distribution network according to their demand profiles. They cannot become prosumers owing to technical or economic constraints and are modelled through their electricity demand.

- **Potential prosumers** are agents who may deploy an optimally sized DER installation, turning into actual prosumers; the decision to deploy such an installation depends on its cost-efficiency when compared to the retail price of electricity. After the comparison is computed, a probabilistic investment decision process is laid out to determine whether a given potential prosumer becomes an actual prosumer.

- **Actual prosumers** are passive agents who consume and produce electricity from the distribution network according to their demand and production profiles. Such profiles are established only when potential prosumers become actual prosumers, therefore reflecting the after-the-meter consumption or production accounting for the deployed DER installations.

- The **DSO** manages the distribution network, incurring certain costs in this role. Through its remuneration mechanism, the DSO collects charges for the use of the distribution network by the three types of user (consumers, potential prosumers, and actual prosumers), and is entitled to adjust the distribution tariff so that it recovers the totality of its costs, breaking-even.

Through the agent's interactions over time, it is possible to determine the evolution of the proportions of consumers, potential prosumers, and actual prosumers, as well as the evolution of distribution tariff and electricity exchanges over a provided simulation horizon. The simulation starts with a pool of potential prosumers who may become actual prosumers during the simulation, relying less on the distribution network. The DSO, expecting to collect a certain level of charges from these potential prosumers, in fact collects a different level since the consumption behaviour of actual prosumers is different to that of potential prosumers. As a result, the DSO may adjust the distribution tariff to adapt to the new situation. The full modelling of these agents as well as the simulation procedure is detailed in the following section.

4.4 Modelling and problem formalisation

In this section, we present the models used in our simulation-based computational tool. We start by describing the set of rules defining the technical and regulatory frameworks and then, we formalise the different agents and their interaction mechanisms.

4.4.1 Rules defining the technical and regulatory frameworks

These rules define the playing field for agents to interact. A real-life playing field includes many rules, which may not all be relevant to our modelling. Against this backdrop, we identified and selected a sub-set of rules capturing key drivers for DER deployment: tariff design and technology costs.

Tariff design

This sub-set of rules defines the structure of the distribution costs charged to the users of the distribution network. In our work we consider that the distribution tariff might be based on volume of energy drawn from the grid charged in €/kWh, power drawn charged in €/kWp, or connection point charged in €/user. The amount of money charged by the DSO for its services over a given billing period is obtained as a weighted sum of those fees, whose respective proportions are regulated. To design a tariff, it is possible to use any combination of these fees.

In addition, in our simulation-based approach we introduce ToU tariffs by setting different time-dependent price levels. Those levels can be applied both to volume fees and/or to capacity fees. Accordingly, under a ToU tariff, the volume and/or the capacity fee of the distribution tariff will comprise several sub-fees, depending on the time of consumption.

Technology costs

This sub-set of rules has an impact on the investment costs of prosumers. In our work, we divide these costs in two.

- **Deployment costs** are charges that depend on whether the DER installation is deployed or not. They represent the costs of installation, including the PV, inverter, and (if any) batteries.
- **Scaling costs** are the charges depending on the scale of the installation. We assume these costs to be linearly dependent on the size of the installation, therefore on the total deployed capacity of PV and battery.

These are therefore non-linear costs that we model using a piecewise linear approximation where the two terms are introduced (see 4.4.3 for more details). Furthermore, we assume these two components will linearly decrease over time. This means that the technology will be more expensive at the beginning of the simulated period than at the end. In this sense, prosumers who deploy DER later in time will pay less for their installations.

4.4.2 Users

Users are divided into three groups: (i) consumers, (ii) potential prosumers, and (iii) actual prosumers. The **consumers** group comprises users who will not deploy a DER installation due to economic or technical constraints. Their aggregated demand (also known as the residual demand of the distribution network) is used in the simulation. We define **potential prosumers** as all the users who may deploy a DER installation, provided that the conditions are favourable. Potential prosumers are, initially, consumers importing electricity from the grid to cover their demand. Then, as the simulation proceeds over time, the number of potential prosumers may decrease as they elect to invest in and progressively deploy optimally-sized DER installations, effectively turning into actual prosumers. Finally, **actual prosumers** are able to import and export electricity from and into the distribution network.

To model the interactions of potential and actual prosumers, we make use of an optimisation framework. We formulate this optimisation as a mixed integer linear problem (MILP) aimed at minimising the levelised value of electricity (LVOE) of a DER installation. We introduce the concept of LVOE –whose formulation can be found in Section 4.4.3– as an extension of the traditional levelised cost of electricity (LCOE). The difference between these two concepts is that whilst the LCOE can only account for the costs incurred by the DER installation, the LVOE can take into consideration both costs and revenue (for instance revenue obtained from electricity sold). Adding the dimension of revenue was not needed in the past, where net-metering was predominant, since, with this system, the revenue are implicitly taken into account. However, with the introduction of other mechanisms such as net-billing, where imports and exports are measured separately, the concept of LCOE falls short in accurately describing the dynamics of prosumers, being necessary to introduce the LVOE to explicitly integrate the revenue. The LCOE is therefore computed as costs divided by demand, whereas the LVOE is expressed as costs minus revenue divided by demand (in all cases an annual discount rate is applied to costs, revenue, and demand). Hence, the LVOE provides an indication of the net economic gain of potential prosumers, should they become actual prosumers. Moreover, by comparing the LVOE with the electricity costs without DER we can compute the probabilistic investment decision process of potential prosumers becoming actual prosumers. Both the MILP and the investment decision process are presented in the remainder of this section.

4.4.3 Optimisation framework formalisation

For every individual potential prosumer, this optimisation program is used to compute the electricity trades (imports and exports), the minimised LVOE, and the optimal sizing configuration of the DER installation leading to the minimum LVOE. Hence, both sizing and operation are optimised under a perfect forecast assumption. The optimisation horizon is set to $Y \in \mathbb{N}$ years, where $\mathcal{Y} = \{0, \ldots, Y-1\}$ (not to be confused with the simulation horizon, which will be presented later in Section 4.4.4). Each year is divided into T time-steps. Let $\mathcal{T} = \{0, \ldots, T-1\}$, where $T = 8760$ represents a time discretisation of one year in hours. The MILP requires several parameters as inputs; these parameters are constant over the simulation horizon Y since they do not evolve from year to year of the optimisation (note that some of them will evolve over the simulation horizon, see Section 4.4.4). Let G denote a 4-tuple gathering these inputs:

$$G = (P, \Pi, H, \mathbf{U}) \in \mathcal{G}, \quad \text{with}$$
$$\mathcal{G} \subset \left(\mathbb{R}_+^4\right) \times \left(\mathbb{R}_+^5\right) \times \left(\mathbb{R}_+^5\right) \times \left(\mathbb{R}_+^2\right)^T$$

where:

- $P = \left(Q^{(pv)}, Q^{(bat)}, P^{(pv)}, P^{(bat)}\right)$ represent the deployment costs of PV ($Q^{(pv)}$) and batteries ($Q^{(bat)}$), as well as the scaling costs of PV per kWp ($P^{(pv)}$) and batteries per kWh ($P^{(bat)}$). See Section 4.4.1 for a reminder on deployment and scaling costs.
- $\Pi = \left(\Pi^{(ot)}, \Pi^{(sp)}, \Pi^{(vol)}, \Pi^{(cap)}, \Pi^{(fix)}\right)$ are price signals. $\Pi^{(ot)}$ is the aggregation of energy costs, transmission costs, and taxes, in €/kWh. $\Pi^{(sp)}$ corresponds to the price at which prosumers sell the electricity in €/kWh. $\Pi^{(vol)}$ is the volumetric term of the distribution tariff in €/kWh. $\Pi^{(cap)}$ represents the capacity term of the distribution tariff in €/kWp. $\Pi^{(fix)}$ represents a fixed charge to be paid by every user connected to the distribution network, in €. In the case of ToU tariffs, $\Pi^{(vol)}$ and/or $\Pi^{(cap)}$ will present different levels depending on the time of consumption.
- $H = \left(\eta^{(-)}, \eta^{(+)}, F^{(-)}, F^{(+)}, B\right)$ defines the battery parameters. $\eta^{(-)}$ is the charge efficiency. $\eta^{(+)}$ is the discharge efficiency. $F^{(-)}$ represents the maximum charge rate. $F^{(+)}$ stands for the maximum discharge rate. Finally B is the battery lifetime in years ($B > 0$).
- $\mathbf{U} = \left\{\left(U_t^{(c)}, U_t^{(p)}\right)\right\}_{t=0}^{T-1}$ is a time-series of pairs representing the potential prosumer consumption profile $\left(U_t^{(c)}\right)_{t=0 \ldots T-1}$ (in terms of hourly energy consumption), and the solar load factor $\left(U_t^{(p)}\right)_{t=0 \ldots T-1}$ (in %), respectively.

Let $\mathcal{A} = \left\{(p,b)\,|p \in [0,\overline{p}]\,; b \in [0,\overline{b}]\right\}$ denote the space of sizing variables containing: PV size (p) in kWp, battery size (b) in kWh; with $\overline{p}$, and $\overline{b}$ being parameters denoting the upper bounds on PV and battery capacities, respectively. Furthermore, let $\tau^{(pv)}$ and $\tau^{(bat)}$ denote binary variables enforcing the deployment costs when either PV or batteries are installed. Finally, let χ represent the investment costs of PV and batteries, which are linearised by means of a piecewise affine function, and are dependent on the sizing variables $A \in \mathcal{A}$.

$$\chi = p \cdot P^{(pv)} + \frac{Y}{B} \cdot b \cdot P^{(bat)} + \tau^{(pv)} \cdot Q^{(pv)} + \tau^{(bat)} \cdot Q^{(bat)} \tag{4.1}$$

where the control of the binary variables $\tau^{(pv)}$ and $\tau^{(bat)}$ is given by:

$$p \leq \overline{p} \cdot \tau^{(pv)} \tag{4.2}$$
$$b \leq \overline{b} \cdot \tau^{(bat)} \tag{4.3}$$

The yearly costs incurred by a prosumer are represented by ϕ_y, and computed by means of the following equation:

$$\phi_y = v_y + \psi_y + m_y, \quad \forall y \in \mathcal{Y} \tag{4.4}$$

where v_y represents the yearly electricity distribution costs, computed according to Equation (4.5). ψ_y stands for the yearly costs of electricity not related to distribution costs, i.e. transmission and energy costs, computed using Equation (4.6). m_y are the costs of operating and maintaining the DER installation; these costs are computed as in [97], following Equation (4.7).

$$v_y = \xi_y \cdot \Pi^{(vol)} + \gamma \cdot \Pi^{(cap)} + \Pi^{(fix)}, \quad \forall y \in \mathcal{Y} \tag{4.5}$$
$$\psi_y = \xi_y \cdot \Pi^{(ot)}, \quad \forall y \in \mathcal{Y} \tag{4.6}$$
$$m_y = \frac{1}{200} \cdot p + \frac{1}{100} \cdot b, \quad \forall y \in \mathcal{Y} \tag{4.7}$$

in these equations, ξ_y and γ represent the yearly consumption and the peak demand of a prosumer, respectively. They are computed as follows:

$$\xi_y = \sum_{t=0}^{T-1} \rho_t^{(-)}, \quad \forall y \in \mathcal{Y} \tag{4.8}$$
$$\gamma = \max\left\{\rho_t^{(-)} | t = 0, \ldots, T-1\right\} \tag{4.9}$$

where $\rho_t^{(-)}$ are the hourly imports of a prosumer. To define the energy balance we need to define: the exports of electricity $\rho_t^{(+)}$, the PV output of each DER k_t (Equation 4.10), and the energy flows into and out of the battery $j_t^{(-)}$ and $j_t^{(+)}$ respectively

(Equations 4.11 to 4.14).

$$k_t = p \cdot U_t^{(p)}, \ \forall t \in \mathcal{T} \tag{4.10}$$

$$j_t^{(-)} \leq b \cdot \frac{1}{F^{(-)}}, \ \forall t \in \mathcal{T} \tag{4.11}$$

$$j_t^{(+)} \leq b \cdot \frac{1}{F^{(+)}}, \ \forall t \in \mathcal{T} \tag{4.12}$$

$$j_t^{(-)} \leq \bar{b} \cdot \sigma_t, \ \forall t \in \mathcal{T} \tag{4.13}$$

$$j_t^{(+)} \leq \bar{b} \cdot (1 - \sigma_t), \ \forall t \in \mathcal{T} \tag{4.14}$$

In these equations, σ_t is a binary variable taking a value of 1 when the battery is charging, and 0 if it is discharging. Then, the energy balance is given by:

$$U_t^{(c)} + \rho_t^{(+)} + j_t^{(+)} = k_t + \rho_t^{(-)} + j_t^{(-)}, \ \forall t \in \mathcal{T} \tag{4.15}$$

The last variable of our model is the state of charge of the battery, ϖ_t.

$$\varpi_t \leq b, \ \forall t \in \mathcal{T} \tag{4.16}$$

$$\varpi_t = \begin{cases} \varpi_{t-1} - \dfrac{j_t^{(+)}}{\eta^{(+)}} + j_t^{(-)} \cdot \eta^{(-)}, \ \forall t \in \mathcal{T} \setminus \{0\} \\ 0 \text{ if } \ t = 0 \end{cases} \tag{4.17}$$

Finally, let *LVOE* denote the general objective function of the MILP that represents the levelised value of electricity. This function will be minimised when the MILP is instantiated and solved, it is a mapping from $(\mathcal{G} \times \mathcal{A})$ to $\mathbb{R}$. For a given pair $(G, A) \in (\mathcal{G}, \mathcal{A})$, $LVOE\,(G, A)$ is defined as follows:

$$LVOE\,(G, A) = \frac{\chi + \sum_{y=0}^{Y-1} \dfrac{\phi_y - \zeta_y}{(1+r)^y}}{\sum_{y=0}^{Y-1} \dfrac{\sum_{t=0}^{T-1} U_t^{(c)}}{(1+r)^y}} \tag{4.18}$$

where ζ_y is the revenue of the prosumer from electricity sales, and r is the discount rate. By subtracting ζ_y from the operational costs ϕ_y, we compute the actual value offered by the DER installation (LVOE), instead of simply its levelised cost. This term depends on the total amount of energy exported to the grid and on the selling price of electricity at which the prosumers can sell the electricity to the grid, as expressed in eq. (4.19).

$$\zeta_y = \sum_{t=0}^{T-1} \rho_t^{(+)} \cdot \Pi^{(sp)}, \ \forall y \in \mathcal{Y} \tag{4.19}$$

From this MILP we extract the values of several variables to be used later on, they are the optimal sizing variables p and b; the yearly consumption ξ_y the yearly peak demand γ.

4.4.4 Expanding the optimisation framework to multiple time-steps and prosumers

At the heart of the simulation-based approach lies a discrete-time dynamical process computing the evolution of a set of indicators. Let $n \in \mathcal{N}$ denote the discrete-time variable used to refer to the iterations of this dynamical process, where $\mathcal{N} = \{0, \dots, N-1\}$, and $N \in \mathbb{N}$ is the time horizon. Furthermore, to represent the diversity of users, we introduce a set of $I \in \mathbb{N}$ potential prosumers, with $\mathcal{I} = \{1, \dots, I\}$. At every iteration n, each potential prosumer $i \in \mathcal{I}$ is characterised by a time series of pairs $\mathbf{U}_{i,n} = \left\{ \left(U^{(d)}_{i,n,t}, U^{(p)}_{i,n,t} \right) \right\}_{t=0}^{T-1}$. Therefore, at every iteration n, and for every user i, we can define:

$$G_{i,n} = (P_n, \Pi_{i,n}, H_n, \mathbf{U}_{i,n}) \quad \forall (i,n) \in \mathcal{I} \times \mathcal{N}, \tag{4.20}$$

where P_n and H_n do not depend on i since they refer to technology costs and technical characteristics, assumed identical for all users. Consequently, we define $\widehat{LVOE}_{G_{i,n}}$ as the minimum value of the objective function, subject to the previous constraints:

$$\widehat{LVOE}_{G_{i,n}} = \min_{\substack{A \in \mathcal{A} \\ s.t.(4.1)-(4.19)}} LVOE\left(G_{i,n}, A\right) \tag{4.21}$$

Furthermore, the optimal sizing configuration is written as:

$$A^*_{G_{i,n}} \in \arg\min_{\substack{A \in \mathcal{A} \\ s.t.(4.1)-(4.19)}} LVOE\left(G_{i,n}, A\right) \tag{4.22}$$

4.4.5 Investment decision process

From one time-step in the simulation horizon to the next, we compute the transition from potential to actual prosumer. For each potential prosumer, the $\widehat{LVOE}_{G_{i,n}}$ is compared to the levelised cost without DER (denoted by $\Lambda_{i,n}$). The outcome of this comparison defines whether or not a transition occurs. Let $\mathcal{J}_n \subseteq \mathcal{I}$ denote the set of potential prosumers at time n. Initially, $|\mathcal{J}_0| = |\mathcal{I}|$. Assuming that prosumers cannot turn back into consumers, one has $\forall n \in \{0, \dots, N-1\}$, $|\mathcal{J}_n| \leq |\mathcal{J}_{n-1}|$. Then, the costs $\Lambda_{i,n}$ are calculated as follows:

$$\Lambda_{i,n} = \Pi^{(ot)}_n + \Pi^{(vol)}_n + \frac{\gamma^{(o)}_{i,n} \cdot \Pi^{(cap)}_{i,n} + \Pi^{(fix)}_n}{\sum_{t=0}^{T-1} U^{(c)}_{i,n,t}} \quad \forall (i,n) \in \mathcal{J}_n \times \mathcal{N}, \tag{4.23}$$

where $\gamma^{(o)}_{i,n}$ is the original peak demand of the user. Then, a price ratio $\Gamma_{i,n}$ can be computed as:

$$\Gamma_{i,n} = \frac{\widehat{LVOE}_{G_{i,n}}}{\Lambda_{i,n}} \quad \forall (i,n) \in \mathcal{J}_n \times \mathcal{N}. \tag{4.24}$$

In this last equation, $\Lambda_{i,n}$ is strictly positive provided that the demand of the user and the electricity prices are strictly positive. $\Gamma_{i,n}$ will therefore adopt a value between 0 and 1, since $\widehat{LVOE}_{G_{i,n}}$ cannot be greater than $\Lambda_{i,n}$, by design of the optimisation problem. To establish whether a consumer will decide to deploy a DER installation, we make use of a Bernoulli random variable whose parameter $p_{i,n}$ is a function of $\Gamma_{i,n}$.

$$\begin{aligned} \forall (i,n) \in \mathcal{J}_n \times \mathcal{N} \quad \exists f_{i,n} : [0,1] \to [0,1]\,, \\ p_{i,n} = f_{i,n}\left(\Gamma_{i,n}\right) \end{aligned} \tag{4.25}$$

For simplicity, in the following we assume that all the previously defined mappings $f_{i,n}$ are equal to a unique linear mapping, given by:

$$p_{i,n} = (\alpha \cdot \Gamma_{i,n} | \alpha \in [0,1]) \quad \forall (i,n) \in \mathcal{J}_n \times \mathcal{N}, \tag{4.26}$$

where α is included to model a broad range of investment behaviours, e.g. a small value implies a increased tendency to invest. Then, the random variable $\beta_{i,n}$, that controls the decision of investing or not in a DER installation of size $A^*_{G_{i,n}}$, is drawn from the Bernoulli distribution $B(1, p_{i,n})$:

$$\beta_{i,n} \sim B(1, p_{i,n}) \quad \forall (i,n) \in \mathcal{J}_n \times \mathcal{N}. \tag{4.27}$$

Finally, the decision for every potential prosumer is given by:

$$\theta_{i,n} = 1 - \beta_{i,n} \quad \forall (i,n) \in \mathcal{J}_n \times \mathcal{N}, \tag{4.28}$$

with $\theta_{i,n} \in \{0,1\}$ by definition of the Bernoulli distribution. If $\theta_{i,n} = 1$, a DER installation of size $A^*_{G_{i,n}}$ is deployed by the agent i. This agent is then removed from the set of users $\mathcal{J}_n$. In this way, when a DER installation of size $A^*_{G_{i,n}}$ is deployed, the user i is prevented from investing in the future. If $\theta_{i,n} = 0$, the DER installation is not deployed, and another opportunity will be given to user i at the following step $n+1$. The set $\mathcal{J}_{n+1}$ can thus be computed as follows:

$$\mathcal{J}_{n+1} = \mathcal{J}_n \setminus \{i | \theta_{i,n} = 1\}. \tag{4.29}$$

Modelling the investment decision-making process in such fashion ensures the deployment of some DER units even when the viability of the DER installations lie at the economically feasible limit (for instance when the technology costs are high or the retail price of electricity is low), representing the behaviour of those users who are eager to invest. Likewise, this investment decision-making mechanism will prevent some agents from investing even under favourable conditions, representing those agents more reluctant to invest. Also, slightly randomising the decision process using a Bernoulli distribution allows to aggregate the effect of variables that influence the decision making process but that are not explicitly modelled in this article, such as the access to capital for investing in DER, or the interest in renewable energy.

4.4.6 Distribution system operator's remuneration mechanism

The DSO distributes electricity to the users of the distribution network, charging a distribution fee for the service. This fee must be sufficiently large so as to collect the revenue that allows the DSO to break-even financially. Hence, assigning an adequate level of a distribution fee is a delicate process. An under-estimated fee may lead to insufficient remuneration, creating an economic imbalance that must eventually be socialised via higher rates. On the other hand, an inflated tariff may place excessive economic strain on users. Both deviations from the optimum are symptoms of an inefficient DSO remuneration strategy. To model the interactions of the DSO, we represent its remuneration mechanism, which includes the adjustment of the distribution fee when needed. Note that the tariff design cannot be modified by the DSO since it is controlled by the incumbent regulatory authority, and it is thereby out of the scope of our work.

The remuneration mechanism computes the distribution fee by comparing the costs (Θ_n) and the revenue (R_n) of the DSO in the previous tariff period and computing its difference $\Delta_n = \Theta_n - R_n$. If $\Delta_n = 0$, it means that the distribution tariff level is adequate. However, if $\Delta_n > 0$ or $\Delta_n < 0$, it indicates an under- or over-estimation of the distribution fee, respectively. It is important to note that the applied fee is always an estimation of the real one, based on forecasts of consumption. In our work, we assume that the forecast used by the DSO is a continuation of the last observed state of the system. Furthermore, we assume that at the initial state, the system is economically balanced, i.e. $\Delta_{-1} = 0$ and therefore $\Theta_{-1} = R_{-1}$. Hence, the initial costs of the system can be calculated by determining the initial revenue. The general expression to compute the DSO revenue is:

$$R_n = \left[\Pi_n^{(vol)} \cdot (\Omega + \Xi_n)\right] + \left[\Pi_n^{(cap)} \cdot \sum_{i=1}^{(I+I_0)} \gamma_{i,n}\right] + \left[\Pi_n^{(fix)} \cdot (I + I_0)\right] \quad \forall n \in \mathcal{N}, \tag{4.30}$$

where $\Pi_n^{(vol)}$, $\Pi_n^{(cap)}$, and $\Pi_n^{(fix)}$ represent the volumetric, capacity, and fixed fees, respectively, at the n^{th} time-step. I_0 stands for the number of consumers who make up the residual demand (i.e. non prosumers). $\gamma_{i,n}$ represents the optimised peak demand of the i^{th} user, output of the MILP. Ω represents the residual demand of the system, which is an input of the simulation and is held constant throughout the entire simulation process. Finally, Ξ_n represents the aggregated consumption of the agents in $\mathcal{I}$, computed as:

$$\Xi_n = \sum_{i=1}^{I} \rho_{i,n}^{(-)} \quad \forall n \in \mathcal{N}, \tag{4.31}$$

where $\rho_{i,n}^{(-)}$ represents the optimised imports of the i^{th} potential or actual prosumer at the n^{th} time-step, which is an output of the MILP.

To begin the simulation we need the initial costs (Θ_{-1}). These are, as previously explained, equal to the initial revenue (R_{-1}). The latter can be easily computed by means of Equation (4.30), since the demand profiles of the potential prosumers and the residual demand are known. Once the initial revenue (and therefore the initial costs) of the DSO are computed, the remuneration mechanism can distribute them across the different types of fees: volumetric, capacity, or fixed, thus obtaining three different fees which are applied to the final customers' electricity bills (note that ToU fees are a particular case of volumetric fees). The same distribution mechanism is used for computing the initial fees and to update them in subsequent time-steps of our discrete-time dynamical system. Such a computation is given by the following expressions:

$$\Pi_{n+1}^{(vol)} = \left[\frac{\Theta_n + \Delta_n}{\Omega + \Xi_n}\right] \cdot \mu_1 \quad \forall n \in \mathcal{N}, \tag{4.32}$$

$$\Pi_{n+1}^{(cap)} = \left[\frac{\Theta_n + \Delta_n}{\sum_{i=0}^{(I+I_0)} \gamma_{i,n}}\right] \cdot \mu_2 \quad \forall n \in \mathcal{N}, \tag{4.33}$$

$$\Pi_{n+1}^{(fix)} = \left[\frac{\Theta_n + \Delta_n}{I + I_0}\right] \cdot \mu_3 \quad \forall n \in \mathcal{N}. \tag{4.34}$$

In these equations, μ_1, μ_2, and μ_3 represent the share of the volumetric, capacity, and fixed fee, respectively, imposed by the DSO remuneration strategy, and thereby by the regulatory framework set by the regulator. These shares comply with $\sum_{j=1}^{3} \mu_j = 1$.

To compute the fees for time-step $n = 0$, we know Θ_{-1} as it equals the revenue at this time-step. Furthermore, we know that $\Delta_{-1} = 0$. The rest of the elements in Equations (4.32), (4.33), and (4.34) are given by the profiles of the users, which are known. Once the simulation starts, at every time-step n, some potential prosumers may turn into actual prosumers, impacting the revenue of the DSO and, in particular, Ξ_n and $\gamma_{i,n}$. The DSO, in turn, reacts by updating the different components of the distribution tariff. Finally, since we work under the assumption that the DSO uses its last observed state of the system as forecast for the following tariff period, the costs at a given period will be the same as the revenue at the previous one $\Theta_n = R_{n-1}$.

4.4.7 User's electricity bill

The electricity bills of the distribution network's final customers depend on their imports and their exports (if any) of electricity. In this paper, we assume a full roll out of smart meters, therefore these two electricity flows are registered independently by the metering device, and have two different price signals associated.

Imports of electricity This is the overall price of electricity the final customers (consumers and potential and actual prosumers) pay to use the network and consume electricity from it. This price includes commodity, transmission, distribution and others. In this work we are interested in the distribution part, therefore, all the other elements making up the electricity price are grouped in one element, $\Pi^{(ot)}$, introduced in eq. (4.6) and set in €/kWh. As for the distribution fee, the smart meters allow us to split the distribution component of the electricity bill into its constituents: $\Pi^{(vol)}$, $\Pi^{(cap)}$, and $\Pi^{(fix)}$, as in (4.5). The contribution of each element is given by μ_j (see eqs. (4.32) - (4.34)) and depends on the DSO remuneration mechanism.

Exports of electricity This is the selling price of the actual prosumers when exporting electricity to the grid. It is introduced by $\Pi^{(sp)}$ in eq. (4.19) and set in €/kWh.

4.5 Test case: simulator demonstration

To test and illustrate the proposed simulation-based approach, this section presents an extensive range of tests showcasing the potential of the presented methodology to flexibly simulate a wide range of scenarios. To create these scenarios, we need: (i) a set of users, and (ii) a set of rules representing a regulatory framework (designing the DSO remuneration strategy). Then, by using the same set of users for different remuneration strategies, we can analyse the impact of the latter on different features inherent to distribution networks, notably the distribution network prices and the level of penetration of distributed generation in the distribution network.

Set of users:

Users are characterised by individual demand and production profiles. A bottom-up approach, the CREST model [98], was used to generate demand profiles. Using the CREST model we produced a range of daily profiles representing weekends and weekdays and then, by means of a randomisation process, different demand profiles spanning one year and with a resolution of one hour, were generated. As for the production profiles, they were generated with the same time span and resolution (one year and one hour, respectively), representing the potential for PV generation of prosumers. To do so, the Python library PVLIB [99] was used. The profiles thus produced are based on solar radiation historical data, obtained through typical meteorological years (tmy), which were downloaded from the Joint Research Centre of the European Commission[2]. From a range of different tmy, and making variations on the tilt and orientation of the PV panels (parameters of PVLIB), different profiles were generated. These profiles represent the load factor, i.e. percentage of the total installed capacity that is produced at each time-step.

In total, 1,000 demand and production profiles were generated, to represent 1,000 potential prosumers. In addition to them, 5,000 consumers were created for whom

[2] Joint Research Centre photovoltaic geographical information system `https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#TMY`.

only the aggregated yearly demand and the peak demand is needed as they make up what we call residual demand of the system. Both groups of customers (consumers and prosumers) have been created according to the Belgian reality, that is, the profiles are consistent with electricity consumption and solar radiation in Belgium. The proportion prosumers/consumers is selected so as to reflect the real-life situation in Belgium, as described in footnote 7 of [44].

Set of rules of a regulatory framework

Two groups of scenarios are proposed:

- **Simulation-based approach capabilities:** First we generate several scenarios showcasing the capabilities of the proposed simulation-based approach to compute a prediction of the evolution of distribution network features (distribution prices and penetration of DER). These scenarios represent various DSO remuneration strategies.

- **Sensitivity analyses:** Then, the sensitivity of our approach to several parameters is tested, reporting on the impacts these parameters have on the simulation-based approach capabilities to predict the distribution network development.

4.5.1 Simulation-based approach capabilities

In this part of the simulation results, we test seven scenarios mimicking different initial conditions set by the regulator. Accordingly, we can introduce different values of μ_j for each scenario. These values will impact on the evolution of the different elements of the distribution tariff, as described by Equations (4.32), (4.33), and (4.34). In these equations, all the variables are known. Therefore, to start the simulations we only need an initial state, i.e. the initial costs of the system (by assumption equal to the initial revenue $\Theta_{-1} = R_{-1}$). To compute the initial revenue, in this example we use the current situation in Belgium, where the distribution fee is based on a volumetric tariff which, on average, amounts to 0.08 €/kWh (i.e. $\Pi_{-1}^{(vol)} = 0.08, \Pi_{-1}^{(cap)} = 0, \Pi_{-1}^{(fix)} = 0$) and determine R_{-1} as expressed in Equation (4.30). Since this initial revenue must be the same regardless of the scenario we want to test, we can break it down for different initial states representing different distributions of volume, capacity, and fixed fees (i.e. different scenarios), using Equations (4.32), (4.33), and (4.34). Using this procedure, we have built seven scenarios, showcasing a range of different possible tariff designs. Along with these, one additional scenario has been created to test the impact of ToU distribution tariffs based on volumetric fees. All these scenarios are listed in Table 4.1.

Finally, Table 4.2 lists the rest of the inputs used to run the scenarios. To assess each scenario, we use three metrics: (i) the penetration of actual prosumers relative to the maximum potential; (ii) the evolution of the electricity costs for consumers and prosumers; and (iii) the actual deployed PV and battery capacities (in kWp and kWh respectively).

TABLE 4.1: Construction of the different scenarios

Scenario	Description	μ_1	μ_2	μ_3
`VOL`	Based on fully volumetric distribution fees	1	0	0
`CAP`	Based on fully capacity distribution fees	0	1	0
`FIX`	Based on fully fixed fees, per connection point	0	0	1
`VOL_CAP`	Based 50% on volume and 50% on capacity fees	1/2	1/2	0
`VOL_FIX`	Based 50% on volume and 50% on fixed fees	1/2	0	1/2
`CAP_FIX`	Based 50% on capacity and 50% on fixed fees	0	1/2	1/2
`EVEN`	Based on a even distribution of the weights	1/3	1/3	1/3
`TOU`	Time-of-use tariff*	1	0	0

* The ToU distribution tariff is created by using a fully volumetric fee such as `VOL`, where different levels of the fee are applied depending on the time of the day. In our particular example, three different levels are applied corresponding to peak rates, off-peak rates, and shoulder rates: **Peak rates (+10%)**: 07:00–08:00 & 11:00–12:00 & 17:00–19:00. **Off-peak rates (–)**: 06:00–07:00 & 08:00–11:00 & 12:00–17:00 & 19:00–22:00. **Shoulder rates (-10%)**: 22:00–06:00.

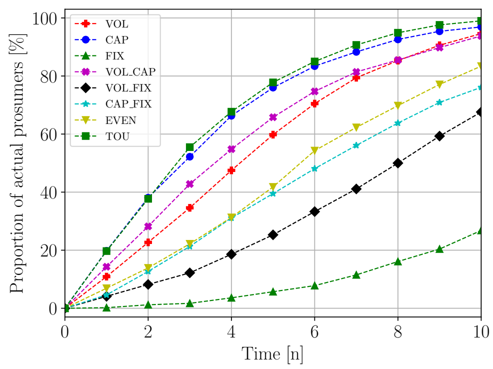
TABLE 4.2: General inputs of the multi-agent model

Parameter	Value	Units
$P^{(pv)*}$	1200	[€/kWp]
$Q^{(pv)*}$	500	[€]
$P^{(bat)*}$	200	[€/kWh]
$Q^{(bat)*}$	200	[€]
$\Pi_n^{(ot)}$	0.132	[€/kWh]
$\eta^{(-)}$	0.95	[%]
$\eta^{(+)}$	0.95	[%]
$F^{(-)}$	2.5	[-]
$F^{(+)}$	4	[-]
B	8	[years]
$\overline{p}$	10	[kWp]
$\overline{b}$	30	[kWh]
α	1	[-]
Y	20	[years]
r	2	[%]
Ω	85% of total load	[kWh]
I	1000	[#]

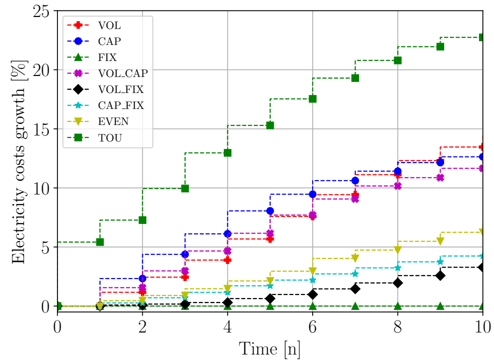
* Prices at time $n = 0$, they linearly decrease over time by 5% each tariff period.

Results

To quantitatively show the evolution of the penetration of actual prosumers over time, Figure 4.1a presents the percentage of actual prosumers with respect to the maximum potential, for each time-step of the dynamical system. Furthermore, to show the evolution of the distribution tariff, driven by Equations (4.32), (4.33), and (4.34), we compute the total costs for consumers, which depict the same evolution as only the distribution component of the overall retail electricity tariff can change over time[3]. We compute these costs at each time-step and normalise them by the initial costs $t = 0$, displaying the evolution in Figure 4.1b.



(A) Penetration of DER in the distribution network as a proportion of the total potential penetration over time.



(B) Growth of the overall electricity cost for consumers over time.

FIGURE 4.1: Evolution of the DER penetration and the electricity prices for consumers over the simulation period.

On the one hand these plots show the effectiveness of each scenario to stimulate the adoption of PV and batteries (i.e. prosumers), and on the other hand the repercussions of such a deployment in terms of electricity costs for the regular consumers of the distribution network. In these examples, all the scenarios with the exception of the one based on only fixed fees (FIX), lead to increased electricity costs. However, the information in these plots is incomplete, since they do not provide any details on how the actual amount of PV and batteries deployed by prosumers. Figure 4.2 shows the total accumulated installed capacity of PV and batteries for each scenario. This information adds to that previously provided by including details of the composition of the prosumers' installations.

Finally, Table 4.3 shows the annual electricity costs for an average consumer and an average prosumer at the end of the simulated period (i.e., at time-step 10). This provides the actual value in EUR consumers and prosumers pay to cover their electricity needs for each scenario.

We can extract a few general remarks from Figures 4.1a, 4.1b and 4.2, and from Table 4.3.

- Tariff structures prominently based on volumetric fees induce a large deployment of PV panels and batteries (mainly the former) as well as rapid transition from potential to actual prosumer. This deployment is followed by an also large growth of the overall electricity costs for consumers. Moreover, these

[3]Note that for this calculation only consumers are used and not prosumers. The reason for this is that the electricity costs of prosumers depend on their DER installations as well as on the distribution tariff, and consequently the evolution described by these costs is not equal to the one described by the distribution tariff alone. Therefore, as our only interest is to show the evolution of the distribution tariff, prosumers can be left out from this computation.

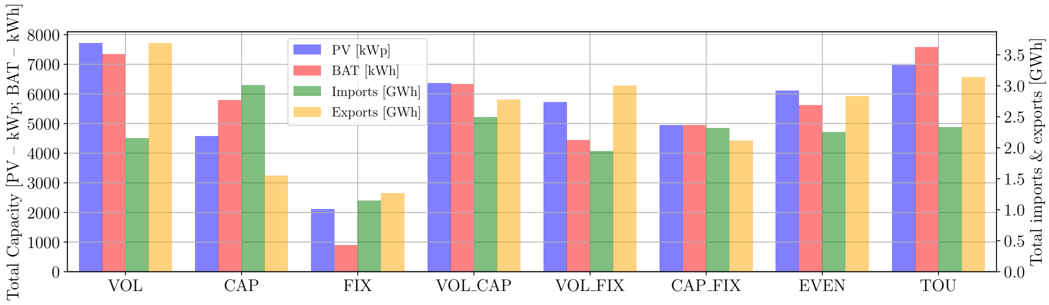


FIGURE 4.2: Total capacity of installed PV capacity (blue), total capacity of installed battery (red), total imports from the distribution network (green), and total exports to the distribution network (yellow) at the end of the simulation period.

TABLE 4.3: Annual electricity costs for an average consumer and an average actual prosumer at the end of the simulated period.

Scenario	Annual consumer costs [€]	Annual prosumer costs [€]
`VOL`	1514.52	1063.21
`CAP`	1491.59	1008.10
`FIX`	1317.79	1235.72
`VOL_CAP`	1487.72	1043.81
`VOL_FIX`	1378.31	1149.53
`CAP_FIX`	1384.60	1139.22
`EVEN`	1415.09	1112.93
`TOU`	1624.50	1085.86

tariffs lead to substantial exports from prosumers' DER installations to the distribution network, owing to larger PV capacities. In addition, these tariff structures lead to substantial inequalities in the electricity costs, in particular when no other component is added to the tariff (i.e., fully volumetric structures such as `VOL` and `TOU`); in these cases the economic burden of maintaining the DSO is mostly carried by consumers.

- When the tariff design is weighted toward capacity fees, the deployment of PV panels and batteries is also spurred, although to a lesser extent and inclines the balance toward more batteries this time. However, the induced increase in electricity costs is larger than in the previous case. The bias of these scenarios toward using batteries is explained by the ability of actual prosumers to shave their peaks (γ_i in Equation (4.5)) thus paying less in capacity fees. This is consistent with the findings in [100]. Moreover, tariffs based on these fees tend to import more electricity than export it – this electricity is stored in the larger batteries to shave the peak demand. Regarding the cost distribution shown in Table 4.3, these types of tariff result in highly unequal distributions, similar to those observed with volumetric fees, where the financial burden of the DSO is born by consumers.

- Adding a fixed term helps reduce the impact on the electricity costs for consumers in either volumetric or capacity fees. However, using purely fixed fees does not seem to promote the deployment of PV panels and batteries, in particular the latter. Balancing several part tariffs results in a trade-off that must be carefully studied (as exposed by P. Simshauser in [35]), falling outwith the scope of our work.

- Using ToU tariffs creates the more extreme outcome – the quickest transition from potential to actual prosumers among all assessed scenarios is only followed by the largest increase in electricity costs for consumers. The incentive to install PV panels is the second largest (after `VOL`), whereas the incentive to install batteries is the largest one. These results are explained by the possibility of actual prosumers benefiting from both PV panels to limit their exposure to the volumetric fees and batteries to shift load from peak and off-peak to shoulder hours ($\rho_t^{(-)}$ in Equation (4.8)). In a similar way as with volumetric fees, ToU fees lead to more exports than imports. However, in this case, the spread between both is smaller, since the electricity surplus with ToU tariffs can be stored in the batteries to shift demand.

Discussion

These analyses show that different initial conditions, notably including various tariff structures, induce vastly different outputs that can be quantitatively assessed. The presented simulation environment can be used to discriminate between the possible outcomes of employing distinct tariff structures. It may therefore be valuable for assessing a distribution tariff structure before putting it in force.

Extracting meaningful conclusions with this tool necessitates a previous tuning phase where the various parameters of the simulation-based approach (e.g., α, prices, bounds $\overline{p}$ and $\overline{b}$) must be adapted to the particular context that one wants to simulate. In this regard, in [44] this simulation-based approach is employed to simulate a generic distribution network with the characteristics inherent to the Walloon region of Belgium, providing policy recommendations for this particular case.

Although the example provided in this section does not correspond to any particular context (i.e., no previous tuning phase has been performed to adapt the simulation-based approach to any particular case), there are a few general observations that can be drawn. In particular, these observations are based on the principles for distribution tariff design, as presented in the CEER report [89] and by I. Abdelmotteleb in [82].

- Distribution tariff designs based on volumetric fees (totally or partially) promote the largest adoptions of PV panels and batteries; however, they lead to the largest inequalities between consumers and prosumers. On the one hand, their implementation is straight forward, complying with the principles of transparency, simplicity, and predictability. On the other hand, they distort the decisions concerning the use of the network, they are not cost reflective (in fact prosumers, who use the network more, end up paying significantly less than consumers), resulting in discrimination among the users where not all of them pay the same for the same service.

- Capacity charges lead to high battery deployment and relatively high PV panel adoption. However, as with volumetric charges, the economic inequalities between consumers and prosumers are substantial. In terms of the tariff design principles, capacity charges are not as predictable, transparent and simple as volumetric ones, and moreover they induce distortion and discrimination among the network users. Finally their cost-reflectivity in already developed distribution networks is questionable, as typically network costs are sunk.

- Fixed fees comply with most of the principles of tariff design (non-distorting, non-discriminatory, transparent, predictable and simple). However, they do not promote the adoption of DER installations, which has been a high-level goal of all energy policies over the last few years (see for instance the European renewable directive [11]).

- Applying ToU charges on top of volumetric ones results in the largest battery deployment and the second-largest PV panel deployment leading to the highest cost different between consumers and prosumers where the former pay substantially more than the latter for their network use. This type of charges is transparent, predictable and relatively simple, although, as volumetric ones, they are not cost-reflective and they distort and discriminate among users.

- Tariffs based on a mix between different types of charge result in a trade-off between promoting PV panels and battery adoption, distributing the costs among the users in a more equal fashion, and complying with the principles of distribution tariff design.

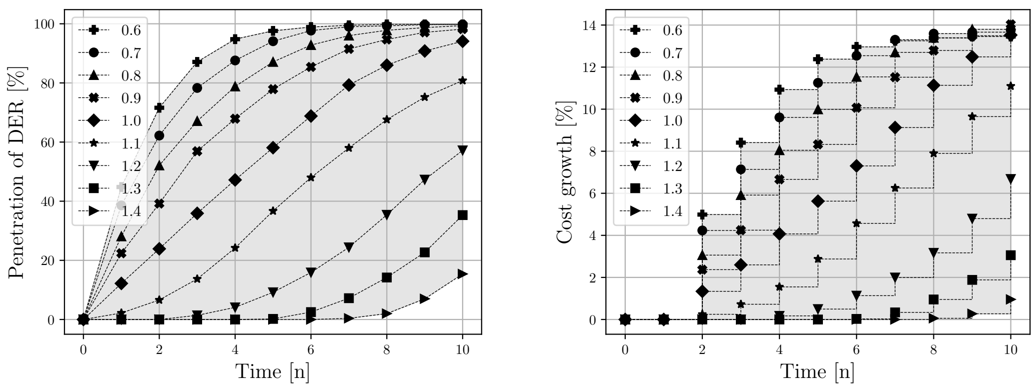
These remarks confirm that selecting the tariff design is not a trivial process, where no perfect tariff exists. In general, applying fully volumetric, capacity, or fixed fees does not seem to yield the most adequate results where either DERs are not promoted, or they are promoted but the costs for it are mostly born by consumers instead of prosumers (who generate them). A solution could be to resort to designs where all these components are present. In these cases, a middle-ground target can be achieved, promoting some DER adoption whilst maintaining a relative level playing field for consumers and prosumers. Overall, promoting DER has a cost associated, and it is the decision of regulators and policy makers to choose how to cover it.

4.5.2 Sensitivity Analyses

In this section, the sensitivity of the proposed simulation-based approach to several parameters is tested. In particular, we perform sensitivity analyses on the α parameter, the selling price of electricity for prosumers (sp), and the prices of PV panels and batteries (tp). For these analyses we use the same basic data listed in Table 4.2, only modifying the parameter we wish to study.

Sensitivity to α

The first of the analyses presented in this section corresponds to the sensitivity to the α parameter, as shown in Figure 4.3 and Table 4.4. As explained in Section 4.4.5, this parameter controls the speed at which the DERs are deployed by potential prosumers. It works by biasing the p parameter of a Bernoulli random variable (i.e. the probability of drawing a 0 or a 1). The p parameter is typically computed as the difference between the LVOE of a DER installation and the electricity costs the potential prosumer would otherwise face without the DER installation. We further develop this definition introducing the α parameter multiplied by the cost difference (see Equation (4.26)). Since the investment decision is inverted (see Equation (4.28)), a low value of α fosters the deployment of DER whilst a high value should limit it.



(A) Sensitivity of DER deployment.

(B) Sensitivity of electricity costs for consumers.

FIGURE 4.3: Sensitivity to α.

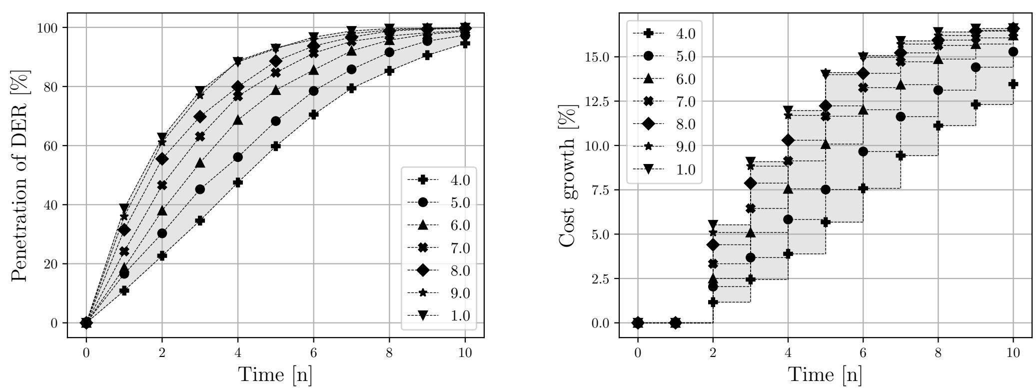
TABLE 4.4: Sensitivity of PV- and battery-installed capacity to α.

	α=0.6	α=0.7	α=0.8	α=0.9	α=1.0	α=1.1	α=1.2	α=1.3	α=1.4
Total PV capacity [kWp]	6,071.4	6,374.6	6,738.7	7,124.9	7,673.1	7,456.1	6,506.9	4,688.2	2,460.0
Total battery [kWh]	6,379.8	6,571.9	6,828.7	7,009.1	7,295.6	6,833.6	5,713.4	4,061.8	2,161.2

As we can observe in these figures, the lower the α, the greater the deployment of DER. This greater DER penetration, in turn, results in a higher increase of the overall electricity cost of traditional consumers. When looking at the total PV capacity and battery capacity deployed, it can be noted that for low values of α the resulting total capacity is lower than for values close to 1. This is explained by the fact that, since the DER installations need to be more profitable when $\alpha = 1$ than when $\alpha = 0.6$ to be deployed (i.e to draw a 0 in the Bernoulli random variable), only large and profitable installations will be deployed. This behaviour results apparent when $\alpha > 1$. However, since in those cases the simulator does not reach 100% of DER deployment, the total DER capacity at the end of the simulation horizon is lower than for $\alpha = 1$. A longer simulation horizon will prove those scenarios to present the largest total deployment of PV panels and batteries. This parameter presents an enormous variability in the outcome; this is why, before making use of the proposed simulation-based approach, it is key to tune this parameter to adapt it to the conditions of the distribution network it aims to simulate, as done in [44].

Sensitivity to the selling price

The second analysis tests the sensitivity of the model to the selling price of electricity of prosumers, as shown in Figure 4.4 and Table 4.5. These users primarily use their local electricity production to meet their demand, however, when there is more production than demand, they can sell this surplus to the distribution network. Modifying the selling price has therefore the potential to affect the behaviour of those users as the value associated to their electricity exports changes.



(A) Sensitivity of DER deployment.

(B) Sensitivity of electricity costs for consumers.

FIGURE 4.4: Sensitivity to the selling price (sp).

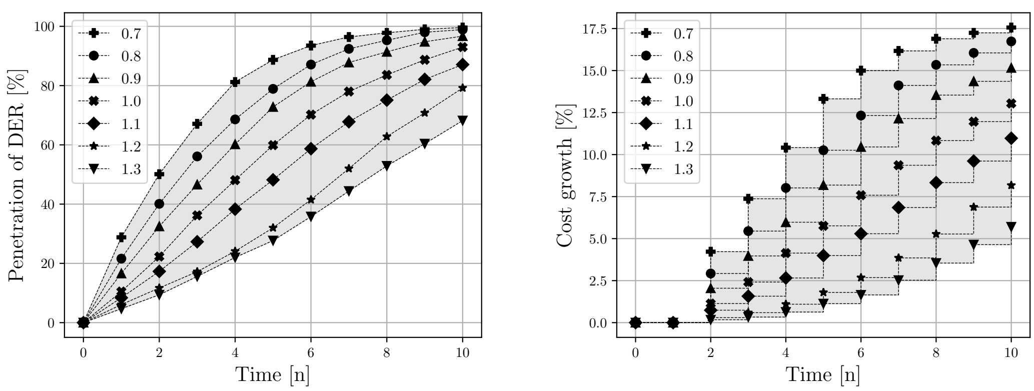
TABLE 4.5: Sensitivity of PV- and battery-installed capacity to the selling price (sp).

	sp=0.04	sp=0.05	sp=0.06	sp=0.07	sp=0.08	sp=0.09	sp=0.10
Total PV capacity [kWp]	7,712.4	8,961.0	9,748.5	9,928.5	9,970.0	9,970.0	9,970.0
Total battery [kWh]	7,339.0	7,484.4	7,442.9	7,384.4	7,293.4	7,217.9	7,204.4

From Figure 4.4a we can observe that higher selling prices leads greater DER adoption and, in turn, to an overall increase in electricity costs, as shown in Figure 4.4b. From the total deployed capacity of PV and batteries (Table 4.5), it can be deduced that the greater the selling price, the larger the PV installation. This relation, nonetheless, is the opposite in the case of batteries, where a higher selling price leads to lower battery adoption. These effects are a result of the business model of these two behind-the-meter devices. A greater PV capacity results in a larger production surplus that can be sold to the network and, therefore, a higher selling price will spur larger PV installations with substantial production surpluses. Larger PV installations will in turn require fewer batteries to operate, since they will produce sufficient electricity to cover the prosumers' demand, even at times where there is a limited solar availability. Even though the selling price clearly imposes some changes in the adoption rate of PV and batteries, these changes are less significant than in our first analysis. The selection of this parameter is easier than the other two (α and technology price) for it should reflect the regulation in place.

Sensitivity to the technology price

The last of the introduced analyses deals with the sensitivity to the technology price. To carry out this assessment, as the starting point we take the technology costs (PV and battery) listed in Table 4.2. We then multiply them by a factor to increase or decrease the initial technology costs, analysing the sensitivity to different factors (costs). Note that these are the initial technology costs, which then decrease by 5% every year. The results of this sensitivity analysis is presented in Figures 4.5 and Table 4.6.



(A) Sensitivity of DER deployment.

(B) Sensitivity of electricity costs for consumers.

FIGURE 4.5: Sensitivity to the technology price (tp).

A linear relation can be seen between technology price and adoption rate of PV and batteries. Unsurprisingly, the higher the price the lower the penetration of actual prosumers and, as such, the lower the impact on overall electricity costs. On the other hand, the lower the technology price, the faster and larger the deployment of

TABLE 4.6: Sensitivity of PV- and battery-installed capacity to the technology price (tp). Note that the shown percentages are relative to the prices used for the first simulation.

	tp=70%	tp=80%	tp=90%	tp=100%	tp=110%	tp=120%	tp=130%
Total PV capacity [kWp]	9,942.0	9,436.6	8,502.8	7,541.1	6,584.7	5,751.9	4,225.1
Total battery [kWh]	8,857.0	8,383.7	7,847.4	7,187.2	6,409.5	5,417.4	3,925.5

DER installations. As expected, this parameter has a strong influence on the shape of the trend curves – it is therefore crucial to find the right level of technology prices.

4.6 Conclusion

This paper formalises and builds a framework based on a simulation-based approach to assess the impact of a wide range of DSO remuneration strategies on the economic sustainability of the distribution network. The potential of this simulation-based approach lies in its ability to accurately discriminate between the possible outcomes of employing distinct remuneration strategies in order to provide sound arguments that underpin the selection of one of them. It therefore serves as guidance for policy makers and regulators to build new remuneration strategies for DSOs, aiming to achieve certain specific objectives (e.g. promote the adoption of renewable distributed generation). By means of this simulation-based tool they can compare the strengths and drawbacks of distinct options before applying them in real life. The proposed simulation environment contributes to the existing literature by:

- Providing the mathematical formalisation of a simulation-based approach based on a dynamical system and on an optimisation framework that progressively deploys DER installations over time and, as a result, adapt the distribution network charges to make sure any imbalance of the DSO is corrected.
- Encapsulating all the most commonly used DSO remuneration strategies –(i) volumetric fees based on energy consumed, (ii) capacity fees based on power withdrawn, (iii) fixed fees based on the availability of a connection point, and (iv) time-of-use fees that depend on the time of energy consumption– in the developed mathematical formalisation of the simulation-based approach.
- Providing a computational tool encoding such a mathematical formalisation to help policy makers and regulators decide which DSO remuneration strategy to employ according to a specific target.

The simulation-based approach presented in this paper is written to be sufficiently generic so that it can adapt to any context (i.e. distribution network) with ease by tuning certain parameters as, for instance, the Bernoulli bias α, or the technology costs. This means that before being used, this tool must be tuned so as to match the distribution network where the experiments are to be run.

The presented approach has been extensively tested with a case study featuring eight different scenarios which illustrate the various options of the proposed simulation environment to guide future developments in distribution network tariff structures. This test case shows how prosumers' choices vary from one remuneration strategy to another, suggesting that it is valuable to check by simulation that a remuneration strategy yields the desired outcome. Although this test case does not intend to offer insights regarding any particular distribution network (i.e. the parameters are set by default), it does provide some guidance on how to design the remuneration strategy of a DSO:

- Strategies based on volumetric fees (including time-of-use) offer the best incentive for PV unit and battery deployment. However, this leads to the highest inequalities between consumers and prosumers in terms of electricity costs.
- Strategies based on capacity fees promote the integration of storage devices as they take action to limit the peak of consumption of prosumers, leading once again to a cost distribution between consumers and prosumers where the former bear most of the network costs.
- Strategies based on fixed fees significantly limit the incentives for DER deployment (PV or battery), therefore they hardly show any impact on the distribution of grid costs.

Furthermore, the sensitivity of the model to several input parameters –the Bernoulli bias α, the selling price of electricity for prosumers, and the technology price– has been reported, showing that the trends remain constant when applying different values to the parameters, only changing in the rate at which DER installations are deployed and electricity prices increase.

Chapter 5

Regulatory challenges in distribution networks: policy recommendations

In this chapter, the third and last of Part I, we make use of the tool developed in the previous two chapters to simulate a real life distribution network based on a specific region – Wallonia, Belgium's southern region. To that end, we calibrate the simulation-based approach introduced in Chapters 3 and 4 to the specific desired regional context. This simulator enables us to highlight how the emergence of prosumers featuring solar photovoltaic (PV) installations impacts the distribution network tariff and how this tariff, in turn, affects the gradual deployment of distributed electricity generation resources (DER) by prosumers.

In Wallonia, the distribution component of the overall electricity retail tariff is essentially volumetric, i.e. based on the final customers' energy consumption (in €/kWh). Residential prosumers, moreover, are connected to the grid via a net-metering system. In this context, our simulation-based approach permits the evaluation of several tariff reforms currently under discussion in this region: the introduction of a prosumer fee, the introduction of a capacity component into the distribution tariff, and a switch to a net-billing metering technology (also known as net-purchasing). Some of these reforms, however, require the use of smart meters, which is infeasible in Wallonia in the short run. Short run reforms, therefore, can only test the prosumer fee, which consists of a fee paid by all prosumers depending on the total installed PV capacity (in €/kWp), as well as adding a fixed term to the tariff. In the long run, the roll out of smart meters enables the introduction of a net-purchasing system and of a distribution tariff with a capacity component. In this chapter we simulate both short and long run reforms using the simulation-based approach introduced in previous chapters. Our analysis highlights one key added value of smart meters: they allow network tariffs that are fairer and sustainable.

5.1 Introduction

Distributed electricity generation based on renewable energy sources has boomed globally in recent years. The deployment of this type of decentralised generation helps decarbonise the energy system. However, since distributed generation units are connected to the distribution network –traditionally designed to unidirectionally distribute electricity from the transmission network to residential areas– they induce challenges to the operation of the electricity system. In particular, they change the nature of energy exchanges within the distribution network, which are now bidirectional as households deploying solar photovoltaic panels on their rooftop not only import but can also export electricity. In light of this paradigm change, regulatory interventions related to how these flows are measured and priced are key in the emergence of a more sustainable energy system. For that reason, reforms of the distribution tariffs are on the agenda in many jurisdictions.

The situation of Wallonia, Belgium's southern region, is particularly interesting in many respects. Households have made substantial investments in decentralised energy production sources over the last few years. By the end of 2019, despite a relatively low solar irradiance, over 10% of the households had installed solar PV panels and became *prosumers*. This large adoption of PV installations can be explained by two main factors: (i) subsidies and (ii) network regulations. First, generous upfront investment subsidies (either in the form of direct financial support or in tax cuts) as well as production subsidies, mainly via a green certificate system [101], were granted by various jurisdiction levels. Second, favorable network regulations for prosumers helped substantially decrease the electricity bills of PV owners at the household level. According to these network regulations, distribution tariffs in Belgium were (and still are) predominantly based on units of energy consumed, that is, volumetric fees typically in €/kWh. In addition, prosumers are integrated into the grid via a net-metering system, where the exports of electricity are registered by subtracting from the meter the units of energy injected into the grid (which in practice means that the solar production is valued at retail price). In such a context, investing in PV panels substantially decreased the prosumers' electricity bills, as their meters readings, and thereby their electricity bills, could be greatly reduced.

This high take-up rate of PV adoption led to a tense debate in the public and political arena. From 2016 to 2019, 40 out of the 93 Energy Commissions of the Walloon Parliament discussed issues related to prosumers. Since 2018, all forms of subsidies have been phased out for new PV installations. However, the current network regulations have barely changed. One key issue facing the regulator is that Wallonia is lagging behind other European regions in terms of smart meter adoption [102]: as yet, albeit there is a regional target coverage of 80% of households by 2030, few smart meters have been installed [103]. This is 10 years behind the goal set by the 2009 Electricity Directive set at the European Union level. Hence, the mechanical single meters, i.e. the technology in place, limit the way distribution costs can be billed to the grid-connected users, and only the structure of the tariffs can be changed, e.g. by relying more on fixed fees rather than on volumetric ones. Fixed fees can be applied to all users or to prosumers only. The switch to new bi-directional meters for prosumers (mechanical or smart) will make it possible to consider a different price for electricity imported from and exported to the grid, via a net-purchasing system. The roll-out of smart meters will in addition facilitate the introduction of capacity fees (based on units of power withdrawn from the grid, typically in €/kW). Facing a similar policy context in Flanders, Belgium's northern region, The VREG, the energy regulator, decided to switch towards capacity-based starting from 2022 on [104].

This chapter analyzes how different distribution tariff regulations impact the consumption, production, and (possibly) storage behaviors of residential households. For this purpose, we rely on a tariff simulator developed by [30] and we use regional-specific load and solar irradiance profile curves to apply the model to the case of Wallonia. Compared with other simulators used in [105] or [31] to study a related research question, we use an agent-based modelling approach incorporating the region-specific consumption and production profiles of several thousands of heterogeneous households. This simulator enables us to evaluate the impact of various changes in regulation with respect to PV and battery investments, the evolution of distribution network tariffs, the levelised value of electricity (LVOE) of prosumers and non-prosumers, as well as the formers' rate of self-consumption, and the peak power withdrawals and injections. Our work highlights the importance of considering both the distribution tariff design and the technology connecting all electricity users to the network, as only a subset of tariff regulations can be implemented in the absence of smart meters. And, even if our simulations are computed to represent the specific situation of one region, our policy conclusions carry further away to other legislations that want to adapt their distribution tariff to integrate distributed generation.

This chapter is organised as follows. In Section 5.2, we review the literature on the integration of distributed generation into the grid. In Section 5.3, we describe the current distribution network regulations in place in Wallonia. The tariff simulator is presented in Section 5.4. Section 5.5 analyzes the regulatory scenarios implementable with the metering technology in place. Section 5.6 describes the regulatory reforms and their impact that can be set in the long run with a change of meters. Section 5.7 concludes our work.

5.2 Literature review

Our work relates to the literature focusing on the relationship between the emergence of decentralised generation units and the financing of the distribution system, in the context of an unbundled energy system. In the face of decreasing volumes of the electricity sales owing to the presence of prosumers, the distribution system operator (DSO) requires a higher distribution tariff level in order to break-even [37]. However, as expounded by [106] and [33], such a reform, in a context of largely volumetrically based tariffs, makes PV investments even more profitable, further leading to inefficiently large investments in solar PV. This unsustainable financing of the grid is often referred to as the utility death spiral [35].

Our numerical model follows up on the works focusing on this feedback loop to analyze different distribution network regulations. While our conclusions are similar to the works previously done on this topic, we contribute to this literature by better fitting our model with respect to the policy context studied, the Walloon Region, on three different levels.

First, compared to [31] and [32], we use an agent-based modelling approach that considers a large amount of residential households. The energy consumption and production profiles of 6000 heterogeneous households are considered. Thanks to this approach, we are able to make more realistic predictions regarding the decision to invest in PV panels and batteries, including regarding the size of these investments. Similar to the work of [105], our simulator allows us to discuss how tariff regulations impact self-consumption and peak power withdrawals. In addition, we also analyze how peak power injections, a key cost driver for a DSO, are influenced by network regulations.

Second, the policy setting is greatly influenced by the metering technology in place. The issue of death spiral is particularly important when a net-metering system is in place, as the energy exported to the grid is sold at the attractive retail price. This is the current metering technology in Wallonia[1]. Hence, the simulator used in this chapter is closely related to the ones developed in [74, 108, 109] to analyze network regulations in respectively California, Colombia and New South Wales Australia [2]. Compared to these works, we differentiate the implementable regulations in the short and long run, depending on the available metering technology. In the short run, only the tariff structure can be changed, for all on only a subset of energy users. In the long run, a net-purchasing system can replace the net-metering system to set different prices for the electricity imported from or exported to the grid. In addition, smart meters, will allow complex tariff structures such as capacity-based one. Hence, we believe that it is important to differentiate short run, second best, regulations from long run ones that can take advantage of the technological features of more evolved meters than those currently in place that record flows only with a single meter.

Third, we calibrate our simulator to the context of Wallonia, though not just with respect to the solar irradiance and the typical production profile, as traditionally

[1]Note that a net-metering system is also in place in a majority of U.S. states, in European countries like Denmark, Netherlands, Greece, Hungary or Latvia as well as in various lesser developed countries like India or Brazil (see [107]).

[2]In comparison, the following papers [110, 111, 112] present a simulator suited respectively for Queensland Australia, Portugal, UK and Germany where a net-purchasing system, coupled with a feed-in tariff, is currently in place.

done in the literature. In this regard, our simulator is parameterised in such a way that the impact of a distribution tariff increase on the decision to invest in a PV installation be similar to the one measured in [75] using PV installation data in Wallonia.

We trust that these three key aspects allow robust policy conclusions.

5.3 Distribution network tariff and the integration of residential solar PV in Wallonia

Distribution tariffs in Wallonia have been regulated by the regional regulator (CWaPE) since 2014. The regulator uses a cost-plus methodology to fix the distribution tariff. There are 7 DSOs and 13 tariff zones, where the distribution tariff levels vary substantially between zones. The tariff structure, however, is similar in all zones, with a distribution tariff that is essentially volumetric (in €/kWh), and which includes very small fixed fees (around 20 € per household per year, covering the rental of the meter). The other components of the electricity bills (transmission, energy, taxes and other levies) are also based on the consumption level in kWh. Some retailers also include a relatively small fixed fee in their contracts. In 2018, the volumetric part of the distribution tariff ranged from 7.3 c€/kWh to 14.9 c€/kWh, with an average tariff equal to 11 c€/kWh. In Wallonia, the distribution tariff represents 36% of the consumer's final electricity bill, including VAT [113]; this relatively large share can be explained, at least partially, by the large public service obligations imposed to the DSOs, which include public lighting, social energy tariffs, and the promotion of renewable energy integration.

In Wallonia, almost all meters are mechanical and PV adopters connect their PV installation to the existing meter. Prosumers then have a single meter that runs forward when electricity is imported from the grid, and backward when it is supplied to the grid. To switch to net-purchasing with a different price for power injections and withdrawals, prosumers need to change their metering technology. They can either install a second mechanical meter to register power injection or a smart meter. Smart meters can measure power in addition to energy, thus enabling the introduction of more sophisticated tariff designs such as adding a capacity-based component to the tariff.[3]

Over the current regulatory period (2018-2022), the regulator introduced a prosumer fee in October 2020 [114]. This fee is to be paid by the prosumers in contribution to the network costs. Such a fee is based on the PV capacity of each prosumer,

[3] Smart meters still have other advantages that we do not consider here, e.g. the possibility of having time-of-use tariffs. As consumption is recorded almost instantaneously, the tariff can be adapted to follow the trends of the wholesale market price. Our scenarios do not consider such a pricing but only time-independent distribution network fees and electricity prices. For the time being, meters measure net consumption on a yearly basis. Negative meters could also be reset to zero on a weekly or monthly basis. Our main reason for not discussing these changes is that, to our knowledge, there is no discussion to date of implementing such tariffs in Wallonia. This standpoint might change in a foreseeable future as the Electricity Directive [11] requires Member States to implement dynamic electricity price contract whenever smart meters are installed.

and is computed to compensate the avoided distribution network fees assuming a self-consumption rate of 37.76%. Its level depends on the tariff zones, but is on average equal to 85 €/kWp per year. Prosumers have the option to opt-out and install a dual meter (net-purchasing) and pay the regular distribution tariff for their electricity imports.[4] However, while it is useful to measure the concomitance of decentralised production and consumption, the roll-out of smart meters has been slow compared to the targets set at the EU level and the adoption rates of other Member States. The goal is to have 80% of users of the energy network equipped by 2030. [5]

5.4 Tariff simulator

We rely on a multi-agent model to simulate the impact of distribution tariffs on residential consumers' investments in PV modules and batteries. The model is introduced in [43] and described in further details in [30]. We present the main ingredients of this model in Section 5.4.1, and the main assumptions on which it relies in Section 5.4.2. We describe the simulated scenarios in Section 5.4.3.

5.4.1 Model description

This simulation-based approach relies on a discrete time dynamical system with two types of agents, the users and the Distribution System Operator (DSO), which interact with each other for a given regulatory environment. Users are classified into three categories of agents: consumers, potential prosumers, and prosumers. The interaction between the different categories is represented in Figure 5.1.

The model is composed of several modules: an individual optimisation module (OPT) that for each potential prosumer computes the levelised value of electricity (LVOE), given their consumption and production profiles and the regulatory environment in place. The LVOE differs from the traditional levelised cost of electricity (LCOE) in that the LCOE only accounts for costs (i.e. it is computed as discounted costs divided by discounted aggregated demand), whereas the LVOE accounts for costs and revenues (i.e. it is computed as discounted costs minus discounted revenue divided by discounted aggregated demand). The second module models the investment decision process (IDP), where the comparison between the LVOE of each

[4] There is currently a disagreement between the regulator and the regional government on this prosumer fee. For political reasons, the latter wants to compensate the prosumers for the introduction of the fee. As of today, it is not clear how the government plans to do so, except that it wants corrective measures to encourage self-consumption.

[5] There are two other regions in Belgium. The situation in Flanders is very similar to the one in Wallonia where a prosumer fee has already been implemented since 2015 [115]. One key difference is that the roll-out of smart meters will soon be completed and that capacity tariffs, similar to the ones discussed here, will be implemented from 2022 on [104]. However, note that, in the energy decree modified in 2019, the Flemish government has committed to maintain the net-metering system as a way to value energy flows, for at least 15 years starting from the date of the PV installation. In Brussels, a densely populated region with mostly shared rooftops, PV investments have been scarcer and a net-purchasing system is in place where the import price of electricity is slightly higher than the export price.

individual potential prosumer and the retail electricity price determines the probability that they invest and become actual prosumers. The last module represents the remuneration mechanism (RM) of the DSO – it computes the adjustment of the distribution network tariff performed by the DSO as a consequence of PV (and/or battery) investment. In this regard, the tariff is adjusted so as to cover the costs of the DSO.

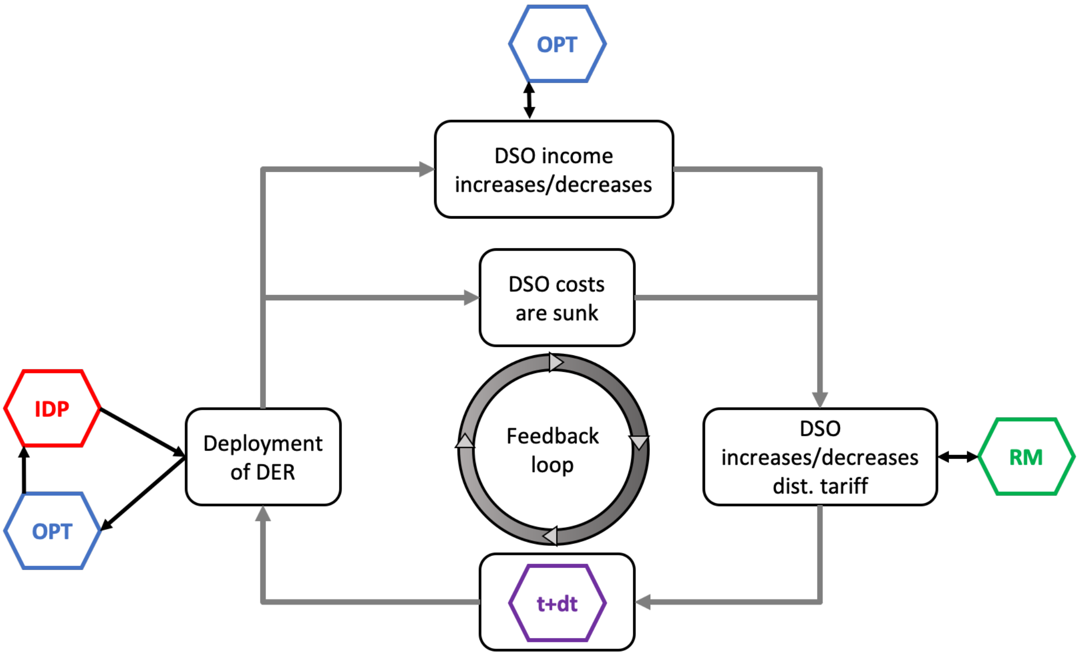


FIGURE 5.1: Multi-agent interaction model with the feedback loop created by the deployment of residential PV panels and by the DSO's remuneration mechanism.

Consumers and Prosumers

At the start of the simulation, there are no prosumers and all users draw electricity from the distribution network. However, as the simulation proceeds over the discrete time dynamical system, a subset of users, i.e. potential prosumers, take action to gradually deploy optimally sized PV installations and batteries, thus becoming prosumers. A potential prosumer turns into an actual prosumer depending on the difference between the LVOE and the actual electricity costs without PV installation and on an exogenous probability. We use the results of Gautier and Jacqmin (2020) to calibrate this probability. On the basis of data from residential prosumers in Wallonia, these authors estimate, by means of an econometric analysis, the elasticity of investment in solar PV due to an increase in the volume-based tariff and, therefore, of the electricity price. They estimate that a 1 c€ increase in the price of electricity increases the probability of investment in a PV installation by 8%. We then created a scenario mimicking the conditions observed in [75], called baseline. In this scenario, an increase of 1 c€ in the price of electricity for the initial period leads to an increase in PV investment by 8%. Then from the second period on, this probability evenly decreases as the deployment of PV installations converges to 100% of the potential prosumers (see benchmark in Section 5.5). Once a user has invested, thus becoming a prosumer, this agent is removed from the subset of potential prosumers and added to the subset of prosumers, which prevents further investment from this particular user.

DSO

The DSO is a regulated entity. The distribution tariff is set by the regulator and computed to a sufficient level so as to cover the costs deriving from the provision of the electricity distribution service. In our model, there is no explicit cost modelling for the DSO. We consider the distribution costs to be constant over time and equal to their historical value. Hence, we model the financing of the DSO as a zero-sum game: the fixed cost of the DSO must be covered and the different grid tariffs will allocate relatively more or less of this cost to a category of consumers or another. Prosumers' investments in PV installations then change the revenues of the DSO, since these are less reliant on the imports of electricity from the distribution network, but they do not change the grid costs[6]. At every time step of the discrete time dynamical system, the DSO then is allowed to adjust the distribution tariff in order to cover its cost (i.e the DSO must break even and the regulator allows it to increase the tariff to this purpose). The DSO, however, is constrained by the tariff structure, which cannot be changed. Tariff changes then impact electricity costs by typically increasing them, and hence the incentives to invest. Thus, there emerges a feedback loop between the prosumers and the DSO, which is illustrated in Figure 5.1.

5.4.2 Main assumptions

Table 5.1 reports the main parameters used for running our simulations. The parameters are calibrated to represent the tariff and electricity prices in Wallonia as well as reasonable estimates of PV and battery prices and their evolution. In addition, we use solar irradiance data from Wallonia and standard consumption profile curves for representative consumers for the region. These load profiles have been generated by detailing a household's list of electric appliances and other characteristics. In total, we generated 1000 load profiles, corresponding to different configurations of electric appliances and inhabitants per household using the CREST Demand Model [98]. These profiles represent 1000 potential prosumers. In addition, 5000 consumers are introduced by using an average yearly load of consumers in Wallonia. Thus, the total population size is 6000 (5000 consumers and 1000 potential prosumers). While potential prosumers may become prosumers over the time of the simulation, the 5000 usual consumers are regarded as the residual load of the distribution network, representing those users who cannot become actual prosumers due to technical or

[6] In practice, the deployment of solar PV modifies the power injections and withdrawals on the grid and thereby impact the grid cost. We discuss further this issue in Section 5.6.3.

economic constraints. The set of potential prosumers and its size depend on the characteristics of both the habitations (apartment vs. houses, rooftop size and orientation) and the households (renters vs. owners, income, etc.).

In Wallonia, around 40% of the houses are detached and 66% of the households are owners. There is, however, a lack of reliable data for PV adoption in Wallonia because all subsidies for solar PV installations have been phased out only recently (July 2018) and previous adoptions were massively subsidised. Hence it is difficult to benchmark it with historical data. The comparison with Flanders, a region that bears many institutional similarities with Wallonia, makes us confident that our model provides a good approximation. There, subsidies were suppressed earlier and we observed that, on average, 0.8% of the households installed PV each year, during the period 2016-2018. This adoption rate was slightly increasing over the period and was 1.07% in 2018. If this rate is kept constant over 10 years, we would have that 10.7% of the households representing 64.2% of the potential prosumers turn to prosumers at the end of the estimation period. As Flanders applies a prosumer fee, the closest scenario to represent the situation in Flanders is the net-metering system with a prosumer fee (NM_{fee} in the subsequent analysis). In our estimations, we find that around 90% of the potential prosumers turned to prosumers in this scenario. This makes us believe that the potential prosumer set is not undersized and the diffusion of PV investments approximates well historical data.

The simulation-based approach is run for 10 periods, each of which corresponds to one year. At the end of each period, the simulation-based approach retrieves the amount of potential prosumers and of prosumers, the capacity of deployed PV panels and batteries, and the distribution tariff level, among other parameters (see Table 5.1 for a detailed list of the parameters). Then, the simulator starts the simulation of a new period using as starting conditions, our exogenous parameters set initially and the endogenous parameters retrieved from the previous period. Table 5.1 indicates the initial conditions used for the first step of the simulation.

TABLE 5.1: Key parameters of the model

Commodity price (€/kWh)	0.132
Initial distribution tariff (€/kWh)	0.088
Selling price (NP) (€/kWh)	0.040
Population size	6000
Potential prosumers	1000
Initial PV Price (€/kWp)	1500
Initial battery price (€/kWh)	300
Yearly change PV price (%)	-5
Yearly change battery price (%)	-5
PV lifetime (years)	20
Battery lifetime (years)	8
Charging rate (in C.)	4
Discharging rate (in C.)	2.5
Interest rate (%)	2

5.4.3 Simulated scenarios

We use the simulator to generate six different scenarios, four with the net-metering (NM) system and two with the net-purchasing (NP) system. We consider different tariff structures, mixing fixed (Fix), volumetric (Vol), and capacity (Cap) elements for the distribution tariff. The selected scenarios discuss the most likely reforms of the tariff structure that are being considered in Wallonia. These scenarios are summarised in Table 5.2. The first three scenarios can be implemented with the current single meters whereas the other three require a change in the metering technology. Scenario 5 can be implemented by installing an additional mechanical meter to the one currently in place or a smart meter. In addition, smart meters also allow the implementation of scenario 4 and 6 with the inclusion of a capacity component in the tariff.

For each scenario, we report the following elements: (i) the percentage of potential prosumers who invested in solar PV and/or batteries, thus becoming prosumers; (ii) the installed capacity of solar PV (in kWp); (iii) the installed capacity of batteries (in kWh); (iv) the mean LVOE of the prosumers; (v) the percentage increase in the electricity costs for the traditional consumers, calculated as the mean percentage increase among the traditional consumers; (vi) the percentage of self-consumption i.e. the share of electricity produced by the PV installations that is consumed on site by prosumers; the peak demand withdrawn from the network; and (vii) the peak production injected into the network.

TABLE 5.2: Simulated scenarios

Number	Scenarios	NM/NP	Tariff structure
#1	Baseline	NM	Vol (100%)
#2	NM_{fee}	NM	Vol(100%) + prosumer fee (85 €/kWp)
#3	NM_{fix}	NM	Vol (70%), Fix (30%)
#4	NM_{cap}	NM	Vol (50%), Cap (50%)
#5	NP_{vol}	NP	Vol (100%)
#6	NP_{cap}	NP	Vol (50%), Cap (50%)

5.5 Benchmark and short-term reforms

We set out considering three basic scenarios that can be easily implemented in the short-term, without a change in the metering technology. The current net-metering technology in place exclusively and mechanically registers the yearly energy net consumption. In this context, few reforms are possible. The simplest ones consist in rebalancing the structure of the distribution tariff bill to decrease the volumetric part, and as compensation, adding a fixed fee, either applied exclusively to prosumers or applied to all consumers.

We consider the scenario baseline as a benchmark. This scenario simulates the current situation in Wallonia. We then consider two scenarios where, in addition, non-volumetric fees are introduced.[7] In the first, prosumers pay a fee linked to the installed power of their PV installation (scenario NM_{fee}). This reform is applied since October 2020 on with an average prosumer fee of 85 € per kWp of PV installed. In the second scenario, there is a fixed fee imposed to all users, prosumers and consumers (scenario NM_{fix}) alike. In this case, we consider that the fixed fee must cover 30% of the distribution network costs, the remainder being covered by a volumetric tariff. This threshold has been defined to match the average tariff structure currently applied in Europe [117].

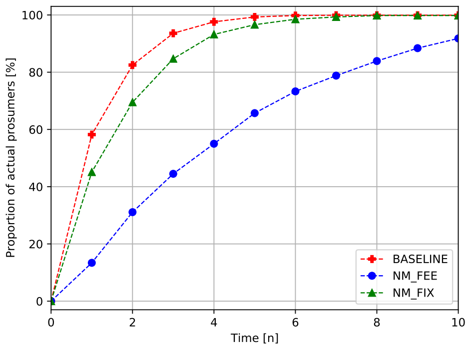


FIGURE 5.2: Evolution of the share of prosumers among potential prosumers.

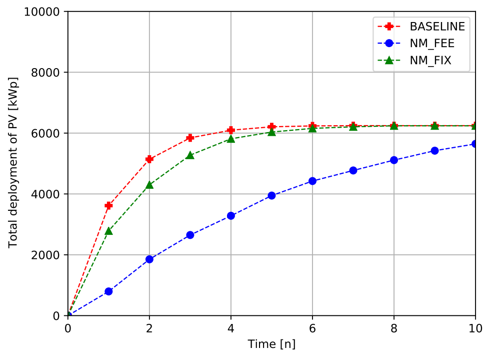


FIGURE 5.3: Evolution of the installed capacity of PV installations.

As shown in Figure 5.2, the baseline scenario is the more favorable one for PV investments given that the electricity generated by the PV panels is valued at the retail tariff, which includes the price of the commodity as well as the distribution/transmission fees and taxes. Unsurprisingly then, by the 5^{th} of the 10 periods considered, nearly all potential prosumers had already deployed a PV installation. Figure 5.3 shows that this scenario is the fastest one to reach the full potential deployment of PV capacity.

The large and rapid deployment of solar PV panels reduces the total consumption registered by the DSO (as the meter runs backward for prosumers) and, to cover the DSO costs, the volumetric fee, as well as the fixed fee for scenario 3 must be increased by the regulator. Figure 5.4 shows that the overall cost of electricity increases by around 30% at the end of the 10 periods for traditional consumers. These consumers have to bear a larger proportion of the grid costs. As this upward change

[7] We will focus on distributional issues between prosumers and traditional energy users. However, as, on average, low income consumers tend to consume less electricity, increasing the fixed part of the bill can be detrimental to low income consumers, who are also less likely to invest PV as they are typically tenants and face a binding financial constraint. This other dimension of the distributional issue can be problematic especially in the scenario NM_{fix}. However, as discussed in [116], it is possible to design fixed charges based on demand characteristics or income to mitigate the regressiveness related to fixed charges.

in tariff makes investing in a PV installation even more favorable to potential prosumers, the financing of the DSO is not sustainable and we can observe what is traditionally referred to as the utility death spiral.

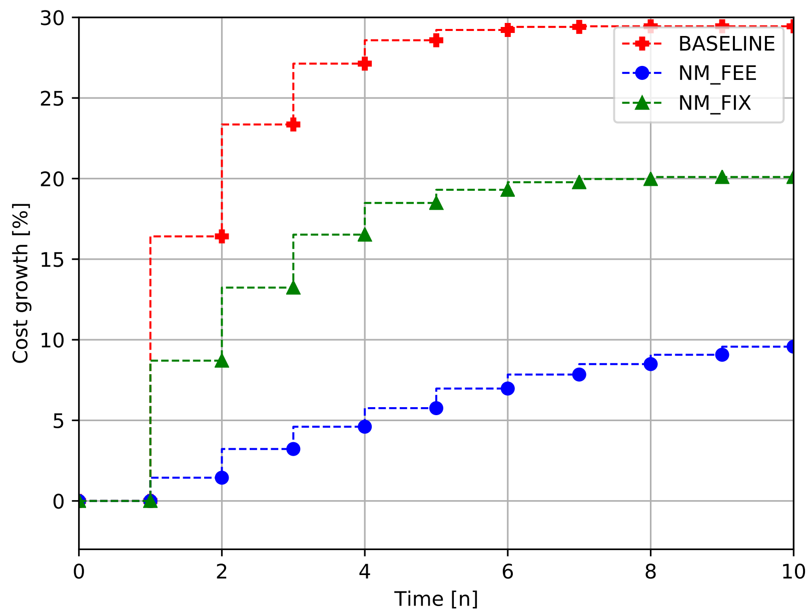


FIGURE 5.4: Evolution of the total tariff bill of a consumer

Introducing either a prosumer or a uniform fixed fee aims at decreasing the volumetric component of the distribution tariff, and hence the benefit of net-metering. Consequently, solar PV installations are less attractive and the rate of investment is, by and large, lower, as seen in Figure 5.2. In Figure 5.3, a similar trend is observed for the installed capacity of PV. In the NM_{fee} scenario, the fee does not apply to the historical installations but only to the new ones, which implies that the initial tariff is equal to the tariff in the baseline scenario. In this case, the distribution tariff increases less compared to the benchmark (see Figure 5.4) because, on the one hand, there are fewer PV installations, and, on the other, prosumers pay a fixed fee that partially compensates the loss of revenue of the DSO due to the meter rolling backward.

The prosumer fee reduces the rate of investment by prosumers. In the baseline scenario, over 80% of the potential prosumers have invested after two periods while in the NM_{fee} scenario, less than 30% have made such an investment. By the end of the simulation horizon, in the NM_{fee} scenario, 90% of the potential prosumers have invested. This value, although similar to that of the baseline scenario, requires about six or seven periods more than the baseline scenario. Note that with an increase in potential prosumer population, the final values for both scenarios would tend to differ more. Finally, the introduction of a uniform fixed fee (NM_{fix}) hardly has an impact on the deployment of PV installations and simply serves as a re-distributive tool to share the grid costs between prosumers and traditional consumers differently.

The key driver of these results is that the prosumer fee substantially increases the LVOE of PV installations, as pictured in Figure 5.5. Especially, we can observe that, under the NM_{fee} scenario, the mean cost is 81% higher than in the benchmark baseline scenario. With a uniform fixed fee, as in the NM_{fix} case, the mean increase is limited to 27%. The corollary is that the cost for non-prosumers is lower in the NM_{fee} and NM_{fix} scenario compared to our benchmark case. Hence, the cross-subsidisation of prosumers by traditional consumers via the grid financing system is lower than in our benchmark case.

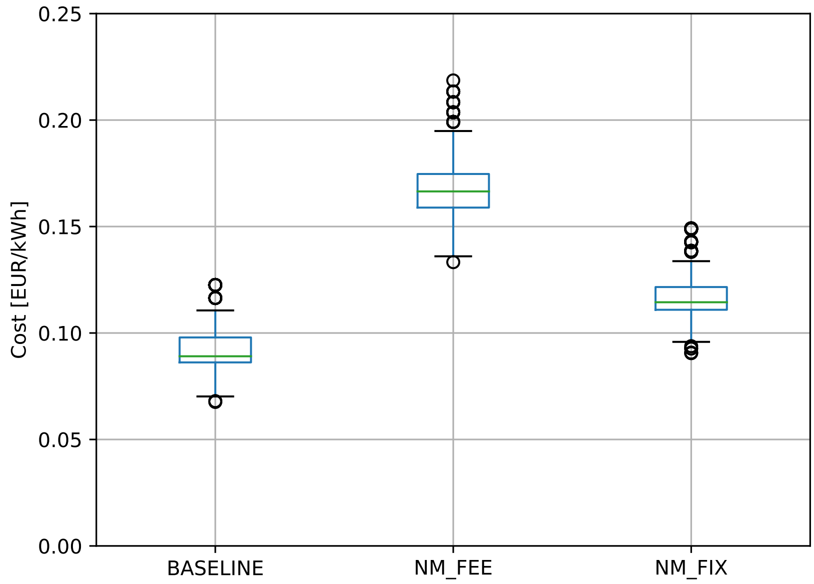


FIGURE 5.5: Evolution of the LVOE of PV installations.

The following point still needs mentioning: in none of the three scenarios do we observe the deployment of batteries. Under net-metering, the grid acts as a giant storage facility since exporting electricity and storing it into a battery offers the same monetary value. In fact, deploying a battery will make the users lose some energy owing to the round-trip efficiency of batteries. In such a setting, residential batteries offer no added value to this kind of investment, given that the price of electricity consumed and sold is the same.

5.6 Long-term reforms

Other metering technologies, like the installation of an additional meter to record the energy exported to the grid or a smart meter, allow for a larger set of feasible tariffs for financing the grid. They allow to price differently the imports and exports of energy. Smart meters can measure and record energy consumption not only on a yearly basis but also in short intervals, such as every 15 minutes, and be remote-controlled. As a consequence, they can record the peak consumption over the short interval measured (the shorter the interval, the more accurate the measurement).

We consider two kinds of structural regulation taking advantage of these metering technologies. The first one looks into changing the tariff structure and allowing for capacity fees in addition to the traditional fixed and volumetric distribution tariff fees. The second one looks into the possibility of switching from a net-metering to a net-purchasing system.

With net-metering, imports and exports of electricity are not differentiated in terms of prices. Hence, there is no monetary incentive to self-consume and, as shown above, prosumers do not invest in residential batteries. By measuring electricity imports and exports separately, a net-purchasing system makes it possible to differentiate the prices of the two flows. This, in turn, changes the incentives to invest both in solar PV and storage systems. Furthermore, consumers may adapt their behavior to increase their self-consumption, e.g. by shifting demand to synchronise consumption and production.

In the net-purchasing case, we consider that the price of exported electricity is equal to the average of the wholesale electricity price (around 40 €/MWh) and there is no distribution fee collected on exported electricity[8]. The electricity imported by prosumers is charged at the same price as for traditional consumers.

5.6.1 Net-metering system with a capacity component

In the NM_{cap} scenario, the distribution tariff is half composed of a volumetric fee and half of a capacity fee. The capacity fee is based on the peak consumption (in kWp) recorded during the billing period. With a capacity fee, a battery can be used to shave the peak consumption by displacing consumption from peak to off-peak hours. This investment may drastically reduce the prosumers' bills. In this scenario, prosumers are still connected to the grid via the net-metering technology.

As shown in Figures 5.6 and 5.7, the change in the tariff structure only slightly curbs the deployment of solar PV compared to the fully volumetric case presented in our benchmark baseline scenario. A major difference is that we now observe the deployment of batteries (see Figure 5.8). This evolution, however, is rather limited in size and is only observed from period five on (due to lower technology costs and increasing volumetric charges). While the presence of a net-metering system provides no incentive to invest in batteries, we observe that batteries enable prosumers to shave their peak production, i.e. to decrease their electricity bill, which is partially capacity based.

[8]Increasing the purchasing price of electricity above the wholesale price increases the incentives to invest in a PV installation, but decreases the incentives to invest in a battery. With a purchasing price equal to the retail price, the net-purchasing scenario would be equivalent to the baseline scenario. At least, this would be so provided that the amount of electricity that can be exported is capped to the level of electricity consumed on a yearly basis.

Compared to our benchmark, the capacity fee scenario (NM_{cap}) increases the LVOE for prosumers, but to a relatively lesser extent than when a prosumer fee is implemented, as considered under the NM_{fee} scenario (see Figures 5.5 and 5.9). In Figure 5.10, the electricity tariff paid by traditional consumers increases almost in the same proportion as in the baseline scenario. This can be explained by the fact that non-prosumers do not have the possibility to displace their peak production by using batteries. Therefore we observe, as in the benchmark, that a larger fraction of the grid costs are paid by non-prosumers.

5.6.2 Net-purchasing system

A net-purchasing system can be implemented by the installation of an extra mechanical meter or of a smart meter. We consider two scenarios: a fully volumetric distribution tariff (NP_{vol}), and a tariff combining capacity and volumetric terms (NP_{cap}) with an equal contribution of the two components to the grid costs. The latter is only possible in the presence of a smart meter. Thus, the tariff structure of NP_{vol} is the same as in the baseline scenario and the one of NP_{cap} is the same as in scenario NM_{cap}.

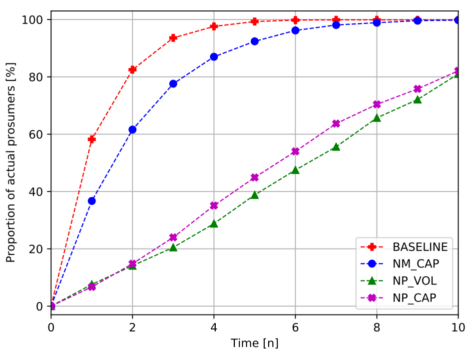


FIGURE 5.6: Evolution of the share of households with a PV installation.

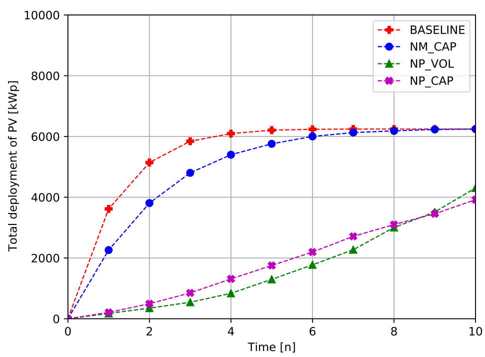


FIGURE 5.7: Evolution of the installed capacity of PV installations.

In figures 5.6 and 5.7, we observe that the two net-purchasing scenarios lead to a lower number of PV installations than under any net-metering system. At the end of the 10 periods considered, we find that 79% and 85% of the potential prosumers have become actual prosumers under the NP_{vol} and NP_{cap} scenarios, respectively. The growth trend of the investments made is constant and similar across the 10 periods considered. In terms of deployed PV capacity, both scenarios display a similar total installed capacity. This is because a volumetric tariff induces a larger average installation size but fewer installations.

The high deployment of batteries is another key difference between the net-metering and the net-purchasing scenarios, as Figure 5.8 shows. Under the NP_{vol} scenario, over 3000 kWh of batteries are installed, while under the NP_{cap} scenario

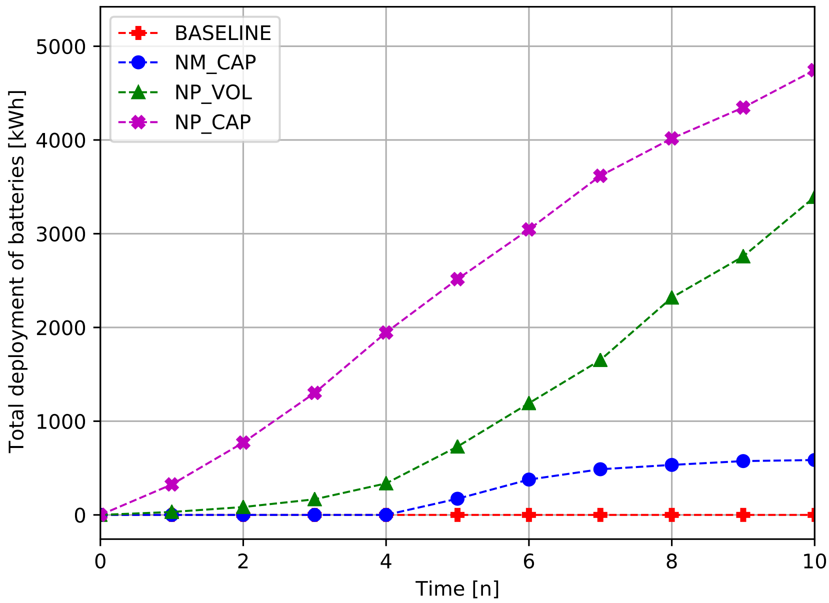


FIGURE 5.8: Evolution of the deployment of batteries.

5000 kWh of storage capacity is available. In addition to a slightly lower LVOE under the NP_{cap} scenario than under the NP_{vol} scenario (see Figure 5.9), the different reasons behind the decision of investing in batteries explain the differences in the number and size of the batteries installed in these two scenarios. Under NP_{vol}, batteries are installed because, financially speaking, it is more advantageous to store (and later consume) electricity than to sell it to the grid at selling price and later consume it at retail price. Under NP_{cap}, in addition to the previous reasons, there are additional incentives to invest in storage as batteries help reduce the electricity bill by shaving the peak demand. This behavior, moreover, is rational and relatively simple to explain from the prosumer standpoint.

Overall, switching to a new metering technology that differentiates the price of electricity imports and exports (i.e. net-purchasing instead of net-metering), as well as switching to distribution tariffs based partially on capacity components, leads to a lower amount of PV installations. This change can slow down our transition to a decarbonised energy system. However, the diffusion of panels is more even out over the years. The extent of the cross-subsidisation of prosumers by traditional users via the financing of the grid is less present. Prosumers, besides, are far more likely to invest in storage devices such as batteries, and the more so when capacity fees are in place. Finally, it is important to mention that the net-purchasing system offers an additional degree of freedom by making it possible to adapt the selling price of electricity. In our work, we have considered a rather small selling price, set at the commodity price (average wholesale market price). Choosing a higher selling price makes it possible to encourage more PV investments. This, though, would induce lower investments in storage devices and an increasingly unequal electricity bills

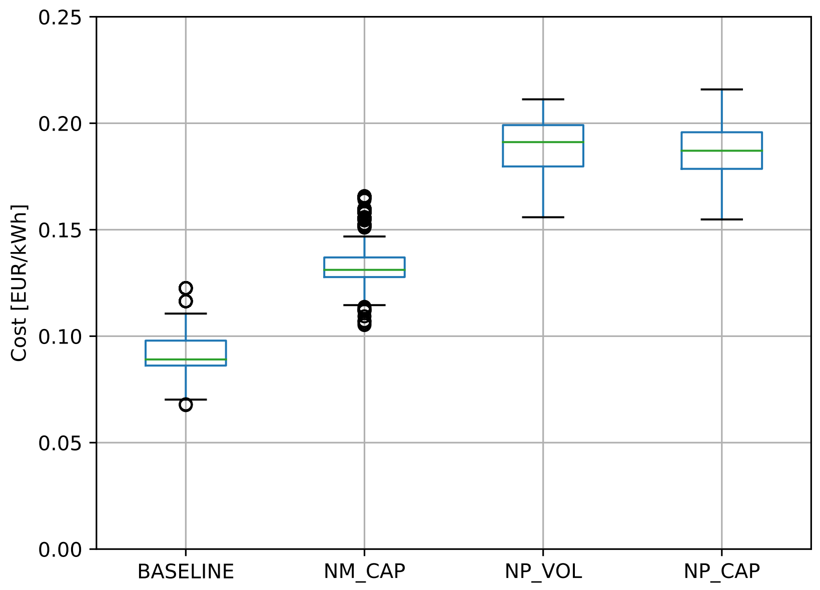


FIGURE 5.9: Evolution of the LVOE of PV installations.

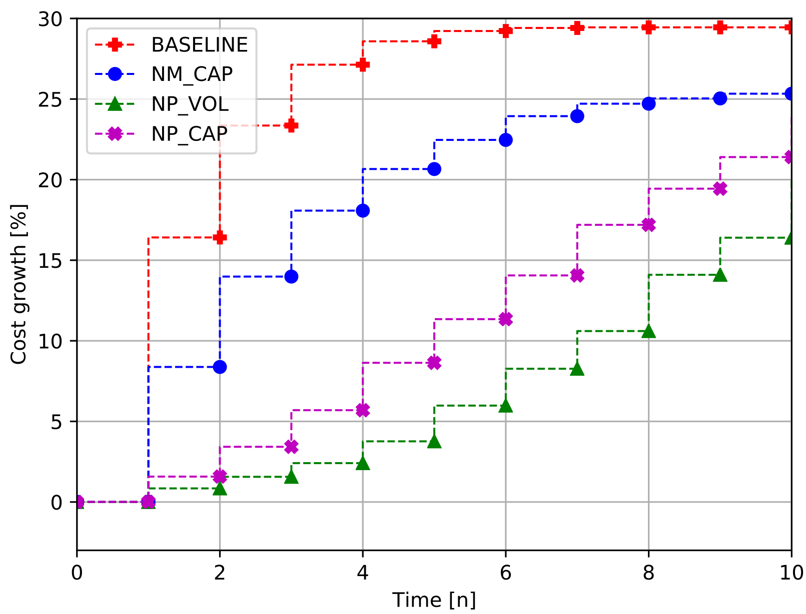


FIGURE 5.10: Evolution of the total tariff bill of a consumer

between prosumers and consumers.

5.6.3 Self-consumption and power exchanges with the grid

Finally, for each scenario, we compute the average self-consumption rate. The share of self-consumed electricity corresponds to the total consumption minus the imports from the grid divided by the total consumption. By increasing self-consumption, peak consumption from the centralised energy system can decrease, which is known as being one of the main drivers of the grid costs [118]. Promoting self-consumption is also important because power injections to the distribution network might be costly. Indeed, as production is correlated locally, there may be large power injections made by several prosumers at the same time in the same low-voltage feeder, e.g. at noon on a holiday weekend, when decentralised production is high and consumption low. These power injections may cause over-voltages on the local distribution network, and the inverters to disconnect the solar PV from the network, inducing a loss for the prosumers. Furthermore, owing to prosumers' excessive electricity injection, the DSOs might need to reinforce the distribution network, in which context self-consumption reduces the overall costs of the DSO. These investments might require new on-load tap changers, booster transformers, and static volt ampere reactive control compensator [107]. Hence, while self-consumption is not necessarily a goal in itself, it can be beneficial for the grid by decreasing peak consumption from the grid and peak injection to the grid.

The self-consumption rate is usually lower for residential households than for commercial activities [41]. Moreover, there is a high discrepancy in Wallonia between production and consumption: in the summer months, production is the highest and consumption the lowest and conversely in the winter months. Despite the lack of financial incentives, around 40% of prosumers claim to take actions to synchronise their consumption and production. According to [119], this is mainly true for those who tend to spend more time during daytime at home as, for instance, retired people.

We do not explicitly model the impact of self-consumption, via a change in aggregated peak consumption and injection, on the grid costs. Nevertheless, we compute the self-consumption rate for each of the six scenarios and the corresponding peak power withdrawals and injections. Focusing only on prosumers, we measure these two variables as the maximum aggregated amount of electricity withdrawn or injected over a one hour period among the yearly profile. Table 5.3 presents the figures. It shows that the net-metering system does not promote self-consumption; all three net-metering scenarios present a self-consumption rate close to 30%. Aggregated peak power withdrawals and injections are marginally differing, except for the NM_{cap} where lower peak power withdrawals are observed due to the capacity component (peak shaving behaviors).

A switch to the net-purchasing system implies an increase in the self-consumption rate from 30% to 46-50%, which can easily be explained by the presence of batteries. As a consequence of promoting self-consumption, aggregate peak power withdrawals and injections are also decreasing. Under the NP_{vol} scenario, the two peaks decrease by respectively 0.76% and 4.62% compared with the baseline scenario. When coupled with a capacity component, a net-purchasing system is able to decrease the peaks more substantially by 64.2% and 18.95% (withdrawals and injection, respectively).

Hence, a net-purchasing system with capacity-based tariffs can substantially decrease the grid costs by shaving the import and export peaks. Compared to the baseline scenario, the peak demand and the peak injection decrease by respectively 60% and 19%. In the present chapter these metrics can be measured only from a physical standpoint, with no associated monetary value of the reduction in the grid costs. Note, however, that these gains are possible thanks to private investments into batteries rather than a collective effort from the DSO. Those cost reduction for the DSO could be passed through consumers under the form of a lower grid tariff. Under this NP_{cap} scenario, these financial investments made by prosumers are estimated at around one million euros. If this figure from our model is extrapolated to the size of Wallonia, we have that households' investments in batteries will amount to 600 million euros to reduce grid costs. Overall, to judge the efficiency of the tariffs we would need to balance more precisely these private investments made by prosumers into batteries and the reduction in grid costs they create.

TABLE 5.3: Self-consumption and aggregate power exchanges

Scenarios	Absolute value	Self-consumption rate	Peak Power withdrawals	Peak Power injections
baseline	1,776.89 kWh	29.67%	2,806.90 kW	4,975.55 kW
NM_{fix}	1,780.35 kWh	29.72%	2,805.65 kW	4,975.55 kW
NM_{fee}	1,775.98 kWh	29.65%	2,808.54 kW	4,975.55 kW
NM_{cap}	1,623.91 kWh	27.11%	2,682.68 kW	4,967.99 kW
NP_{vol}	2,809.44 kWh	46.91%	2,784.24 kW	4,745.83 kW
NP_{cap}	2,997.92 kWh	50.05%	1,004.53 kW	4,032.66 kW

5.7 Conclusion and policy implications

This study has aimed to assess the impact of various tariff regulations and metering technologies on the evolution of the electricity system and, in particular, the electricity distribution network in a case study applied to Wallonia, the southern region of Belgium. Findings expressed in comparison to the baseline scenario (describing the current situation in Wallonia) are summarised in Table 5.4. They suggest that choosing between a net-metering and a net-purchasing technology to measure the imports and exports of electricity from/to the distribution network is critical. The net-metering system highly enhances the adoption of PV installations, which is one of the primary energy targets in the European Union, compared to the other scenarios. However, this comes at a cost. Regardless of the distribution network tariff structure considered, net-metering does not incentivise investments in battery installations at all and, therefore, does not encourage self-consumption. Peak power withdrawals and injections are decreased under a net-purchasing system, in particular when capacity-based fees are applied. Net-purchasing and capacity-based tariffs tend to strongly complement each other. Moreover, the net-metering technology leads to largely differing electricity bills for prosumers and non-prosumers, where non-prosumers end-up bearing most of the costs of the DSO. This issue can potentially impair the acceptance of electricity generation technologies coming from renewable energy.

TABLE 5.4: Summary of the results (evolution compared to the baseline scenario)

	NM_{fix}	NM_{fee}	NM_{cap}	NP_{vol}	NP_{cap}
PV adoption	=	-	-	- -	- -
Battery installations	=	=	+	++	++
Energy cost for non-prosumers	-	- -	- -	- -	- -
Peak power withdrawals / injections	=	=	-	-	- -

5.7.1 Policy implications

The CWaPE, the energy regulator in Wallonia, pursues various objectives relating to: (i) economic efficiency, (ii) equity, and (iii) the stability of the revenues of the DSO; moreover, the CWaPE aims at (iv) designing distribution tariffs that pave the way for the energy transition. Where the net-metering technology is in place, only the latter objective is partially fulfilled as it encourages large investments in PV production sources. This situation, however, is unsustainable as the network costs are financed by non-prosumers who see their electricity bills increase. The goal of the regulator is not to financially support investments in renewable production sources but to facilitate the energy transition via regulations targeting the DSO. As other tariff regulations only marginally change these results, our analysis leads us to conclude that a net-purchasing system should be adopted. If, in addition, a capacity component is introduced in the tariff, less investments would be required to reinforce the grid as such a system substantially decreases peak power withdrawals and injections. As these changes would require smart meters, we highlight the need to deploy this technology more urgently than currently planned by the regulator. This would shorten the gap between short and long run policies, the latter of which enables the implementation of more adequate regulations.

One reason for the relatively high electricity bills in Wallonia is that they do not only cover the costs of the commodity and the distribution network. The bills also charge users for various public policies, such as subsidies for investments in renewable energy production sources, reduced energy prices for precarious households, for the financing of public lighting, or the costs of the planned nuclear phase-out [113]. As distribution tariffs are computed on a volumetric basis, considering these additional costs to compute the electricity bills makes the system even less sustainable financially and prone to un-even allocation of those additional costs where prosumers may end up not paying for public services such as lighting. All these public policies should be financed by the public finance system. This, in addition, would be a much more transparent and democratic procedure as they would fall under parliamentary oversight. Changing the financing sources of these policies would decrease the pressing concerns of a utility death spiral and equity issues between prosumers and traditional consumers.

Finally, this analysis shows the importance of designing holistic policies supporting PV adoption and regulating the electricity distribution network, both concerning tariffs and metering technology, so as to facilitate a sustainable energy transition.

5.7.2 Limitations and future research

Our model relies on various assumptions relating to prosumers and the grid, which could influence some of our results. Yet, we believe that extending the model to consider these assumptions would lead to qualitatively similar results. To fully examine them, future research will be needed.

In our model, potential prosumers are presumed to choose to invest in a PV installation or in both a PV and a battery installation. As a consequence, early PV adopters do not have the opportunity to later invest in an additional battery system. Allowing for this possibility would not impact the scenarios considered in the short run, i.e. where a net-metering system is in place, as anyway no investment in batteries is done. However, in the net-purchasing cases considered in the long run, both investments in PV and in batteries would increase. Changing this assumption would further strengthen the main conclusion of our analysis.

Our model considers a wide, yet for simplicity's sake, fixed variety of consumption load profiles. It is unlikely, though, that they will not evolve over time. For example, owing to the deployment of electric vehicles, consumption profiles are likely to change. While electric vehicles increase consumption, they also act as a storage device potentially enabling peak shaving. As the functionalities of their batteries are similar to those of an ordinary battery, considering evolving load profiles would lead to lower investments in batteries in the long run scenario with a net-purchasing system or a net-metering system with tariffs with a capacity component. The ensuing higher consumption levels would lead to a greater deployment of PV installations along with even larger rebates on the energy bill. Overall, taking these aspects into consideration would not qualitatively impact the key insights of the current simulator.

One final limitation deserves to be mentioned. In this chapter, we model the financing of the network grid as a zero-sum game. Further, we have shown that some grid regulations, and especially capacity tariffs coupled to a net-purchasing system, lead to a decrease in peak power imports and exports. These collective benefits can be translated into lower grid costs that are possible thanks to the private investments into batteries by prosumers. We hope that further research will allow a more precise quantification and comparison of these aspects.

Part II

Decentralised electricity markets

Chapter 6

Model of interaction for renewable energy communities

This chapter introduces Part II of the thesis, which deals with the integration of distributed energy generation resources (DER) by means of new frameworks for (local) decentralised electricity markets, such as the renewable energy community (REC). As the business of electricity retailing changes following the current evolution of the electricity system, new opportunities arise for emerging technologies. An example of this evolution is the increasing number of final customers installing sophisticated energy management systems (EMSs) – these systems can control the production or consumption of a large variety of devices such as solar photovoltaic (PV) panels with storage solutions. EMSs provide prosumers with an agile and flexible way of managing their DER installations. Additionally, they offer a seamless communication channel between those prosumers and their retailers. This communication channel opens the door to new products and services, such as the provision of flexibility from prosumers to retailers, role that in the context of RECs can be adopted by the REC manager (ECM). The the retailer (or the ECM) may then use this flexibility in the wholesale electricity markets and imbalance settlement mechanisms, or trade it with other balance responsible parties (BRP). Using these ideas, Chapters 6 and 7 explore the potential of REC members to offer flexibility bids to their ECM[1].

The first step toward exploring this potential, and the one introduced in this chapter, consists of building a model of interaction between the different agents involved in our system. In the case of an REC, the agents whose interactions are modelled are the ECM and the REC members. These interactions comprise forecasting the electricity demand of consumers and prosumers as well as forecasting the local production of prosumers. If flexible consumption is offered by the REC members, it is also part of these interactions. This model of interaction relies on smart meters to register the electricity exchanges and requires no modification of the current rules and regulations of the European electricity system. Both the model of interaction and a numerical example are provided in this chapter. Note that, to produce

[1]The model developed in this chapter can also work with other entities aggregating a portfolio of final customers, such as aggregators or retailers.

a generic framework, we use the term retailer throughout the chapter – this retailer can be an aggregator or, as explained above, the ECM of an REC.

6.1 Introduction

The role of a traditional electricity retailer comprises acting as an intermediary between its clients and the rest of the electricity system. In its role, a retailer purchases electricity for its clients based on consumption forecasts, acts as BRP for the transmission system operator (TSO), and invoices its clients. The interaction between the retailer and its clients works one way: the client benefits from the system but does not contribute to it. To be able to manage this interaction efficiently, an increasing number of clients are installing (or upgrading) sophisticated EMS to save energy in a cost-efficient manner [120]. An EMS is an automated energy controller using a computer as a central processor. The capabilities of the EMS may vary widely depending on the selected model. Nonetheless, its basic capabilities are almost universal, and notably comprise the scheduling of the electricity flows, fixing the set-points of the batteries, alarms and safety measurements, and basic system monitoring.

An EMS can manage the production or consumption of a large variety of devices, such as photovoltaic panels, storage solutions (e.g. batteries), and flexible loads (e.g. demand-flexible boilers). The nature of the constraints of these different devices thus requires dedicated management, for instance, one EMS may be designed to control the appliances of a house, as described in [121], whilst another one could be designed to control a microgrid with several companies, photovoltaic panels, a run-on-the-river generator, and a storage system, as detailed in [122]. Furthermore, there might be cases where an EMS simply controls demand response devices. From the standpoint of a retailer, an EMS represents a higher-level manager of all these devices (i.e. generation, storage, or flexible demand) to provide flexibility. The flexibility thus provided by the clients' EMSs is then forwarded by the retailer to the day-ahead and intraday electricity markets. Alternatively, it can be exchanged with other BRPs, or be used by the retailer to participate in balancing mechanisms. In this regard, the retailer can be interpreted as a smart BRP providing single generic access to various flexibility products, aggregating this flexibility to meet minimum volume constraints, simplifying accounting, and managing the flexibility of its clients. This chapter aims at defining an interaction model between a retailer and several clients (through the clients' EMSs) to exchange flexibility. The interactions are based on a generic interface with the EMS, ensuring the scalability of the method, which should be simple for the most basic EMS, yet able to include the constraints of the controlled devices and, in particular, rebound effects [123]. In this context, flexible trading should be an addition to traditional electricity retailing. If no flexibility is traded, the contract between the client and the retailer corresponds to a classic retailing contract. The scientific literature covers most of the components required to define such an interaction model. However, to date, there is no implementation covering all the requirements together.

For the remainder of this chapter: the next section reviews the relevant literature. This review is followed by an outline of the proposed interaction model. Specific components of the model are detailed in dedicated sections: the baseline and its update, the flexibility bids, and the deviation mechanism. Finally, the last section concludes the chapter and identifies the potential future prospective work.

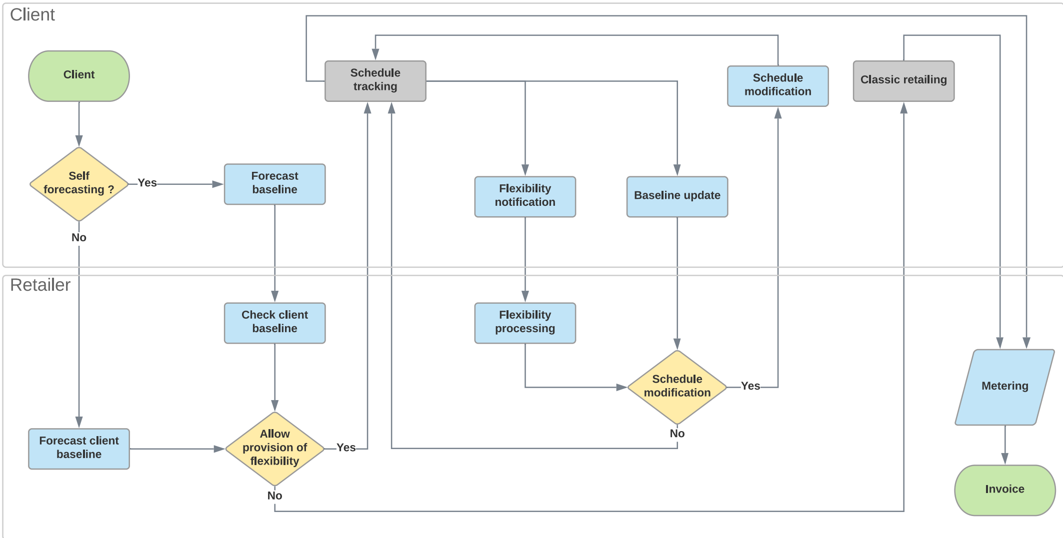


FIGURE 6.1: Flow of interactions between a client and its retailer. A baseline is computed for each client. Then the retailer allows, or not, the provision of flexibility of the client. If it is not accepted, the client falls under a classic retailing contract. If accepted, the client notifies its capability to provide flexibility. If the retailer contracts the flexibility, the schedule of the client is modified accordingly. This schedule may be modified upon notification of the client. The client is invoiced based on the final schedule and the metered energy.

6.2 Literature review

The existing literature regarding the use of demand response to provide flexibility is abundant, see for instance reviews [124] and [125]. The latter was conducted in 2018 and presents the results of 60 works. Furthermore, many projects on this topic have been conducted over recent years. ADDRESS started in 2008 and is one of the earliest European projects dedicated to demand response [126]. BRIDGE is a European Commission initiative that unites Horizon 2020 Smart Grid and Energy Storage Projects [127]. The BRIDGE project recommends implementing the Winter Package directives into the market system regulation based on dedicated recommendations related to specific dimensions: demand response access to markets, service providers' access to markets, product requirements, measurement and verification, payments, and penalties [127]. To enable flexibility services, the authors in [126] highlight the importance of introducing minor modifications in existing markets, rather than creating new ones. In this process, the retailer is well-placed to act as a facilitator.

The interaction model proposed in this chapter is a market-based approach. Other examples of such approaches for flexibility aggregation can be found in the Flexiciency [128] and PowerMatcher [129] projects. The former details a European market place facilitating interaction between agents with advanced monitoring, local energy control, and flexibility of aggregated customers. Flexibility services are very generic and must define various parameters such as the payment model, preconditions for service, or detailed description of service delivery. Concerning PowerMatcher, this project represents a practical implementation of market-based aggregation; it operates as a smart grid coordination mechanism balancing distributed energy resources (such as renewable ones) and flexible demand. First, different devices send bids detailing their willingness to consume energy, and then the aggregator sends back a price signal so that they can determine its consumption volume at this price.

The mentioned projects interact with various types of devices, either using generic but complex models, or several specific ones. The authors in [125] claim that, to create a well-functioning interaction model, it is necessary to formulate standardized but simple definitions of flexibility products, accounting for energy-constrained resources, flexibility capacity shortage situations, and including the rebound effect. One step toward the definition of such flexibility products is proposed in [130], where a solution is tailored to harness the flexibility from heat pumps. The flexibility product introduced in the latter work is used as the base block of the interaction model proposed in this chapter.

6.3 Proposed interaction model

The proposed interaction model between a client willing to provide flexibility and its retailer complies with the following outline: a client provides a baseline, based on its own consumption forecasts and additional forecasts if needed. If the EMS of the client has no forecasting capabilities, a reference is built from historical values. The retailer accepts or declines the participation of the client in its flexibility pool. Once accepted, the EMS of the client computes its capability to provide flexibility and communicates it to the retailer. The retailer processes all flexibility offers coming from the different clients' EMSs, taking into account the current status of the energy markets and its requirements as a BRP. If the retailer contracts flexibility, the schedule of the relevant clients are modified accordingly. Simultaneously, forecast updates may be requested by the client. The retailer checks if the new baseline is valid and does not impair the provision of previously accepted flexibility. Finally, the client is invoiced based on the final schedule and the metered energy. Deviations from the reference, with a specified tolerance, are penalized by the retailer. The flow of interactions is illustrated in Figure 6.1. This interaction model relies on smart metering and requires no modification of the current electricity market.

6.4 Baseline and updates

A baseline is necessary to define the flexibility provided at a resolution of a minimum 15 minutes, for its use in most electricity markets. Such a baseline is a specific requirement of this kind of client-retailer interaction. For classic retailing contracts, the baseline of a client is not compulsory. The retailer assumes the role of BRP for the clients it represents. In this setting, the TSO computes the potential imbalance of the retailer with respect to its net position. The computation of the net position of the retailer is based on its electricity purchases, which are in turn based on the forecasts of its clients. Large consumers may be requested to provide baselines to the retailer. In that instance, a communication of the baseline will be imposed by the retailer's contract (i.e. as an agreement between the client and the retailer). Hence, the TSO may not be aware of the baseline of the client and only has information concerning the schedule of the retailer's portfolio.

If flexibility is sold to the TSO, the baseline may be defined by the TSO itself [131, 132]. Taking another reference would create a mismatch between the flexibility remunerated by the TSO and the flexibility provided by the client. In this case, the retailer communicates to the client the reference taken by the TSO, or the method if the necessary data are not available in advance.

If flexibility is sold only as a result of a change in the retailer's net position, the definition of the client baseline is only an agreement between the client and the retailer. Since it is technically challenging to predict the state of an EMS without the details of the underlying devices, the EMS should provide its planned schedule to the retailer. According to [133], baseline and flexibility should be computed by the EMS to ensure end-user privacy and comfort. However, a concern regarding the self-computation of the baseline and flexibility is that customers might attempt to purposely manipulate their baseline in order to maximize their profits. The typical way of "gaming" the baseline is that customers may declare a higher consumption than their needs during their peak demand to sell flexibility in the form of a fictitious reduction of consumption. However, such abuses may not be intentional. Any optimization-based controller naturally exploits the flaws of a deficient interaction model. To prevent these problems, a retailer can compare the information provided by the client with its own forecasts. This check is essential to detect anomalies and can be used to avoid abuses of the flexibility mechanism. One method to prevent such potential abuses is to check the similarity of the communicated baseline with historical measurements, applying a tolerance.

The baseline must not only cover the period in which the client is willing to provide flexibility, but also some periods before and after flexibility delivery, to consider the rebound effect. The length of these periods depends, among other factors, on the storage capacity behind the EMS controller. The order of magnitude of residential thermal storage, for instance, is one and a half hours [130], whereas exploring the opposite extreme, a microgrid storage system may shift consumption by several hours.

Considering these orders of magnitude, a baseline window of one day around a flexibility window is considered for the present chapter.

A baseline should be defined before the clearing of the day-ahead energy market so that the retailer has sufficient time to compute and issue its offers. This baseline should therefore be computed based on day-ahead forecasts. Typically, more accurate forecasts can be obtained closer to real-time, leading to the need for baseline updates. However, an update may not always be accepted, since it could compensate for previously sold flexibility or an unspecified rebound effect. Thus, two verification points are suggested: (i) a maximum relative deviation with respect to the initial baseline, and (ii) prevention of baseline modification in the opposite direction to the provision of flexibility services. Figure 6.2 shows a schedule update which cancels out already sold flexibility: (a) assuming a client with a flat baseline; (b) the client sells flexibility and the schedule is modified accordingly; (c) the client requests a schedule update in the opposite direction to its sold flexibility. If this update is accepted, the client is paid for a flexibility it does not provide. To avoid such potential abuses, the retailer should not accept a baseline update of an opposing sign than the sold flexibility. In practice, a small tolerance corresponding to acceptable forecast errors should be considered.

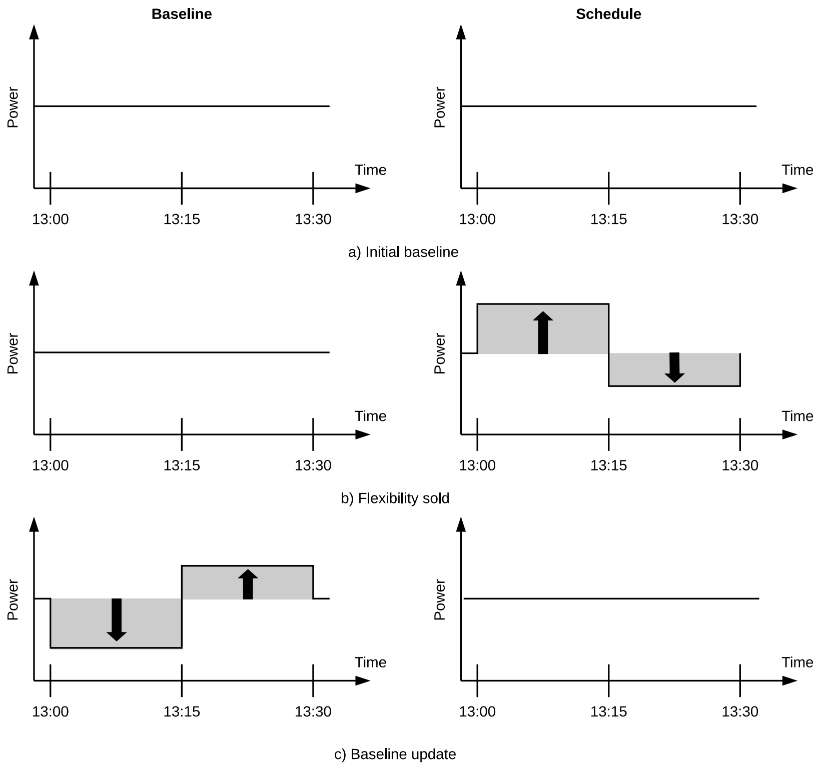


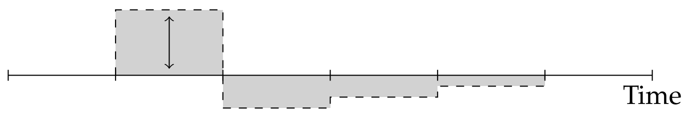
FIGURE 6.2: Case of a schedule update that cancels out already sold flexibility.

6.5 Flexibility bids

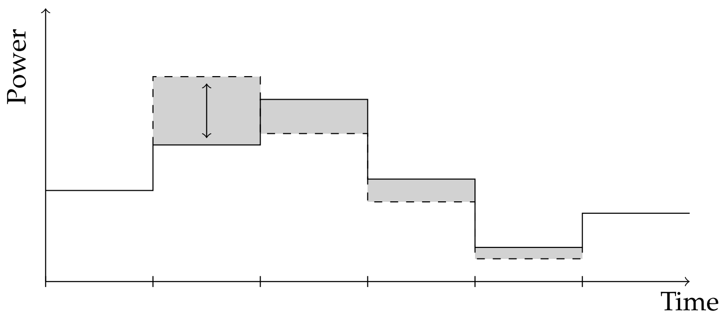
A client communicates its flexibility by means of bids. This flexibility product is inspired by proposals of articles [130] and [134]. It consists of an offer covering multiple market periods in which signs may vary. This product generalises the case of a single period offer. A bid communicates the flexibility over multiple time-steps and includes the following information:

- Energy volume for each time step;
- Type: partial/binary acceptance;
- Cost of the bid; and
- Expiration time.

A graphical representation of such a bid is provided in Figure 6.3. The retailer selects interesting bids, either to directly use them, or to be sold (aggregated or not) to other BRPs or to the intraday market. As for the market clearing process, many implementations can be investigated. In any case, the clearing procedure should be adequate to exchange flexibility close to real-time as, for example, in the real-time balancing settlement. The latter encourages the use of continuous clearings.



(A) Modulation signal.



(B) Modulation added to the baseline.

FIGURE 6.3: Example of upward modulation with three payback periods.

By default, a bid allows partial acceptance of the offered flexibility volumes. The accepted flexibility volume at each time-step is given by the offered volume multiplied by the acceptance ratio. The client can prevent the possibility of partial acceptance for any bid, imposing the complete acceptance or rejection condition, namely, using the binary bids.

The response of the retailer to the bid submission is the status of the bid, which can take the following values:

- FREE: Bid submitted and free to be revoked by the client.
- REVOKED: Bid revoked by the client.
- PENDING: The retailer is processing the flexibility bid and it cannot be revoked.
- EXPIRED: The bid reached its expiration time without being accepted or rejected.
- REJECTED: Bid rejected by the retailer.
- RESERVED: The bid is reserved and waits for its acceptance by its future beneficiary.
- ACCEPTED: The bid is accepted and an acceptance ratio is communicated.

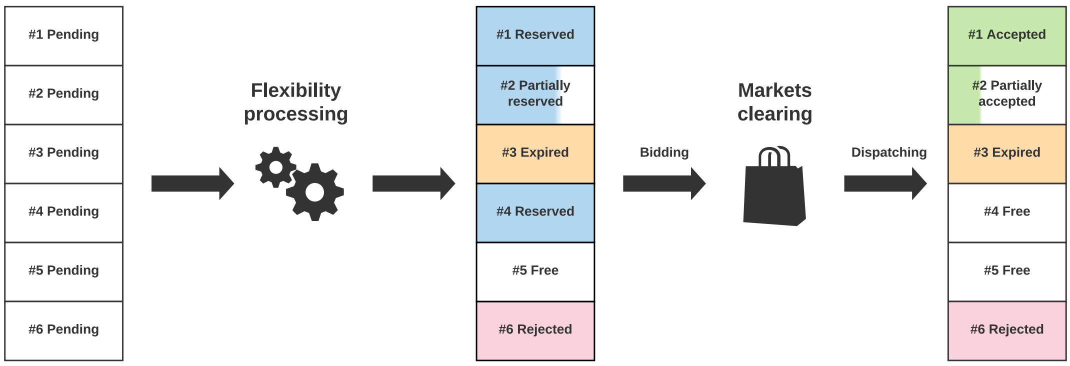


FIGURE 6.4: Evolution of flexibility bid statuses.

Figure 6.4 illustrates the evolution of bid statuses. Clients submit their offers to the retailers, which are initially in a free state. They are always free to revoke an offer if it has not been processed. Periodically, the retailer processes the current free offers. During the processing phase, the statuses of the concerned offers is set as pending. The retailer first filters offers that have expired due to a time-out. Next, it selects offers to be submitted to the markets or proposed to the TSO or other BRPs. These offers are then set to a reserved status, waiting for acceptance, while the rest of them are switched back to the free status. The retailer could implement a wide range of strategies to process bids. A basic one would be to forward the bids directly to the markets, in order of profitability, discarding the ones not suitable for participation (e.g. the ones which will not generate profits). A more advanced strategy could consist of building a market offer by aggregating a collection of flexibility bids, however, the definition of this kind of algorithm is out of the scope of this document. The algorithm proposed in this chapter is assumed to send offers to the market, communicating back to the retailer the provided flexibility. The retailer then dispatches this flexibility to the reserved offers and sets their status as accepted. Concerning the rest of the offers, they are switched back to the free status for the next selection process.

Once a flexibility bid is accepted, the schedule of the corresponding client is modified accordingly. Note that following this principle, a client has an alternative to the baseline update mechanism to modify its schedule. The client could bid the expected schedule update at an appealing price with respect to the one of the intraday market. Thus, the retailer could buy or sell the corresponding energy on the market and update the schedule of the client accordingly.

6.6 Deviation mechanism

A deviation is given by the difference between the measured consumption and the baseline (i.e. the foreseen consumption plus the provided flexibility). Nonetheless, these deviations are not considered an imbalance in this document since the clients are not BRPs.

The retailer benefits from averaging its portfolio of clients to mitigate the variability of its forecasts and deviations. The client cannot benefit from this averaging effect owing to its small size and limited flexibility. Before pricing a deviation, a retailer may therefore grant a tolerance to its clients for deviations with respect to their schedules. Beyond this tolerance, a price needs to be associated with this deviation. The imbalance price is a good candidate since it corresponds to the cost faced by the retailer. Furthermore, exposing the client to imbalance prices might encourage them to enroll in a flexibility program. The retailer could reduce the deviation price by a factor corresponding to the reduction of the risk resulting from the aggregation of the clients. This reduction can be computed as follows. Considering a retailer with k identical clients with forecast errors following Gaussian distributions correlated by a factor ρ. The production of the i^{th} client is given by $p_{i,t}$, whereas its production forecast is $\hat{p}_{i,t}$. Then, the covariance of a pair of clients i, j is given by $\rho\sigma_i\sigma_j$. The sum of correlated Gaussian random variables is studied in paper [135]. In this paper, the authors prove that the sum of correlated normally distributed random variables is equal to one single random variable following a normal distribution of variance $\sigma_Z = \sigma_i^2 \sum_{i=1}^{k} \sum_{j=1}^{k} \rho_{i,j}$ where $\rho_{i,j}$ is the covariance.

Using this finding, the aggregated forecast error is given by the sum of the individual distributions. Let P_t and $\hat{P}_t$ denote the production and the estimated production of the retailer, which corresponds to the sum of the production and estimated production of its clients.

$$
\begin{aligned}
E\left[P_t - \hat{P}_t\right] &= N\left(0, \sigma_i^2 \sum_{i=1}^{k} \sum_{j=1}^{k} \rho_{i,j}\right) \\
&= N\left(0, \sigma_i^2 \sum_{i=1}^{k} \left(1 + (k-1)\,\rho\right)\right) \\
&= N\left(0, \sigma_i^2 k \left(1 + (k-1)\,\rho\right)\right)
\end{aligned}
$$

The relative standard deviation of the error C is given by:

$$C = \frac{E\left[P_t - \hat{P}_t\right]}{E\left[P_t\right]} = \frac{\sqrt{k + k\left(k-1\right)\rho}}{k} c_i$$

where c_i is the relative standard deviation of the client's error. We can define the factor ϕ, representing the influence of the correlation of the client's production on the total production of the retailer as:

$$\phi = \frac{C}{c_i} = \frac{\sqrt{k + k\left(k-1\right)\rho}}{k}$$

The computation of ϕ for different numbers of clients k and for different correlation coefficients ρ is showcased in Table 6.1. This table shows that for a sufficient number of clients, with a realistic correlation of 0.2, the relative forecast error of the retailer is 45% of the one an individual client would obtain. Thus, 45% could be used as a potential discount on the imbalance price to define the deviation price of the client.

TABLE 6.1: Influence of the correlation of the clients' production on the total production of the retailer, as a function of the number of clients k and the correlation of their production ρ.

k / ρ	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
1	100%	100%	100%	100%	100%	100%
2	71%	74%	77%	81%	84%	87%
3	58%	63%	68%	73%	77%	82%
5	45%	53%	60%	66%	72%	77%
10	32%	44%	53%	61%	68%	74%
100	10%	33%	46%	55%	64%	71%
1000	3%	32%	45%	55%	63%	71%
10000	1%	32%	45%	55%	63%	71%

6.7 Conclusion

This chapter presents an interaction model allowing a set of clients equipped EMSs to provide flexibility services to the electrical system through their retailer. The scope of this interaction model covers energy exchanges spanning from the day-ahead to real-time. These exchanges may be simple for the most basic EMSs, while allowing clients with device constraints such as rebound effects to include them in such exchanges. The trading of flexibility is an addition to traditional retailing. If no flexibility is traded, the contract between the client and the retailer corresponds to a classical one.

Chapter 7

Introducing demand response into renewable energy communities

The potential of final customers to offer flexibility based on the idea of renewable energy communities (RECs) is further elaborated in this chapter. Making use of the interaction model developed in the Chapter 6, we design an REC where part of the REC members are flexible consumers who can post flexibility bids upon request from the energy community manager (ECM). These bids, if accepted by the ECM, will change the demand profile of the (flexible) members and, as such, of the REC. The decision of activating flexibility bids may respond to different criteria – this chapter presents a flexibility activation decision mechanism based on a cost minimisation criterion.

To perform this cost minimisation, we assume that the only retailer of the REC is the ECM[1]. Thus, the ECM, as provider of electricity for the REC, can trade in the wholesale electricity market, in this case the day-ahead market, to purchase the electricity needs of the community. When performing a typical demand provisioning, the ECM or the retailer must use forecasts of load, production within the community and electricity prices. In addition, in this chapter we introduce one extra element the ECM must account for: flexible consumption by flexible consumers equipped with energy management systems (EMSs) in the form of flexibility bids spanning several time-steps. Taking all these elements into consideration, the ECM performs the demand provisioning in the day-ahead market, aiming to minimise the electricity costs of the REC. To that end, a strategy must be developed to decide which flexibility bids to activate. Owing to the complexity of flexibility bids, comprised of three elements: initial activation of flexibility, idle time, and rebound (detailed later in the chapter), the strategy for bid activation is not straightforward. In this chapter we propose an optimisation framework at the core of such an activation strategy – one that not only accounts for the initial activation, but also for the idle time and the rebound of the bid, which may take place several time-steps after the initial activation.

[1] As per current European regulations, the ECM does not need to have the role of the retailer of the community. However, in this paper we assume this is the case to avoid the extra layer of communication with the retailer. The model presented in this chapter can work equally assuming the standpoint of a retailer instead of an ECM.

Our results show that creating an REC can significantly reduce the electricity costs of the REC members. Furthermore, we show that introducing flexibility bids further reduces the total system costs thanks to a better matching of local supply and demand.

7.1 Introduction

Electricity retailing is rapidly evolving in response to the emergence of new technologies such as smart meters or EMSs. These new technologies enable new forms of decentralised electricity trading [125]. In this regard, the European Parliament in its 2018/2001 directive has introduced the concept of RECs [11]. RECs are usually composed of consumers and local renewable generators which are connected to the same low voltage feeder. When an REC is established, their users may benefit from lower electricity bills owing to: i) a greater synchronisation between renewable electricity production and consumption; and ii) a potential discount on the distribution fee offered by the distribution system operator for all locally consumed electricity. RECs are managed by an ECM, in charge of billing the users and ensuring the adequate functioning of the REC. The role of the ECM then, includes managing the generation assets within the REC in order to maximise the global self-consumption of the REC, and creating an adequate business model where the financial balance is positive.

To maximise the REC self-consumption, the ECM needs to synchronise supply and demand. However, when relying on renewable resources such as solar photovoltaic (PV), the generation output cannot be controlled. A solution might involve the deployment of storage devices such as batteries, yet their limited capacity as well as their price make them an impractical solution for large scale implementations. Hence, another potential way of boosting the supply and demand synchronisation is the use of demand response (DR) or other flexibility services provided by the users. In this regard, this chapter focuses on the development of a novel method to deal with DR in the context of an REC with generation assets in the form of solar PV, owned by an investor (for instance the ECM). This REC is composed of non-flexible consumers who simply consume electricity, flexible consumers who consume electricity and offer DR, and generation assets that can sell the electricity either to the REC or to the main network.

In this set-up, flexibility bids can be offered by the REC's flexible consumers one day before physical delivery. Every day at noon, the flexible consumers can post their flexibility bids for every quarter of the following day. The ECM must then select the bids according to the best interest of the system (e.g. self-consumption maximisation). To that end, the ECM makes use of forecasts of consumption, production, and day-ahead market prices. It is important to note that network constraints of the REC are not considered during this process.

Several works in the existing literature have tackled the issue of flexibility. In [136], the authors present an optimisation model to study the participation of a DR aggregator with a portfolio of DR resources in the wholesale market, highlighting the cost opportunity offered to the aggregator, and the possibility of transferring such a gain to promote the participation of end-users in DR programs. In [137], several "smart" buildings are modeled to provide flexible consumption as fast regulation reserve to the grid, reporting a reduction in operating costs. The authors in [138] study the provision of reserve with DR and stress the importance of accounting for the rebound effect when using flexibility bids. In [139], the authors create a framework in which flexible consumers can provide flexibility bids while an aggregator supervises the flexibility transactions, suggesting the need for interaction between the different agents. In [140], three different market designs are proposed for the activation of flexibility services within distribution networks. This paper focuses on the coordination between retailer, transmission system operation, and distribution system operation (DSO). Another work, [141], proposes the use of hierarchical agent-based modelling for the study of the impact of DR on the day-ahead market, showcasing a cost reduction on the user end while profits are maximised for the retailer.

To date, no work has addressed the issue of introducing flexibility services in the context of an REC. Although there exists literature on peer-to-peer trading, this mechanism is based on a decentralised planner. In this chapter, we take the standpoint of a centralised one, where the novelty lies on the introduction of flexibility trading where consumers can submit their willingness to offer flexibility services in the context of European RECs as they have been laid out by the European Commission. Furthermore, no comprehensive interaction model can be found in the literature where flexibility bids coming from consumers' EMSs can be offered in an REC managed by an ECM. Our work aims at filling this gap, introducing a novel multi-agent model capable of simulating the operation of an REC composed of different agents: flexible consumers, non-flexible consumers, generation assets, and ECM. In addition to the regular operation of the REC, a strategy for activating flexibility bids from flexible consumers, based on an optimisation problem is proposed and tested.

After this introduction, in Section 7.2, we detail the functioning of the proposed the multi-agent the simulator. Section 7.3 presents the mathematical formulation of the optimisation problem written to select the flexibility bids. In Section 7.4, we introduce a test case showcasing and discussing the capabilities of the simulator. Finally, in Section 7.5 we provide the conclusion of this work.

7.2 Simulator

In this section, we present an overview of the proposed simulator, establishing the interactions between the agents of the REC. Moreover, the flow of information in our multi-agent computational tool is explained in detail.

As explained in the introduction, the goal of the developed simulator is the detailed representation of the activities of an ECM and the REC it manages. The REC is composed of a portfolio of flexibility providers among its consumers, namely the flexible consumers. To maximise the self-consumption of the REC (or its welfare as we will see later on the document), the ECM can use the flexibility provided by flexible consumers when purchasing energy in the European day-ahead market.

In the developed simulator, the demand of the REC is introduced by means of several consumers (flexible and non-flexible) that are modeled through their demand profiles. The generation needed to supply such a demand comes from the generation assets of the REC or, if needed, from the main network (outside the REC).

In this work, the ECM produces forecasts of the day-ahead market prices and the demand of the non-flexible consumers. Then, the flexible consumers and the renewable generation assets provide their individual demand forecasts to ECM, who adds them to the forecast of the non-flexible consumers. With all the demand forecasts (flexible and non-flexible), an initial baseline is computed and the flexible consumers are scheduled.

In addition, the ECM receives flexibility bids from the flexible consumers, and activates these bids in order to increase or reduce the demand at certain periods. The ECM will choose the bids that maximise the welfare of the REC which, in the case presented, also maximises the self-consumption of the system (i.e. the part of the demand met by local generation). A detailed explanation of the role of each agent is provided in this section. The selection process of the flexibility bids is presented in Section 7.3.

7.2.1 Agents

In the following, the different agents of the multi-agent simulator are presented, highlighting the interactions between them and their impact on the simulation. The agents of the proposed model are the day-ahead market operator, the flexible consumers, the non-flexible consumers, the generation assets, and the ECM. They all have different roles and ways of interacting.

Day-ahead market operator

this agent is meant to provide the history of day-ahead market prices to the ECM so that the it can produce forecasts. In addition, once the day-ahead market has been cleared and the prices are fixed (not forecasts), this agent provides the actual prices that will be charged to the ECM for its day-ahead provisioning.

Flexible consumers

this group of agents is composed of electricity consumers that can offer demand response (flexibility). Upon request of the ECM, these agents will compute and offer a flexibility bid upward or downward. This flexibility offer states that, if activated, the flexible consumer is obliged to increase or decrease its consumption at a given point in time. This offer also states that, at a later moment in time, the same amount of energy will be returned to the flexible consumer, decreasing or increasing its demand accordingly (rebound). Each flexibility bid is offered at a fixed price. In principle, each flexible consumer should design this price according to their own utility function through a bidding process. In this chapter, however, for the sake of simplicity we consider the same price per unit of energy for all flexibility bids.

Flexible consumers have a baseline and a schedule, and while the baseline represents their consumption without flexibility, the schedule can be adjusted depending on the flexibility bids accepted by the ECM. The EMS of each agent is responsible for the computation of the flexibility bids and for communicating them to the ECM.

The flexibility bids are composed of three elements:

- Initial flexibility: this is the initial change in schedule offered by the flexible consumer, it can be positive or negative and is instantaneous (i.e. it will be activated at the appointed time for the appointed duration). The magnitude of the initial flexibility depends on the baseline of the flexible consumer (it cannot be greater than the baseline itself).

- Idle time: this is the time between the flexibility offered and the start of the rebound, during this time the flexibility bid follows the original schedule.

- Rebound: this is the amount of energy the flexible consumer must recover for the flexibility offered. It may span over several time-steps and its magnitude is equal to the initial flexibility offered, multiplied by a factor (typically greater than 1 in order to account for losses). We assume that the energy is equally distributed over all rebound time-steps.

In Figure 7.1, an illustration of a possible flexibility bid is provided. Note that, in the simulation, all three parameters: magnitude of initial flexibility, duration of idle time, and duration of rebound, can be adjusted.

Non-flexible consumers

this group of agents contains all electricity consumers with non-flexible baselines. These consumers do not offer flexibility bids to the ECM. In this case, the forecasts of these agents' consumption profiles are computed by the ECM and, therefore, deviations between forecast and actual consumption will not be charged to the agents.

Generation assets

in addition to the users, the REC contains generation assets, usually owned by an investor that can be the ECM, one of the consumers, or another entity. These generation assets locally produce electricity, which can be used to meet the demand of the REC, or be sold to the main network. In this work, we assume that solar PV is the

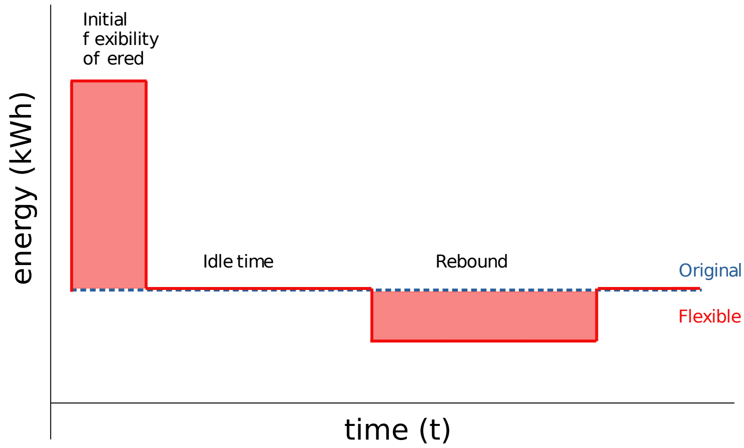


FIGURE 7.1: Flexibility bids' structure with three elements: the initial flexibility, an idle time, and the rebound.

only available generation technology within the REC and that the locally generated electricity will be sold primarily within the REC. However, this last assumption will depend on the optimisation problem. The generation assets forecast their production and submit it to the ECM.

ECM

the last agent of the simulator is the energy community manager. The role of this agent is to receive i) price signals from DAM, ii) forecasts from flexible consumers, and iii) forecasts from generation assets. Additionally, it must forecast the consumption of the non-flexible consumers. With all this information, the ECM decides the demand provisioning of the REC, and the flexibility bids to accept. Regarding the demand provisioning, the ECM will act so as to maximise the self-consumption (or welfare as presented in section 7.3) of the REC according to the optimisation problem laid out in section 7.3, taking into account the flexibility bids. The objective of the optimisation is to maximise the matching of demand with PV production. Finally, the ECM will try to maximise the local electricity exchanges within the REC.

7.3 Day-ahead Flexibility activation

In this section, the optimisation problem that defines the flexibility activation and the day-ahead schedule is formulated. The objective function of this problem aims at maximising the welfare of the REC and, as a result, its self-consumption.

The proposed REC is composed of consumers (flexible or not), and generation assets. This means that the system will have generation and demand profiles and, as such, its consumption can be divided into:

1. Local consumption: corresponds to the self-consumption of the system, i.e. the part of the demand covered with the local PV generation;

2. Global consumption: corresponds to the imports from the main network (outside the REC), and typically covers the consumption not met by the local generation.

In an ideal REC, the total demand should be covered by the local production and, only if it is not sufficient, should the system resort to imports. The rationale behind this is that, when a high-enough percentage of the production of an REC is locally consumed and, under the new European directive, the distribution system operator serving the REC will offer certain discount on all exchanges taking place inside the community. Thus, the ECM can select flexibility bids to increase or decrease the instantaneous demand, taking into account the idle time and the rebound of each bid so as to maximise self-consumption (minimise imports from the main network). To account for the potential negative effect of activating bids due to their rebound effect, a comprehensive bid activation strategy must be developed. One that not only looks at the flexibility offered to match instantaneously demand and local supply, but also takes into account the adverse –or not– effects of the rebound taking place several time-steps later.

For this reason, in this work we propose a framework to perform the flexibility bid activation according to the output of an optimisation problem. The problem is defined as following. Let $\mathcal{T} = \{1, \ldots, T\}$ represent the time discretisation of the horizon T, where $t \in \mathcal{T}$ represents the time-steps (the resolution will depend on the used data set). In addition, we can define a set $\mathcal{U} = \{1, \ldots, U\}$ of users. In the proposed framework, $D_{u,t}$ and $P_{u,t}$ denote the demand and the production forecasts of each user u respectively; Π_t^{l-} is the local energy price (without distribution, transmission, or taxes); Π^{dl} is the local distribution price (which contains also transmission and taxes); Π_t^{g-} is the global energy price (without distribution, transmission, or taxes), this is the price of the energy imported; and Π^{dg} is the global distribution costs (including transmission and taxes).

Additionally, we must define all the parameters related to the flexibility bids. Let $\mathcal{B} = \{1, \ldots, B\}$ denote the set of flexibility bids offered by the flexible consumers. Then, we can define the set $\mathcal{I}_b = \{1, \ldots, I_b\}$ representing the discretisation of the flexibility bid duration in time-steps, where I_b is the length of the idle time plus the rebound effect of bid $b \in \mathcal{B}$. In this context, every bid $b \in \mathcal{B}$ can be defined as $b = (F_{i,b} \;\; \forall i \in \mathcal{I}_b)$, where $F_{i,b}$ denote the volume of flexibility offered at the i^{th} time-step by bid b. The activation time of a bid $b \in \mathcal{B}$ is given by τ_b. Finally, we can define the subset $\bar{\mathcal{B}}(t) \subseteq \mathcal{B}$ denoting the set of flexibility bids which are active at time-step t, thus $\bar{\mathcal{B}}(t) = \{b \in \mathcal{B} \mid t - I_b \leq \tau_b \leq t\}, \;\; \forall t \in \mathcal{T}$. Table 7.1 contains a detailed overview of the notation used.

$$\min \sum_{t\in\mathcal{T}} \left[\begin{array}{l} \rho_t^{g-} \cdot \left(\Pi_t^{g-} + \Pi^{dg} + \Pi^{o}\right) \\ + \rho_t^{l-} \cdot \left(\Pi_t^{l-} + \Pi^{dl} + \Pi^{o}\right) \\ + \sum_{b\in\mathcal{B}} x_b \cdot C_b \\ - \rho_t^{g+} \cdot \Pi_t^{g+} \\ - \rho_t^{l+} \cdot \Pi_t^{l+} \end{array} \right] \quad , \tag{7.1}$$

Subject to, $\forall t \in \mathcal{T}$:

$$\sum_{u\in\mathcal{U}} D_{u,t} + \sum_{b\in\vec{\mathcal{B}}(t)} x_b \cdot F_{t,b} - \sum_{u\in\mathcal{U}} P_{u,t} = \rho_t^{g-} - \rho_t^{g+} \quad , \tag{7.2}$$

$$\rho_t^{l-} = \sum_{u\in\mathcal{U}} D_{u,t} - \rho_t^{g-} + \sum_{b\in\vec{\mathcal{B}}(t)} x_b \cdot F_{t,b} \quad , \tag{7.3}$$

$$\rho_t^{l+} = \sum_{u\in\mathcal{U}} P_{u,t} - \rho_t^{g+} \quad . \tag{7.4}$$

With:

$$\rho_t^{g-}, \rho_t^{g+}, \rho_t^{l-}, \rho_t^{l+} \in \mathbb{R}^+ \quad \forall t \in \mathcal{T} \quad , \tag{7.5}$$

$$x_b \in [0,1] \quad \forall b \in \mathcal{B} \quad . \tag{7.6}$$

The goal of this problem is the selection of flexibility bids offered by the flexible consumers so as to maximise the self-consumption of the REC. The objective function (Equation (7.1)) minimises the costs subtracting the revenues of the REC. Equation (7.2) ensures the energy balance at all time-steps. Equation (7.3) computes the local consumption ρ_t^{l-}. Equation (7.4) computes the share of locally generated energy that is sold locally ρ_t^{l+} (i.e. never leaves the REC). Finally, $x_b \in [0,1]$ is a continuous variable used to activate each bid b if its effect (activation and rebound) contributes positively to the increase of the welfare.

7.4 Test case

In this section, we illustrate the use of the proposed framework and its main features by providing an example for the case of an REC in Belgium with the following characteristics:

- the simulation's resolution is 15 minutes;
- 20 flexible consumers whose demand profiles come from data from real users in Belgium;
- 10 non-flexible consumers whose demand profiles come from data from real users Belgium;

TABLE 7.1: Notation.

Symbol	Meaning	Units
Π_t^{g-}	Global energy price	€/MWh
Π_t^{l-}	Local energy price	€/MWh
Π^{dg}	Global distribution price	€/MWh
Π^{dl}	Local distribution price	€/MWh
Π_t^{g+}	Global selling price of energy	€/MWh
Π_t^{l+}	Local selling price of energy	€/MWh
Π^{o}	Cost of transmission and taxes	€/MWh
$D_{u,t}$	Demand of user u	MWh
$P_{u,t}$	Production of user u	MWh
ρ_t^{g-}	Total imports of the REC from the grid	MWh
ρ_t^{g+}	Total exports of the REC to the grid	MWh
ρ_t^{l-}	Total local consumption of the REC	MWh
ρ_t^{l+}	Total production locally consumed by the REC	MWh
$F_{t,b}$	Flexibility volume offered	MWh
x_b	Acceptance ratio of the bid	%
C_b	Cost of the bid	€

TABLE 7.2: List of prices in the simulations (€/MWh).

Π_t^{g+}	Π_t^{g-}	Π_t^{l+}	Π_t^{l-}	Π_t^{dg}	Π_t^{dl}	Π^{o}
40	60	55	56	85	67.15	75

- 1 solar PV installation of 48 MW whose production profile is computed using the python library PVLIB [99], calibrating the model for a location in Belgium;
- the idle time of the flexibility bids is 120 minutes;
- the payback duration of the flexibility bids is 60 minutes.

The values of the different price components used for the simulations are listed in Table 7.2. Note that, in the proposed test case, the imports from the main grid are charged at retail price. Thus, the ECM has an incentive to reduce the overall consumption by matching PV generation with demand, using the flexibility bids from flexible consumers.

7.4.1 Cost analysis

The costs of the REC (C_{REC}) are given by equation (7.7). Results of the cost analysis are reported in Table 7.3. Three different cases are considered for the computation of the costs:

1. no REC is established: consumers and producers simply buy and sell the electricity from the outside market;

2. the REC is established, but no flexibility is used: consumers and producers benefit from certain discount on the distribution tariff;

3. the REC is established and flexibility is used: consumers and producers benefit from certain discount on the distribution tariff and from flexibility bids.

Furthermore, we provide results for simulations corresponding to 1 day (January 2, 2017), 1 week (second week of 2017), 1 month (January 2017), and 1 year of operation (2017). Note that January is selected to showcase the results of the costs analysis under the worst possible case.

$$
\begin{aligned}
C = & \sum_{t\in\mathcal{T}} \rho_t^{g-} \cdot \left(\Pi_t^{g-} + \Pi^{dg} + \Pi^{o}\right) + \\
& \sum_{t\in\mathcal{T}} \rho_t^{l-} \cdot \left(\Pi_t^{l-} + \Pi^{dl} + \Pi^{o}\right) - \\
& \sum_{t\in\mathcal{T}} \left(\rho_t^{g+} \cdot \Pi_t^{g+} + \rho_t^{l+} \cdot \Pi_t^{l+}\right) \quad .
\end{aligned}
\tag{7.7}
$$

TABLE 7.3: Costs for the three different cases and percentage of difference with respect to the reference (first column).

Case	**NO REC (%)**	**REC NO FLEX (%)**	**REC FLEX (%)**
1 day	262 k€ (-)	260.6 k€ (-0.006)	260.6 k€ (-0.006)
1 week	1,785 k€(-)	1,730 k€ (-3.1)	1,726 k€ (-3.3)
1 month	7,054 k€ (-)	6,863 k€ (-2.7)	6,850 k€ (-2.9)
1 year	65,455 k€ (-)	61,303 k€ (-6.3)	61,019 k€ (-6.8)

From these results, we can observe how the aggregated effect over the entire year leads to significant reductions in the total operation costs when an REC is set in place (6.3%). And an additional reduction of 0.5% is achieved by introducing flexibility.

7.4.2 Performance analysis

To further evaluate the value of RECs and the use of flexibility, we compute the self-sufficiency rate (SSR) and the self-consumption rate (SCR):

$$
\mathrm{SSR} = \frac{\sum_{t\in\mathcal{T}} \rho_t^{l+} + \sum_{b\in\bar{\mathcal{B}}(t)} x_b \cdot F_{t,b}}{\sum_{t,u\in\mathcal{T}\times\mathcal{U}} D_{u,t}} \quad , \tag{7.8}
$$

$$
\mathrm{SCR} = \frac{\sum_{t\in\mathcal{T}} \rho_t^{l+} + \sum_{b\in\bar{\mathcal{B}}(t)} x_b \cdot F_{t,b}}{\sum_{t,u\in\mathcal{T}\times\mathcal{U}} P_{u,t}} \quad . \tag{7.9}
$$

The available flexibility can be used to improve the matching between supply and demand, as illustrated in Figure 7.2. The demand shift of the system (before and after flexibility) is shown by comparing the initial with the flexible demand. In Figure 7.2, we can observe that, in times of high local production, upward flexibility is activated in order to increase the self-consumption of the REC and vice-versa, when there is scarcity of production, the flexible demand decreases as a result of downward bid activation. In Table 7.4, these findings are summarised for the yearly operation of an REC. A substantial increase in the utilisation of local production is achieved when flexibility is considered (+8.1%). Subsequently, the SCR is improved in the REC by 5.01%. A similar trend can be observed for the SSR, which increases by 2.92% when introducing flexibility. It is important to note that these results are sensitive to the amount of offered flexibility and to the REC configuration.

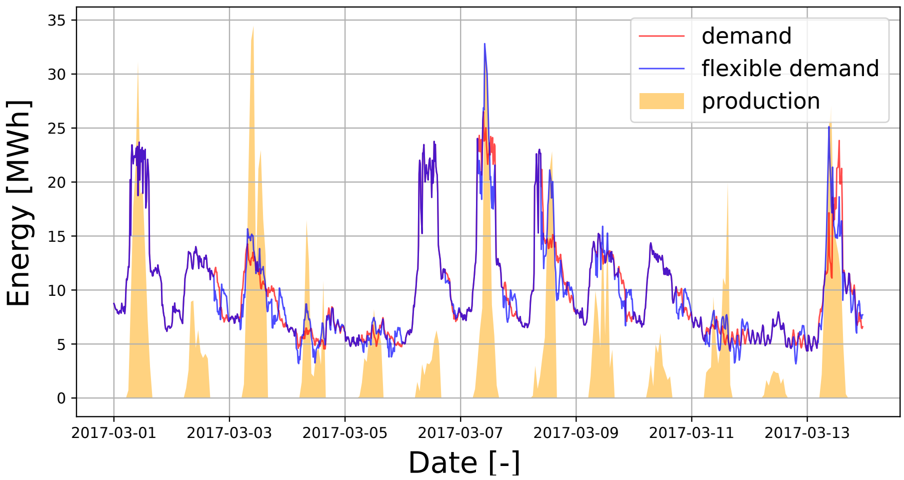


FIGURE 7.2: Initial demand (in red) vs demand after using flexibility (in blue). The PV production is displayed in yellow. Detail of 13 days in March 2017.

TABLE 7.4: Results of the analysis of flexibility use.

Parameter	With no flexibility	With flexibility	Difference
SSR	33.80%	36.72%	+2.92%
SCR	57.22%	62.23%	+5.01%
Total demand	333,325 MWh	333,688 MWh	$\sim$ same
Production	196,918 MWh	196,918 MWh	same
Local production	112,679 MWh	122,546 MWh	+8.1%
Global production	84,239 MWh	74,372 MWh	-13.27%

7.5 Conclusions

In this chapter a modelling framework is proposed for analysing the benefits of creating an REC with flexible and non-flexible consumers, and with PV generation assets. In this framework, an ECM is responsible for managing the REC and its participation in the European day-ahead market. Results show a 6.3% yearly reduction of total costs when an REC is created. A discount on the distribution tariff offered by the DSO when energy is produced and consumed locally has a key role on this cost reduction. Furthermore, we account for flexibility offered by the flexible consumers of the REC. We propose a bid acceptance algorithm according to which the ECM can optimise the amount of flexibility activated in the REC while accounting for the rebound effect. The incorporation of flexibility in the REC is shown to further reduce the total system cost by 6.8%. The importance of the instantaneous matching of supply and demand is showcased by an increase of the SSR and SCR of the REC when flexibility is introduced.

Chapter 8

How to allocate local generation in renewable energy communities

In the previous two chapters, we simulate a renewable energy community (REC) by means of a model of interaction (see Chapter 6), introducing flexible loads into it and formulating an activation strategy for this flexibility (see Chapter 7). These models rely on forecasts of demand and electricity prices to schedule the electricity exchanges among the REC members and between them and the energy community manager (ECM). However, when implementing a real-life REC, models relying on forecasts may lead to suboptimal schedules due to inevitable forecasting errors. To cope with these problems, this chapter (Chapter 8) proposes a novel methodology to allocate the locally generated electricity among the REC members, one that relies on real measurements of demand and production. This methodology consists of an *ex-post* optimisation of *repartition keys*, which represent the proportion of total local production allocated to every REC member.

This optimisation of repartition keys takes place after physical delivery of electricity and, in consequence, the actual electricity exchanges cannot be modified at this point. However, according to the latest European regulation, the DSO allows for modifying the meter readings even after physical delivery. Accordingly, an *ex-post* allocation of local production, where the financial exchanges of the REC are optimised taking into account real measurements, is possible. This *ex-post* allocation is what we call the settlement phase, as opposed to the scheduling phase addressed in previous chapters. The settlement phase is modelled through an optimisation framework which (i) minimises the sum of electricity costs of the REC members, and (ii) can enforce minimum self-sufficiency rates (SSRs) on them. We use the concept of SSR, defined as the proportion of electricity demand covered by local production, to introduce the ability to ensure minimum SSRs to the members of the community. The SSR can be computed per REC member or at the REC level – while the former can be maximised for some members at the expense of others, the latter is derived from the load and production profiles of the REC. Imposing minimum SSRs on the REC members (or on a subset of them), is useful to provide all members with receive enough economic incentives to participate in the REC, since higher SSRs are linked to lower electricity prices, assuming that the local electricity prices are lower than purchasing from a retailer.

The presented framework is designed so as to provide a practical approach that is ready to use by ECMs. It is also compliant with current legislation on decentralised electricity markets. This framework computes a set of optimal repartition keys per metering period and per member – these keys are computed based on an initial set of keys provided in the simulation, which are typically contractual i.e. agreed upon between the member and the manager the REC. Note that in this chapter we employ the term metering period to denote the resolution of the meters.

Finally, we provide a comprehensive range of scenarios where we test the presented methodology, illustrating its ability to optimise the electricity costs of an REC.

Notation

Sets

$\mathcal{T}$	Set of market periods $\{1, \ldots, T\}$
$\mathcal{I}$	Set of REC members $\{1, \ldots, I\}$

Parameters

$A_{t,i}$	Initial allocation of production
$C_{t,i}$	Consumption
$C^n_{t,i}$	Netted consumption
$K_{t,i}$	Initial repartition keys
$P_{t,i}$	Production
$P^n_{t,i}$	Netted production
SSR^{min}_i	Minimum self-sufficiency rate
$X_{t,i}$	Maximum allowed key deviation
ζ^b_i	Purchasing price imports
ζ^s_i	Selling price exports
ζ^{l-}_i	Local price imports
ζ^{l+}_i	Local price exports
ζ^d_i	Price of deviations from $A_{t,i}$

Decision variables

$a_{t,i}$	Optimised allocated production
$\overline{a}^+_t$	Positive deviation from $A_{t,i}$
$\overline{a}^-_t$	Negative deviation from $A_{t,i}$
$k_{t,i}$	Optimised repartition keys
ssr_i	Coverage rate
$v_{t,i}$	Verified allocated production
$y_{t,i}$	Locally sold production

8.1 Introduction

One of the most widely accepted trends in the path toward the de-carbonisation of the electricity sector is the decentralisation of electricity generation assets. This trend challenges common practices in power system operations, where consumer-centric electricity markets now play a key role [142]. Among these new potential markets is the energy community, naturally stemming from the empowerment of final consumers which, according to [143], have made community energy an effective and cost-efficient way to meet the energy needs of citizens. An energy community is a consumer-centric electricity market where several community members may exchange, among themselves, electricity produced from their own generation assets. According to some authors, the main barrier to developing these communities is the lack of sufficient legislation ensuring their viability [144, 145]. Aware of this issue, regional, national, and supra-national authorities are creating new legislations and frameworks that enable the emergence of these energy communities. The European Parliament, in the 2018/2001 directive [11], introduced a series of legal notions such as the renewables self-consumer (or prosumer), and the REC. According to this directive, all customers are eligible to participate in an REC while maintaining their previous status as final customers in a liberalised market, meaning that they are free to choose their retailer. Since any customer is, according to this directive, entitled to become prosumer, RECs may be composed of consumers, prosumers, or generation assets owned by the REC. In this context, RECs are managed by a central entity: the ECM.

Following the latest regulation developments on RECs, the main role of ECMs is to compute the allocation of locally generated production among the REC members, and to communicate it to the distribution system operator (DSO) *ex-post*, i.e., after physical delivery of electricity. This allocation of local generation is computed by the ECM by means of what is known as repartition keys. These keys represent the proportion of available local electricity production –after-the-meter– that is allocated to each of the REC members. After computing these keys, the ECM communicates them to the DSO, which modifies the meter readings of the REC members accordingly. The electricity flows of each member are thus divided into two. The first one corresponds to the local production associated to each member, which is used by the ECM to produce the local electricity bill. The second one corresponds to the demand that is not covered by local production, which is sent to the members' retailers to process the rest of the billing. Such a concept is used by the French [146] and Walloon (region of Belgium) regulation [147]. The French regulation makes use of such a concept [146] and, a similar legislative body exists in the Walloon region of Belgium, although without specifically mentioning the repartition keys [147]. Moreover, other European countries are adopting similar legislative decisions [148].

Using repartition keys to modify the meter readings of REC members affects their SSRs. In this context, SSR represents the proportion of total consumption covered by local production, for each member. The fraction of the total consumption not covered by local production must be supplied by retailer contracts. The proportions of consumption supplied locally (SSR) and by the retailer (100% - SSR) have different prices associated. Both retailer and local REC price comprise commodity, distribution, transmission and taxes, however, as per current European regulations, the DSO may offer a discount on the distribution component of the local REC price. This is why maximising the use of local production, that is, the SSR of the REC members, is economically beneficial for them. Hence, computing the SSRs of the members is crucial since it directly relates to their economic gains for participating in an REC.

According to regulation, a contract between the ECM and each REC member must be set, depending on which, the repartition keys are computed. This computation is a two-step process. First, an initial set of repartition keys are agreed upon between both parties, by signing a contract. These initial keys may be proportional to the investments of the members on generation assets. Second, the actual repartition keys are computed with some general objective, for instance the minimisation of the electricity bills of REC members. The deviations of the actual keys from the initial ones can be limited by contract i.e., the actual keys might be forced to be around the initial ones with a tolerance, for example, of 10%. If no initial keys are set by the contract, or if the maximum tolerance is 100%, the set of actual keys behave as though no initial keys were set, simply optimising the general objective.

The main contribution of this chapter is to provide a methodology to compute actual repartition keys based on a set of initial ones, allocating the local electricity generation of an REC among its members, accordingly. This methodology relies on an optimisation framework targeting a cost minimisation which is ready to use by ECMs, offering the necessary flexibility to be compliant with current regulations. In the rest of the chapter the actual keys are referred to as optimised keys.

Following this introduction, the remainder of the chapter is structured as follows: Section 8.2 presents a review of the existing literature on the topic and expounds the theoretical gap this chapter aims to fill. Section 8.3 describes the problem faced by an REC to allocate the locally generated electricity. Section 8.4 presents the problem formulation. Section 8.5 introduces a broad range of case studies. Finally, Section 8.6 concludes the chapter.

8.2 Literature review

The current literature dealing with decentralised, consumer-centric electricity trading can be broadly divided into two groups: trading in a peer-to-peer fashion and trading through a central entity.

In [149], the authors present an approach for a service management framework to control and monitor decentralised energy consumers, storages, and generators where algorithms for automated control of these consumers are based on P2P trading. On this topic, [150] proposes a P2P algorithm based on multi-bilateral trading and product differentiation where the problem is implemented by means of a distributed relaxed consensus and innovation approach. Another P2P framework, based on game theory is presented in [151], where real-time energy trading is proposed. In the latter work, a community of prosumers is simulated through their net-demands, meaning that prosumers can either be net-sellers or net-buyers, depending on their position. An overview of the application of blockchain technology to P2P prosumer trades is introduced in [152], showcasing a case study of a real community. Another literature review, this time on P2P approaches for energy management using game theory, is presented [48]. The authors in this work claim there exists plenty of research on this topic, and provide a comprehensive overview of the importance of game theory and its potential to be applied to P2P energy trading. In [47], the authors observe a P2P market relying on a consumer-centric and a bottom-up perspective. In their work, they provide consumers with the opportunity to freely choose how to buy their electricity needs. This paper presents an overview of these new P2P markets, exposing their motivation, challenges, market designs, and potential future developments in this field, providing recommendations. A detailed review of market proposals is provided, concluding that there are certain conditions where P2P markets may co-exist with existing market structures. In this paper, three types of P2P markets are presented: full P2P, community-based P2P, and a hybrid of the two. According to the authors, the most suitable one is the hybrid in terms of scalability. A more recent work, [49], presents an analysis where the behaviours of prosumers and prosumers are assessed under a P2P paradigm.

With regards to trading through a central planner, the literature is significantly less abundant and detailed, in particular when it comes to describing consumer-centric markets such as RECs. In [50], the authors present a community based approach to future electricity markets. An energy community is presented where the ECM acts as the interface between community member and the market. In this community, members do not interact with their retailers but rather with the ECM, who has the ability of computing and offering electricity prices to them. Another approach based on central planning is presented in [51] where a benevolent planner maximises the welfare of the community, redistributing revenues and costs amongst the members of the REC so that none of them is penalised as a result of being in a community. This problem is cast as a bi-level optimisation where the lower level solves the clearing problem of the community and the upper level shares the profits amongst the entities. In [46], flexibility bids from flexible consumers in a REC are offered to the ECM, who then selects and activates them to increase the welfare of the community. An approach based on game theory is presented in [142], where the authors present an analysis on the viability of RECs. This paper stresses the importance of allocating correctly the costs and benefits among the participants. They propose to base the sharing rule of the gains stemming from local production and consumption, as opposed to only production as it is usually done. The authors in [145] claim that benefits within REC may come from reductions on the network cost as well reductions on retailer costs, highlighting that proper price schemes may lead to substantial savings.

Whilst these papers offer different approaches to managing an REC, they all address the problem of scheduling the electricity exchanges within the REC, and between the REC and the grid, disregarding the settlement phase occurring after physical delivery. This chapter proposes to fill this gap, completing the already existing methods. Note that the settlement proposed in this chapter considers that the customers maintain their contracts with their retailers, whereas in the existing literature the ECM often provides all market interactions, therefore acting as a retailer. Current regulation, however, dictates for ECM to be a mere facilitator of the internal electricity exchanges of an REC without being a retailer.

8.3 Problem statement

To allocate the available local production injected into the grid among the REC members, the presented methodology must compute one repartition key per member and metering period. The metering period is defined as the meter's resolution, e.g., 15 minutes. Repartition keys are computed with this resolution. These keys represent the proportion of local production injected into the grid from which each member can benefit, directly impacting on their SSRs. In addition to the metering period, a reporting period can be defined, comprising several metering periods. The presented methodology therefore computes repartition keys for all metering periods in one reporting period. Let $\mathcal{T} = \{1, \ldots, T\}$ denote the set of all metering periods in a reporting period where T is the reporting period duration. Accordingly, the metering period is defined by the intervals $(t, t+1]$ contained in the reporting period $\mathcal{T}$.

In addition, a set of I REC members is defined as $\mathcal{I} = \{1, \ldots, I\}$. These members are characterised by their total production (if any) and consumption profiles, given as time-series with a resolution equal to the metering period, and spanning the reporting period. Since REC members may be prosumers, that is, they may consume or produce electricity along the reporting period, their consumption per metering period must be netted. This is done to subtract the behind-the-meter production of these members. The consumption and net consumption are denoted by $C_{t,i}$ and $C^n_{t,i}$, respectively. Similarly, the production must be netted to account for any behind-the-meter consumption. The production and net production are denoted by $P_{t,i}$ and $P^n_{t,i}$, respectively.

$$C^n_{t,i} = \max\{0, C_{t,i} - P_{t,i}\} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I}, \tag{8.1}$$

$$P^n_{t,i} = \max\{0, P_{t,i} - C_{t,i}\} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I}. \tag{8.2}$$

Commonly, producers sell part of their netted production to the community, which may not be able to consume it all. The local production sold by REC member i at metering period $(t, t+1]$ is denoted as $y_{t,i}$ and bounded by $P^n_{t,i}$: $y_{t,i} \leq P^n_{t,i}$.

As stated in the introduction, the challenge of computing repartition keys involves using a set of initial keys agreed upon between the REC members and the ECM. These initial keys are given by $K_{t,i}$, and represent the initial allocation of the available local production (whatever it is). They are set depending on the REC and the different agreements between ECM and REC members. For instance, in the case of an REC where the generation units are deployed thanks to an initial investment of all REC members, the initial keys could be set as the share of each member of the total investment of the REC. If, on the other hand, there is no initial investment, the initial keys may indicate the initial quantity of local production promised by the ECM to the REC members.

In this context, this chapter introduces a methodology to compute an optimal set of repartition keys, represented by $k_{t,i}$, which are based on the initial ones. This computation of optimal keys aims at minimising the sum of individual billing electricity costs of the REC members, which are determined by their electricity bill, expressed as:

$$\begin{aligned} B_{t,i} = &\xi^b_i \cdot \left(C^n_{t,i} - v_{t,i}\right) + \xi^{l-}_i \cdot v_{t,i} - \\ &\xi^{l+}_i \cdot y_{t,i} - \xi^s_i \cdot \left(P^n_{t,i} - y_{t,i}\right) \end{aligned} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I}, \tag{8.3}$$

where ξ^b_i is the overall price for electricity including distribution, transmission, energy price, and taxes for member i; and ξ^s_i is the price at which member i sells any electricity surplus to the retailer. Similarly, ξ^{l-}_i is the electricity price inside the REC, including taxes, local distribution (which may also include a fee for the transmission system operator), and energy price; and ξ^{l+}_i is the selling price of electricity when it is sold within the REC. Finally, $v_{t,i}$ represents the verified allocated production, which is discussed later in this section, and is computed simultaneously with the optimal set of repartition keys.

To compute the optimal set of keys that leads to the minimisation of Equation (8.3), the methodology takes into account three sets of constraints. The first set relates to the maximum allowed deviation of $k_{t,i}$ with respect to $K_{t,i}$. Indeed, a tolerance around the initial set of contractual keys $K_{t,i}$ may be enforced, beyond which the optimal set of keys $k_{t,i}$ cannot deviate. Such a tolerance is given by $X_{t,i}$:

$$X_{t,i} = |k_{t,i} - K_{t,i}| \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I}. \tag{8.4}$$

The second set of constraints defines the meter readings associated to the optimal keys. First, with the initial keys and the optimal ones, an initial allocation of available production and an optimal allocation of available production are computed, represented by $A_{t,i}$ and $a_{t,i}$, respectively:

$$A_{t,i} = K_{t,i} \cdot \sum_{i \in \mathcal{I}} P^n_{t,i} \quad \forall t \in \mathcal{T}, \tag{8.5}$$

$$a_{t,i} = k_{t,i} \cdot \sum_{i \in \mathcal{I}} P^n_{t,i} \quad \forall t \in \mathcal{T}. \tag{8.6}$$

The allocated production, however, is not necessarily the one accepted by the DSO to correct the meter readings. For instance, if the total net production ($P^n_{t,i}$) is greater than the total net consumption ($C^n_{t,i}$), Equation (8.6) may lead to allocations ($a_{t,i}$) that are, in fact, larger than the total net consumption. To avoid such situations, a final check computes the verified allocated production $v_{t,i}$, which takes the value of the optimal allocated production or the net consumption depending on which one is smaller. In addition, the sum of verified allocated production must be equal to the sum of local production sold over the set $\mathcal{I}$, for each metering period:

$$v_{t,i} = \min \left\{ a_{t,i}, C^n_{t,i} \right\} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I}, \tag{8.7}$$

$$\sum_{i \in \mathcal{I}} v_{t,i} = \sum_{i \in \mathcal{I}} y_{t,i} \quad \forall t \in \mathcal{T}. \tag{8.8}$$

The final set of constraints is related to the SSRs of the REC members, i.e. the fraction of the member's net consumption that is covered by local production. That is, covered consumption divided by total consumption. The covered consumption of member i is equal to the local production allocated to this member, which is calculated as $P_{t,i} - y_{t,i} + v_{t,i}$. However, since the allocated production may be greater than the total consumption $C_{t,i}$, the covered consumption must be expressed as $\min \{P_{t,i} - y_{t,i} + v_{t,i}, C_{t,i}\}$. In this last expression, if $y_{t,i}$ is positive, then $P_{t,i} - y_{t,i} + v_{t,i}$ is greater or equal than $C_{t,i}$, and therefore the expression can be simplified as $\min \{P_{t,i} + v_{t,i}, C_{t,i}\}$. Consequently, the SSR of member i is given by:

$$ssr_i = \frac{\sum_{t \in \mathcal{T}} \min \{P_{t,i} + v_{t,i}, C_{t,i}\}}{\sum_{t \in \mathcal{T}} C_{t,i}} \quad \forall i \in \mathcal{I}. \tag{8.9}$$

Furthermore, a minimum SSR may be enforced so that the ssr_i is increased for some REC members, enhancing their economic gains. This constraint, nonetheless, can potentially increase the sum of the electricity bills of the members. An SSR_i^{min} is thereby defined so that:

$$SSR_i^{min} \leq ssr_i \quad \forall i \in \mathcal{I}. \tag{8.10}$$

8.4 Problem formulation

The problem of allocating locally generated production by means of repartition keys can be expressed as a linear program.

$$\min_{z \in Z} \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left(B_{t,i} + \xi_i^d \cdot \left(a_t^+ + a_t^- \right) \right) \tag{8.11}$$

subject to

$$a_{t,i} = k_{t,i} \cdot \sum_{i \in \mathcal{I}} P_{t,i}^n \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.12}$$

$$\sum_{i \in \mathcal{I}} v_{t,i} = \sum_{i \in \mathcal{I}} y_{t,i} \quad \forall t \in \mathcal{T} \tag{8.13}$$

$$y_{t,i} \leq P_{t,i}^n \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.14}$$

$$a_{t,i} - A_{t,i} \leq a_t^+ \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.15}$$

$$A_{t,i} - a_{t,i} \leq a_t^- \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.16}$$

$$v_{t,i} \leq a_{t,i} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.17}$$

$$v_{t,i} \leq C_{t,i}^n \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.18}$$

$$\sum_{i \in \mathcal{I}} k_{t,i} \leq 1 \quad \forall t \in \mathcal{T} \tag{8.19}$$

$$k_{t,i} - K_{t,i} \leq X_{t,i} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.20}$$

$$K_{t,i} - k_{t,i} \leq X_{t,i} \quad \forall (t,i) \in \mathcal{T} \times \mathcal{I} \tag{8.21}$$

$$SSR_i^{min} \leq \frac{\sum_{t \in \mathcal{T}} \min \left\{ P_{t,i}, C_{t,i} \right\} + v_{t,i}}{\sum_{t \in \mathcal{T}} C_{t,i}} \quad \forall i \in \mathcal{I} \tag{8.22}$$

where the vector of decision variables is $z = \left(k_{t,i}, x_{t,i}^+, x_{t,i}^-, y_{t,i}, a_{t,i}, v_{t,i}, a_t^+, a_t^-, ssr_i \right) \in Z \subseteq [0,1] \times \mathbb{R}_+^8$.

The objective function (8.11) aims at minimising the sum of electricity bills of the REC members (see Equation (8.3) in Section 8.3) as well as an additional term, which is introduced to deal with cases with multiple solutions to the optimisation problem. This may, for example, occur when the sum of the net consumption of the members of the REC is greater than the sum of the net production, and all members buy and sell energy at the same price to both retailers and REC. In such a context, this extra term favours a solution that distributes the local production equally among the REC members, something we believe is desirable. Without this term, the allocation in these cases would be uneven, favouring some users depending on the optimisation solver numerical preferences. The fictive costs ξ_i^d associated to this term must be low, e.g. less than 0.1 €/MWh, so that they will not lead to a solution that corresponds to repartition keys associated with larger billing costs.

Equation (8.12) computes the optimised allocated production. Equation (8.13) sets the total allocated production equal to the total production sold by the REC members. Equation (8.14) limits the production sold to the total available production. Equations (8.15) and (8.16) compute the positive and negative deviations of allocated production, respectively. Equations (8.17) and (8.18) limit the verified allocated production to the smaller value between allocated production and demand. Equation (8.19) limits the sum of the repartition keys of the REC members to 100%. Equations (8.20) and (8.21) compute the repartition key deviations. Finally, Equation (8.22) computes the self-sufficiency rate of every member and enforces a minimum self-sufficiency rate. This last equation may lead to infeasible solutions (by enforcing an unattainable SSR_i^{min}), in which case new SSR_i^{min} need to be defined by the ECM.

Note that the numerator of Equation (8.22) is a linear form of the numerator of Equation (8.9). The two versions can be shown to be equivalent. Focusing on the numerator in Equations (8.9) and (8.22): If $P_{t,i} > C_{t,i}$, the net consumption $C^n_{t,i}$ is null, and thereby $v_{t,i} = 0$ as per Equation (8.18). In this case, the two numerators become equal to $\min\{P_{t,i}, C_{t,i}\}$. If $P_{t,i} \leq C_{t,i}$, the net consumption $C^n_{t,i}$ is not null, more precisely $C^n_{t,i} \geq 0$, and thereby $v_{t,i} \geq 0$. Then, by definition of $v_{t,i}$:

$$v_{t,i} \leq C^n_{t,i} = C_{t,i} - P_{t,i} \tag{8.23}$$

$$P_{t,i} + v_{t,i} \leq P_{t,i} + C^n_{t,i} = C_{t,i}. \tag{8.24}$$

As $P_{t,i} + v_{t,i} \leq C_{t,i}$, the numerator in Equation (8.9) becomes:

$$\min\{P_{t,i} + v_{t,i}, C_{t,i}\} = P_{t,i} + v_{t,i}. \tag{8.25}$$

which is equal to $\min\{P_{t,i}, C_{t,i}\} + v_{t,i}$ since $P_{t,i} \leq C_{t,i}$.

8.5 Results

This section introduces four different test cases as well as a complexity analysis. The first and second test cases illustrate the functioning of the methodology for different time horizons and number of REC members. The third one elaborates on the possibility to enforce a minimum SSR for the REC members. The proposed methodology requires an initial set of repartition keys from which an initial allocation of production is determined. How to compute these initial keys is the subject of debate, therefore, the last test case (iv) analyses the impact of using different initial repartition keys. Furthermore, it also tests the constraint enforcing maximum repartition key deviations ($X_{t,i}$). In all test cases except for the last one, the initial keys consist of a pro rata attribution according to each member's average consumption, as shown in [142, 153]. In addition to the initial keys, a set of price signals is needed for the optimisation, listed in Table 8.1.

TABLE 8.1: Price signals in €/MWh.

ζ_i^b	ζ_i^s	ζ_i^{l-}	ζ_i^{l+}	ζ_i^d
220	60	100	98	1

8.5.1 Test case 1: performance on a simplified example

The first test case provides a simplified example to acquaint the reader with the most important features of the tool. This example features an REC with two pure consumers (User1 and User2, in red), one pure producer (User3, in green) and one prosumer (User4, in orange). The optimisation horizon is two metering periods, the first one with more production than consumption, and the second with more consumption than production. Table 8.2 presents the inputs used for this simulation including: (i) consumption which is positive for consumption and negative for production; (ii) initial keys; and (iii) initial allocated production. Note that the units in this example are kWh. All these parameters are computed as a pre-process of the optimisation problem. By comparing the consumption and initial allocated production in Table 8.2, it can be seen that the initial allocation of production is suboptimal. For metering period one, albeit there is more total production than total consumption not all the REC members see their electricity demand met, whereas for metering period two, the distribution of the local production leads to spillage in User4 and to under-supply in User1 and User2.

TABLE 8.2: Test case 1 – inputs.

Metering period	**User1**	**User2**	**User3**	**User4**
		Consumption		
2017-03-01 00:00	0.17	0.21	-0.50	0.08
2017-03-01 00:15	0.21	0.23	-0.30	-0.02
		Initial repartition keys		
2017-03-01 00:00	0.42	0.49	0.00	0.089
2017-03-01 00:15	0.42	0.49	0.00	0.089
		Initial allocated production		
2017-03-01 00:00	0.21	0.24	0.00	0.04
2017-03-01 00:15	0.13	0.16	0.00	0.03

This initial situation is then used by the optimisation problem to recompute the keys. The results of this optimisation are presented in Table 8.3 which lists the consumption-related and production-related outputs. In this table, an overall rearrangement of the keys with respect to the initial ones can be observed. At metering period one, the keys for User1 and User2 are decreased, whereas the key of User4 is increased. Conversely, at metering period two, the inverse flow occurs. The new set of keys leads to an optimal allocation of the production among the REC members by which any deficit of local production is supplied by the retailers, whereas any excess is sold to them.

TABLE 8.3: Test case1 – outputs.

Metering period	**User1**	**User2**	**User3**	**User4**
Optimised repartition keys				
2017-03-01 00:00	0.39	0.45	0.00	0.16
2017-03-01 00:15	0.47	0.53	0.00	0.00
Optimised verified allocated production				
2017-03-01 00:00	0.17	0.21	0.00	0.08
2017-03-01 00:15	0.15	0.17	0.00	0.00
Production sold locally to the REC				
2017-03-01 00:00	0.00	0.00	0.46	0.00
2017-03-01 00:15	0.00	0.00	0.30	0.02
Production sold to the main network				
2017-03-01 00:00	0.00	0.00	0.04	0.00
2017-03-01 00:15	0.00	0.00	0.00	0.00

Additionally, Table 8.3 shows the distribution of local production: local sales (energy delivered to REC members) and global sales (energy sold to the retailer). In the first metering period, local sales amount to 0.46, which is the total demand of the system. The production surplus (0.04), is sold to the retailer as global sales. In the second metering period, local sales are 0.30 + 0.02, which corresponds to the total available production. Since, at this metering period, there is greater demand than supply, there are no global sales. The maximisation of global sales observed in these results depends on the price signals imposed in the simulation. In this case, since the selling price is the same for all producers, the optimisation cannot discriminate between them when allocating local and global sales, and provides one of the possible solutions. However, this parameter can be adjusted in the optimisation (i.e. one price signal per producer), leading to a ranking of producers.

8.5.2 Test case 2: performance on a realistic example

This second analysis introduces a more realistic set-up where an REC with 23 net consumers and 1 net producer is simulated over one year of operation. Input consumption data corresponds to real measurements of small- and medium-volume electricity consumers in Belgium. The initial repartition keys fed to the optimisation are based on a proportionality principle of the annual consumption of the members with respect to the total accumulated consumption of the REC. The maximum key deviation $X_{t,i}$ allowed is not bounded.

Figure 8.1 shows the electricity costs of all members with and without participation in an REC after the optimisation of the keys. In this figure, positive values imply a cost, whilst negative values imply a revenue for the REC members. For this set of prices, deploying an REC reduces the electricity costs of the members by around 30% (some REC members reach more than 50%).

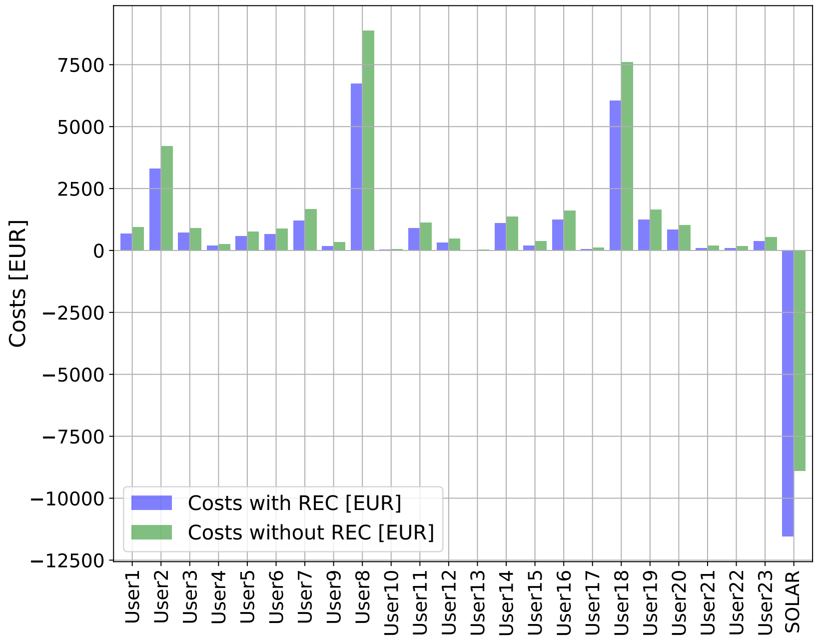
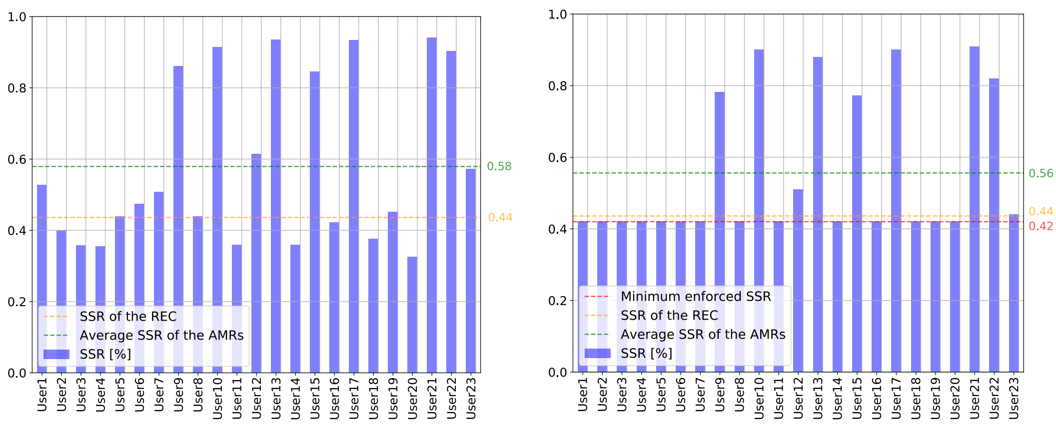


FIGURE 8.1: Costs of the REC members.

8.5.3 Test case 3: minimum SSR

The second test case showcases how the constraint imposing a minimum SSR works. This analysis makes use of the same REC and price signals as in the previous test case.



(A) Without minimum SSR bound.

(B) With an enforced minimum SSR of 42%

FIGURE 8.2: SSR of the consumers after the repartition keys optimisation.

Figure 8.2 shows the SSR of the members of the REC, after running the optimisation with $SSR_i^{min} = 0\%$ and $SSR_i^{min} = 42\%$. In this figure when no bound on the SSR_i^{min} is imposed, the SSR of the members ssr_i is freely selected to minimise the global costs of the REC. The values of ssr_i span from 32.5% for User20 to 94.1% for User21 (see Figure 8.2a). As the problem is progressively tightened by enforcing more restrictive values of SSR_i^{min} for all the REC members, a transfer from the members with highest levels of ssr_i to those with lower levels takes place. Upon reaching the maximum feasible value of $SSR_i^{min} = 42\%$, a more uniform ssr_i for all REC members can be seen (see Figure 8.2b). Note that for this example, enforcing an SSR_i^{min} greater than 42% leads to an infeasible problem where the system does not generate sufficient local electricity to keep increasing it. Tightening the optimisation problem may decrease the average SSR of all members, since some members are forced to give up part of their ssr_i to increase other members' SSRs. In this particular example, the consequence is that the average SSR of the all REC members is eroded, decreasing from 58% to 56%. However, the same does not apply to the SSR of the REC, as this SSR only depends on the total local production, and this does not change by enforcing tighter values of SSR_i^{min}.

Enforcing a minimum SSR has an impact on the electricity costs of the REC members. Figure 8.3 illustrates the difference in costs caused by the enforcement of $SSR_i^{min} = 42\%$ compared to the case where it is left free (0.0%). This figure shows that members who are forced to give up their ssr_i when enforcing an SSR_i^{min}, incur higher costs than before enforcing any SSR_i^{min} and conversely for the others. In particular, the gains of REC members range from 0.25% for User16 to 9.5% for User23, whereas the losses range from -1.5% for User2 to -6.5% for User20.

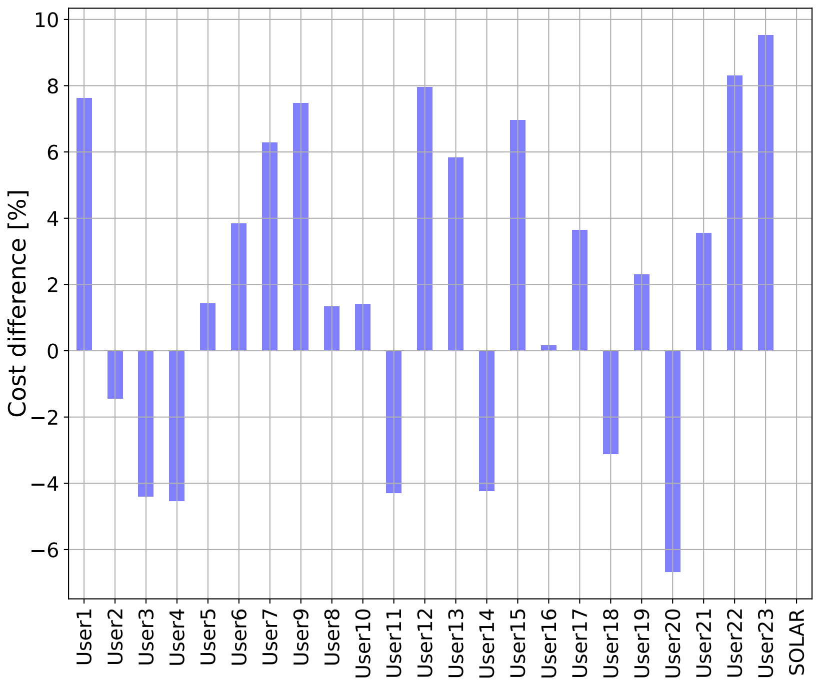


FIGURE 8.3: Difference in the REC members costs, with and without enforcing any minimum SSR of 42%.

8.5.4 Test case 4: impact of initial repartition keys

The last test case presented in this chapter illustrates the impact of employing different initial repartition keys. Moreover, it also showcases the functioning of the constraint imposing a maximum key deviation. In this context, key deviations are represented by the difference between optimised and initial repartition keys of each REC member ($k_{t,i} - K_{t,i}$). To perform this analysis, a smaller REC is selected, composed of six members: five net consumers (User1 – User5) and one net producer (User6). The simulation horizon is reduced to one month (April) because of the high number of runs required to perform the following analyses.

This example tests different types of initial repartition keys:

- Uniform: evenly distributed among the REC members – all members with positive net demand receive the same percentage of the local production.
- Proportional static: Each member obtains a percentage of the local production which is proportional to their average demand over the simulated period – each member receives a different initial key, constant over time.
- Proportional dynamic: Each member obtains a percentage of the available local production which is proportional to their instantaneous demand – each member receives a different initial key per metering period of the simulation.

Table 8.4 lists the total consumption and production of the system and total allocated production achieved with the three types of initial keys. With the proportional dynamic keys, the local production is used up to 76% more than with uniform keys, and 29% more than with proportional static keys.

TABLE 8.4: Allocated production for the different initial keys.

Total demand	37.50 MWh
Total local production	11.35 MWh
Allocated production with uniform keys	5.02 MWh
Allocated production with proportional static keys	6.85 MWh
Allocated production with proportional dynamic keys	8.87 MWh

In the following, the evolution of several parameters over a range of maximum allowed key deviations $X_{t,i}$ given as parameters, is shown. The allowed deviations span from 0%, meaning that the optimised keys cannot deviate from the initial keys, to 100%, meaning that the optimised keys may deviate as much as needed, taking any value in $[0, 1]$. Since dynamic keys lead to the most optimal distribution between local and global sales as long as the price ζ_i^b is the same for all members (i.e., same retailer contract), the sales do not change for different values of $X_{t,i}$ when these keys are implemented. For this reason, the different parameter evolutions shown in the rest of this section do not contain the impact of using dynamic keys. This also indicates that dynamic keys are a suitable solution when no other constraint is required, and purchasing prices ζ_i^b are similar across REC members.

The first of the parameters studied is the spread between local sales ($y_{t,i}$) and global sales ($P^n_{t,i} - y_{t,i}$). This spread is strictly positive if local sales are greater than global sales. Figure 8.4 shows that for both sets of initial keys, allowing free key deviations ($X_{t,i} = 100\%$) leads to the same spread between local and global sales. However, they differ when $X_{t,i} < 100\%$. When applying proportional static initial keys, the spread is always positive and increases with the value of $X_{t,i}$. On the other hand, applying uniform initial keys leads to negative spreads when $X_{t,i} < 5\%$. This analysis shows that when no limitation on the maximum key deviation is imposed, the optimisation finds the same solution regardless of the initial key. However, when this constraint is tight ($X_{t,i} < 100\%$), the selection of initial keys has a notable impact on the results.

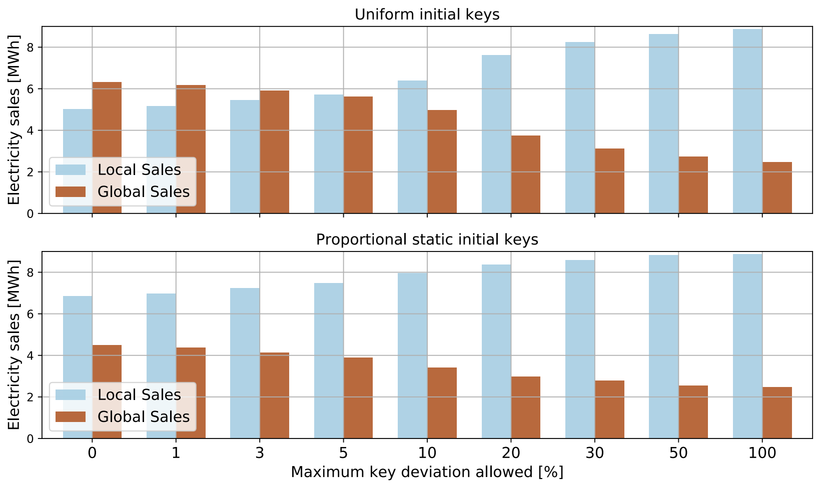


FIGURE 8.4: Total locally sold and globally sold production for a range of maximum key deviations ($X_{t,i}$).

The individual costs of the REC members, for a range of $X_{t,i}$ from 0% to 100%, are shown in Figure 8.5. All net consumers (User1 – User5) see their costs reduced as the maximum key deviation allowed becomes less restrictive. The net producer (User6) electricity revenue increases as the costs of the consumers decrease. In this case, positive values indicate negative costs (or revenue), which increase by the given percentage. The variation in member's costs in response to a relaxation of the maximum key deviation allowed results in similar trends when using either uniform or proportional static initial keys. The extent of these variations is different though, being one order of magnitude larger for uniform keys. The savings of User1 – User5 for uniform keys span from 1% to 8%, whereas for proportional static they span from 0.5% to 4%. The increase in gains of User6 is 16% with uniform keys and 8% with static keys. These differences prove that uniform initial keys lead to a highly suboptimal solution compared to proportional static ones. This remark highlights the idea that creating keys that are proportional to the demand of the REC members seems to be a good practice, which concurs with current practices [153].

A final analysis is presented in Figure 8.6, showing the difference in allocated local production for different initial keys and for a range of maximum allowed key

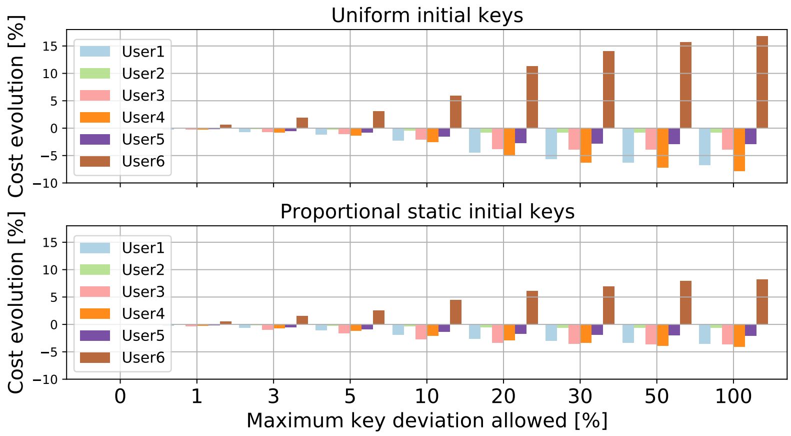


FIGURE 8.5: Costs of the members for a range of maximum key deviations ($X_{t,i}$) relative to the costs when $X_{t,i} = 0$.

deviations, relative to the initial situation when no deviation is allowed. In this last figure, the effect of relaxing the maximum allowed key deviation is not shown for proportional dynamic keys since, as in Figure 8.5, the changes are negligible. The trends followed by the members' allocated production is similar for uniform and static keys. In both cases this trend is upward when relaxing the value of maximum allowed key deviation. However, the extent is different, and the members involved too: while in the uniform keys case the allocated production increases for User1 and User4 to in excess of 100%, for static keys it only reaches 70% for User3. The difference in these results stems from the different demand profiles of the REC members. For User3, the average electricity demand is, on average, lower than for the rest. Thus, when applying uniform keys, the allocated production is sufficient to cover the demand of this member, since the percentage of allocation is the same for all of them. However, when applying proportional static keys, the initial allocated production given to User3 is low – it depends on average demand (which indeed is relatively low), but it has to cover instantaneous demand (which might be high). For this reason, the initial solution does not provide enough supply to User3 with static keys, and therefore the methodology must increase the optimised keys for this particular REC member.

8.5.5 Complexity analysis

In the final section of the results, we present an analysis of the complexity of the methodology proposed. The number of constraints of the optimisation is $N_{cons} = 9|\mathcal{T}||\mathcal{U}| + |\mathcal{T}| + |\mathcal{U}|$ and the number of variables $N_{var} = 17|\mathcal{T}||\mathcal{U}| + 2|\mathcal{T}| + |\mathcal{U}|$. Table 8.5 introduces the running times for different complexities, ranging from 15 days with 10 REC members to one month with 100 members. The optimisation problem is implemented with Pyomo in Python 3.8 and solved with the open source solver CBC. Simulations are performed on a GNU/Linux machine with an Intel® Core™ i7-8665U and 16 Gb of RAM.

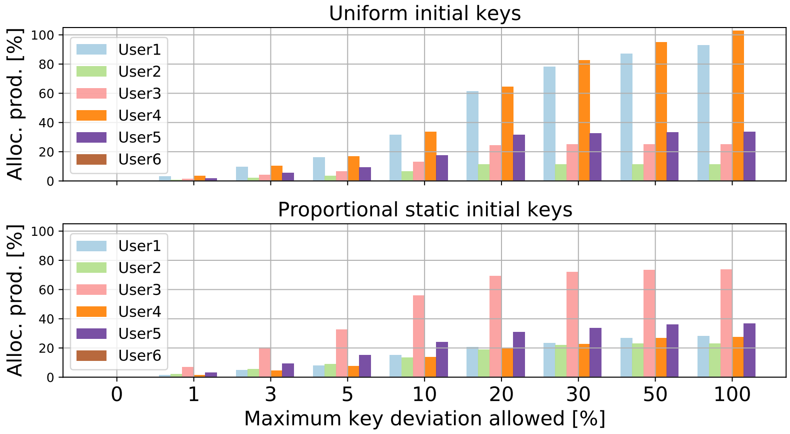


FIGURE 8.6: Allocated production of the REC members for a range of maximum key deviations ($X_{t,i}$) relative to the allocated production when $X_{t,i} = 0$.

TABLE 8.5: Running times of the proposed algorithm.

$\|\mathcal{T}\|$	$\|\mathcal{U}\|$	N_{cons}	N_{var}	Build time [s]	Solve time [s]
1,440	10	131,050	247,690	5.01	5.96
2,880	10	262,090	495,370	9.71	12.23
1,440	50	649,490	1,226,930	20.36	27.72
2,880	50	1,298,930	2,453,810	43.55	56.55
1,440	100	1,297,540	2,450,980	39.67	58.93
2,880	100	2,594,980	4,901,860	85.92	133.93

8.6 Conclusion

This chapter proposes a methodology to deal with the settlement phase of an REC to optimise the sum of electricity bills and to enforce minimum SSRs in some of the REC members – a methodology that is compliant with current regulations and ready to use by an ECM. After physical delivery of electricity, the DSO permits modifying the meter readings. This implies that the financial flows of the REC members can be determined in a settlement phase that changes the meter readings, and that splits these flows into two: one directed to the ECM corresponding to electricity consumption within the REC; and another sent to the retailers corresponding to the electricity consumption covered by a traditional retailing process. To modify the meter readings, this chapter makes use of *repartition keys*, which represent the percentage of total local production provided to each member. The methodology presented in this chapter computes an *ex-post* allocation of local production in an REC by using these keys. The repartition keys are optimally computed by a linear program that minimises the sum of individual electricity costs of the REC members, and that may use an initial set of keys as starting point. This methodology enables, by adding the right constraints, the control of some parameters such as the self-sufficiency rate of the REC members, or the deviations between optimised repartition keys and initial ones. These keys can be optimally computed based on another set of –initial– keys that is an input of the simulation.

Various test cases illustrate this methodology, testing the functioning of the optimisation framework as well as its parameters. Such tests show that this methodology results in an allocation of local production that leads to lower operational costs than when no REC is established. Moreover, this approach can be used to enforce minimum self-sufficiency rates on the REC members, enhancing the economic gains of some of them that might, otherwise, be left without sufficient allocated production by a traditional global welfare optimisation. Finally, simulation results indicate that using initial keys consisting of a *pro rata* attribution of each REC member instantaneous consumption is a good practice when the retail electricity price of all of them is similar. The methodology presented in this chapter has been tested and is currently being implemented by industrial partners in different REC managed by them.

Conclusions and future work

Chapter 9

Conclusion

The unstoppable rise of distributed renewable electricity generation resources (DER), driven over the last decades by commercial and regulatory factors (as seen in Chapter 1) has brought about several challenges for the adequate functioning of the electricity distribution network. Such challenges can be broadly divided into technical and regulatory – this thesis has focused on the latter, exploring this type of challenges from a modelling standpoint. In particular, this research has unfolded in two main directions: (i) the study of regulatory frameworks consisting of the metering technology, the distribution tariff design, and other incentive mechanisms; and (ii) the development of new frameworks for the integration of DER based on decentralised electricity markets. Accordingly, this manuscript has been divided in two main parts that address the two main elements of this research.

9.1 Part I

In the first part of the thesis we have formalised and built a simulation-based approach to assess the impact of a wide range of regulatory frameworks on the penetration of DER and the economic sustainability of the distribution network. Such an approach is based on agent-based modelling where the agents are the final customers of a distribution network and the distribution system operator (DSO). These agents take actions over a discrete-time dynamical system, making the system evolve.

On the one hand, final customers' actions consist in deploying DER installations composed of solar photovoltaic (PV) panels and/or batteries to reduce their electricity costs. This is controlled through an optimisation framework followed by an investment decision process. The optimisation framework is instantiated in the form of a mixed integer linear problem that computes, for each agent, the optimal capacity of PV panels (in kWp) and batteries (in kWh) to be deployed to minimise their levelised value of electricity (LVOE)[1]. As for the investment decision process, it compares, for every customer the LVOE with the LCOE resulting if no DER installation

[1]The LVOE is computed as levelised annual costs (electricity imports from the grid) minus revenue (electricity exports to the grid) divided by levelised annual demand. The difference between the LVOE and the more traditional levelised cost of electricity (LCOE) is that whilst the former accounts for costs and revenue of the prosumers, the latter can only account for costs, therefore not presenting the complete picture of the economic benefit of deploying DER installations since it can only show the avoided costs but not the revenue.

is deployed. The result of this comparison is filtered through a Bernoulli distribution that determines whether the optimally sized DER installation is deployed.

On the other hand, the DSO has the ability to adjust the distribution fee to ensure its economic sustainability. This is controlled through an accurate modelling of its remuneration strategy, which depends on the regulatory framework. In particular, our approach enables the simulation of two different metering technologies, net-metering and net-billing, as well as four different types of distribution fee which depend on energy consumption (volumetric), power consumption (capacity), availability of an access point to the grid (fixed), and time of energy or power consumption (ToU). Additionally it is also possible to introduce any combination of these metering technologies and fees.

The evaluation of these actions at each time-step of the discrete-time dynamical system results in a trajectory of actions from which the evolution of several variables can be extracted: DER adoption, PV panel and battery capacities, electricity imports and exports from and to the grid, and distribution tariff. Finally, using this simulation-based approach with different regulatory frameworks facilitates their comparison based, on the different set of trajectories they induce. The potential of this approach thus lies in its ability to accurately discriminate between the possible outcomes of employing distinct regulatory frameworks in order to provide sound arguments that underpin the selection of one of them. This tool can serve as guidance for policy makers and regulators to build new combinations of metering technology and distribution tariff design, aiming to achieve certain specific objectives (e.g. promoting the adoption of DER). By means of this simulation-based tool, they can compare the strengths and drawbacks of distinct options before applying them in real life.

Concerning the design of this tool, the contributions of this thesis are:

- The mathematical formalisation of the simulation-based approach, which encapsulates the salient features of all the most commonly used metering technologies and distribution tariff designs.

- A computational tool encoding such a mathematical formalisation to help policy makers and regulators design regulatory frameworks.

Furthermore, in the context of this thesis, we have extensively tested this simulation-based approach with a broad range of regulatory frameworks, covering all their most common features. Our findings offer insights on the impact of (i) the metering technology, and (ii) the distribution tariff design.

Regarding the metering technology, we observe that regulatory frameworks based on net-metering provide enormous incentives for potential prosumers to deploy DER installations. In particular, this technology highly boosts the adoption of PV installations. However, it does not incentivise the deployment of batteries under any distribution tariff design. Furthermore, this large DER deployment comes at a high cost: net-metering creates very significant electricity cost differences between consumers and prosumers, where consumers bear most of the distribution costs. This leads to substantial cross-subsidies from consumers to prosumers, and jeopardises the economic sustainability of the DSO. In addition, this metering technology may lead to a "death spiral" where the distribution tariff increases dramatically – the DSO looses revenue due to prosumers reduced contributions and must adjust the tariff upward to compensate (see Figure 1.1). In contrast, employing net-purchasing as metering technology help reduce, though not eliminate, the risks of cross-subsidisation incurred by net-metering. Moreover, this technology reduces peak power withdrawals and injections, in particular when capacity-based fees are applied, suggesting that these two elements strongly complement each other. This system may also lead to a "death spiral", especially if it is associated to a fully volumetric distribution fee.

As for the distribution tariff design, our results suggest that regulatory frameworks based on volumetric fees (including ToU) offer the best incentive for PV panel and battery deployment. These frameworks, though, lead to the highest inequalities between consumers and prosumers in terms of electricity costs. When applying mostly capacity fees, the integration of storage devices is promoted, as these devices can limit the peak of consumption of prosumers. However, these fees lead (as the previous ones did) to a cost distribution between consumers and prosumers where the former bear most of the network costs. Frameworks based on fixed fees significantly limit the incentives for DER deployment, therefore they hardly show any impact on the distribution of grid costs. Finally, frameworks based on a combination of these fees lead to various different outcomes which, to a greater or a lesser extent, induce "death spiral" behaviours and the promotion of DER installations.

An overall conclusion of our analysis is that, whilst the regulatory framework in place plays a major role in the way the distribution network is expected to evolve, all of them lead, to some extent, to an increase in distribution rates as a result of DER deployment (with the exception of fully fixed fees). This indicates that, considering current legislations where the DSO is financed through distribution fees to the final customers, a trade-off will always emerge between promoting the adoption of DER technologies and containing the distribution rates – one is not possible without the other. Designing holistic policies supporting DER adoption and regulating the electricity distribution network is, therefore, key to facilitate a seamless and sustainable energy transition.

9.2 Part II

The second part of this thesis has studied new frameworks to promote the integration of DER based on decentralised electricity trading and, in particular, on renewable energy communities (RECs). According to the latest European regulations, RECs are communities of final customers (consumers or prosumers) who may benefit from renewable electricity produced locally. These communities are managed by a central entity: the REC manager (ECM). Since RECs are a rather new concept, the existing literature in this topic is scarce. Aiming to fill this gap, we have proposing several modelling solutions for RECs, focusing on their economic viability.

The first step toward modelling RECs has been the design of a generic model of interaction, based on agent-based modelling where the generic agents are: consumers and prosumers, retailer and ECM, wholesale market, and transmission system operator. This approach enables simulating different decentralised electricity markets, such as aggregator models or RECs. In addition, our model allows for the introduction of flexible consumers. Since this is a generic model, it is necessary to adapt it to the desired context by selecting the agents to be used in the simulation.

Once designed, the model of interaction has been instantiated to simulate the scheduling of electricity exchanges within an REC. This instance is built so that the consumers and prosumers represent the REC members, and the ECM and the retailer are the same entity. The ECM is therefore responsible for managing the REC and for its participation in the European day-ahead market, acting as the unique retailer of the REC. Flexibility bids are introduced with flexible consumers, and their economic impact is assessed by means of a bid acceptance algorithm. This algorithm is formulated as an optimisation framework that takes into account forecasts of demand and production within the REC, forecasts of day-ahead prices, and flexibility bids from flexible consumers. With these inputs, the optimisation framework determines the flexibility bids to be accepted by the ECM in order to minimise the costs of performing the demand provisioning in the day-ahead market. If the bids can be partially accepted, the optimisation framework can be instantiated as a linear problem. Otherwise it is instantiated as a mixed integer linear problem. A test case running this minimisation problem shows a significant yearly reduction of total costs when an REC is created, compared to the case where the final customers resort to classical retailing contracts. This cost reduction can be attributed to a discount on the distribution tariff, offered by the DSO when energy is produced and consumed locally. Furthermore, our analysis suggests that further cost reductions are possible when flexibility bids are introduced in the simulation, owing, mainly, to a better matching of supply and demand within the REC.

After studying the scheduling of RECs, where the electricity exchanges are computed based on forecasts of demand, production, and electricity prices, we have analysed a settlement phase. Due to forecasting errors, the scheduling phase leads, inevitably, to suboptimal solutions. To overcome this problem, we have created a novel algorithm that allocates locally generated electricity among the REC members in an *ex-post* phase where the actual production and demand are known. This is what we call the settlement phase. This phase takes place after physical delivery of electricity and, therefore, the electricity flows cannot be modified at this point. However, since the financial exchanges depend on the meter readings and these can be modified after physical delivery according to the latest regulations, an algorithm can be laid out to optimise the financial flows of the REC members. At the core of this algorithm is the concept of *repartition keys*, which represent the percentage of total local production allocated to each member. Each REC member is assigned one key per metering period (the resolution of the meter) and thus the production is allocated. In addition, an initial set of keys can be assigned, so that the algorithm can re-allocate an initial distribution of local production. The keys are optimised so as to minimise the sum of individual electricity costs of the REC members. This optimisation is instantiated in the form of a linear program that, in addition to minimise the electricity costs, can enforce minimum levels of self-sufficiency rates (SSRs) on the REC members. This allows for increasing their incentive to participate in the REC since, without a sufficiently high SSR, some REC members may be better-off with classical retailer contracts. This methodology represents a ready-to-be-used approach which is compliant with current regulations. We have extensively tested this methodology, with and without initial repartition keys, demonstrating its ability to lower the operational costs of a group of consumers, when an REC is established.

In this second part of the thesis we have provided the following contributions:

- A generic model of interaction which employs agent-based modelling to simulate RECs accounting for flexible demand.
- An optimisation framework to control the activation of flexibility, aiming to minimise the sum of electricity costs of the REC members.
- An optimisation framework that optimises the financial flows of REC members, using the concept of repartition keys.

Assuming that the electricity exchanges within the REC are associated to a lower price than the retail tariff, the overall conclusion is that creating an REC to replace traditional retailing contracts can result in lower electricity costs for the REC members. If, in addition to a regular REC, flexible consumption is allowed, the electricity costs of the REC members can be further reduced. Finally, optimising repartition keys to determine the allocation of local production after physical delivery is shown to be a practical way of steering clear of forecasting errors whilst minimising electricity costs thanks to the *ex-post* modification of the meter readings.

9.3 Limitations and future research

The models developed in the context of this research present some limitations. The most relevant ones are discussed in this section.

Concerning the simulation-based approach presented in the first part of this manuscript, the investment decision of prosumers is limited to a one-off deployment of DER installations. This means that, once prosumers deploy a DER installation, our approach prevents them from reinvesting, and early adopters cannot expand their installations even if the conditions are favourable. Enabling prosumers to reinvest is a potential improvement of our simulation-based approach. In addition, only a fixed variety of consumption profiles are considered, which cannot evolve over time. Real customers, nonetheless, are likely to change their consumption patterns by, for instance, purchasing an electric vehicle, which is currently not considered in our approach. Our approach relies on several parameters that must be precisely tuned in order to perform real-life simulations, this tuning phase can be challenging since it requires a substantial amount of data and work. Finally, our simulation-based approach models the distribution network as a zero-sum game where the DSO costs are constant over time. However, certain distribution tariff designs may result in collective benefits such as peak power withdrawn or injected reductions that are only possible owing to private investments from prosumers. Quantifying these aspects, allowing for evolving DSO costs can potentially extend the scope of analysis.

As for the limitations of our approach to model decentralised electricity markets such as RECs, the interaction model created to deal with the scheduling phase of RECs is designed so that the ECM activates and benefits from flexibility based solely on energy. However, this approach could be extended by defining capacity products. This capacity would be activated depending on the needs – a flexibility bid of capacity should include a reservation and an activation cost. In our framework, flexibility bids offered by flexible consumers are independent from the actual needs of the ECM, and flexible consumers post these bids based on their own consumption. An alternative option could be for the ECM to notify flexible consumers of a flexibility need, and only then would they post flexibility bids. Moreover, the scheduling phase of the REC only takes into account one market floor: the day-ahead market. An additional optimisation step, closer to physical delivery, might further reduce the electricity costs of the REC due to improved forecasts. As for the settlement, when this phase is simulated, our approach does not consider the real time control of the electricity exchanges, only using the final consumption and production profiles of the REC members. A mixed approach where both electricity (through a control algorithm) and financial exchanges (through the algorithm presented in this thesis) are optimised may help reduce the electricity costs of the REC. Finally, electricity charges based on peak power consumption that better reflect the costs of withdrawing electricity from the distribution network might be included in this phase. These charges can help reduce not only the REC costs, but also relieve potential congestion in the distribution network.

In addition to these limitations and potential for improvement, some additional research directions can be considered. Modelling the physical constraints induced by the integration of DER, such as over-voltages, may provide a broader view of the limits of our approach. In addition, considering the option of changing the topology of the network, aiming to model future investments in infrastructure depending on the DER penetration, can help better evaluate the DSO costs. Finally, restrictions on the imports and exports of prosumers might be introduced. These restrictions may represent some of the physical limits of the installations, offering a more realistic scenario which potentially deteriorates the business case of prosumers.

Appendix

Appendix A

A multi-agent system approach to model the interaction between distributed generation deployment and the grid

This paper introduces a multi-agent dynamical system of the interaction between electricity consumers, the electricity distribution system operator, and the technological (generation, storage) and regulatory (tariff design, incentive schemes) environments. For any type of environment, our dynamical system simulates the evolution of the deployment of distributed electricity generation, as well as the evolution of the cost of distribution. The system relies on the assumption that individual electricity consumers behave statistically as rational agents, who may invest in optimised distributed renewable energy installations, if they are cost-efficient compared to the retail electricity tariff. The deployment of these installations induces a change in the aggregated net consumption and generation of the users of a distribution network. By modelling the cost recovery mechanism of the distribution system operator, the system simulates the evolution of the retail electricity tariff in response to such a change in the aggregated consumption and production.

A.1 Introduction

The integration of distributed electricity generation technologies (DRE), such as solar photovoltaic panels (PV), into the distribution networks (DN) has been made possible by the use of incentive schemes, as these technologies used to be less economically competitive than conventional ones [154]. The inclusion of a sizeable amount of DRE installations, nonetheless, may cause severe strain on the distribution systems, since they are not engineered to absorb large amounts of distributed generation (DG) [86]. The nature of the strain imposed on the system can be multi-faceted, and may stem from technical problems such as over-voltages in the low voltage distribution system [25], or regulatory problems including the over-compensation of DRE owners and the potential failure of the cost recovery mechanisms of the distribution system operators (DSO) [36].

In our work, we aim at creating a methodology for testing the impact of any regulatory and technological environments on the deployment of DRE installations and on the distribution component of the retail electricity tariff (simply distribution tariff from now on). The methodology we describe in this paper is based on a multi-agent discrete-time dynamical system formalisation, in which the agents interact with an environment. On the one hand, the agents of such a system are the DRE owners, the non-DRE owners, and a (unique) DSO. On the other hand, the environment (the DN), is composed of a set of rules including the aforementioned incentive schemes, the tariff design of the DN (e.g. volumetric tariffs or capacity tariffs), and the cost of distributed generation and storage technologies.

The purpose of this paper is to describe and test this methodology. In particular, our main contributions are the following:

- We provide a description of our multi-agent discrete-time dynamical system formalisation, used to simulate the evolution of an electricity distribution system by modelling the interactions of individual agents (DRE owners, non-DRE owners, and DSO), with the environment. This is presented in the Methodology section.

- We introduce a test case in which we compare different incentive schemes. In particular we compare two distinct compensation mechanisms (net-metering and net-purchasing) as described in [33]. This is explained in detail in the Test Case section.

A.2 Methodology

In this section we elaborate on the modelling of our multi-agent discrete-time dynamical system. The purpose of such a system is to evaluate, over a given time horizon, and for any environment,

1. the impact of the environment on the rate of adoption of DRE installations; and

2. the impact of the penetration of a significant amount of DRE installations on the distribution tariff.

The result of the first evaluation impacts the second one, which in turn also influences the first evaluation at the subsequent time step, through a feedback mechanism.

In the proposed approach, electricity consumers, interacting with a unique DN, are modelled as rational agents that may invest in optimally sized grid-tied DRE installations if these are cost-efficient compared to the retail electricity tariff. Moreover, the distribution tariff is adapted according to the evolution of DRE generation within the DN. In this framework, three distinct components defining the behaviour of the agents: (i) the *optimisation of DRE units*, (ii) the *investment decision process*, and (iii) the *computation of the distribution tariff*. As a reminder, the agents are the DSO and the users of the DN. There are two distinct groups of users: group A which denotes the users who may deploy a DRE installation, and group B, which comprises the users who cannot invest in a DRE installation due to technical or economic constraints. The latter is therefore left out of the two first components (optimisation and investment decision), since these two, as discussed below, assign the optimal sizing configuration and the investment decision on DRE installations.

Our multi-agent discrete-time dynamical system works as follows. At the initialisation of the system, we assume zero installed DRE capacity for all users. Then, at every time-step, and assuming a tariff design based on volumes of energy traded, the system updates the proportion of consumers who have deployed a DRE installation, as well as the distribution tariff. The detailed work flow of the model is represented by a data flow diagram in Figure A.1, and the full description of this multi-agent system, including the code, can be found in [155]. The three components are described in the following.

A.2.1 Optimisation of DRE units

As represented in Figure A.1, all potential DRE installations (group A) are optimised following the first component of the multi-agent system. Assuming that the storage dynamics and the investment costs of the DRE can be described by linear mappings, we formalise this optimisation problem as a linear program (LP). The inputs of this LP comprise the consumption and the potential production profiles of each individual agent, as well as several parameters that are user-independent (i.e. the same for all the users). These parameters are the prices of PV and battery, the retail electricity tariff at every time-step, and the efficiency, the depth of discharge and the lifetime of the batteries. The potential DRE installations are optimised so as to minimise their levelised cost of electricity (LCOE). Thus, the resolution of this optimisation problem outputs the optimal sizing configuration (PV and battery capacities) that leads to a minimised LCOE, as well as the LCOE, which is the objective function. We use a standard definition of the LCOE in this model: the average total cost to deploy and operate a DRE installation, divided by the total energy consumed by the user over the project lifetime. The LCOE is formulated according to equation (A.1):

$$LCOE = \frac{i_0 + \sum_{y=0}^{Y-1} \dfrac{\xi_y}{(1+r)^y}}{\sum_{y=0}^{Y-1} \dfrac{d_y}{(1+r)^y}} \tag{A.1}$$

where the capex are represented by i_0, the yearly opex at year y are ξ_y, the yearly demand at year y is defined as d_y, and r represents the discount rate. Finally, the lifetime of the DRE installations (i.e. the optimisation horizon of this LP) is set to Y

years. Note that this horizon is not the same as the horizon over which the evolution of the multi-agent discrete-time dynamical system is studied.

A.2.2 Investment decision process

This component is used to decide, for each individual agent in group A, whether to deploy a DRE installation with the optimised sizing configuration indicated by the DRE optimisation. To model such a decision making process, we make use of a price ratio between the optimised LCOE of each agent, and the retail electricity tariff at every time-step of the dynamical system. Such a price ratio, denoted by Γ, will adopt a value in $[0, 1]$, since the LCOE of the DRE installations cannot be greater than the retail electricity tariff due to optimality constraints (since the DRE installations are grid-tied, the feasible region of the optimisation problem is upper bounded by the retail electricity tariff). Then, by using a Bernoulli distribution in which the probability p is a linear function of the computed Γ, the investment decision can be controlled by a random variable β drawn from the distribution $B\left(1, p\right)$, where $\beta \in \{0, 1\}$ by definition of the Bernoulli distribution. According to such a linear function, low values of Γ (i.e. when the LCOE of the optimised DRE unit is of reduced proportions compared to the retail tariff) result in high probability p of drawing a variable $\beta = 1$, which indicates a positive investment decision. Similarly, when Γ is high, the probability of drawing a variable $\beta = 0$ will be high, suggesting a negative investment decision for the agent. Finally, when all of the possible investment decisions have been computed for all of the individual agents, those agents whose investment decision is positive are prevented from investing in the subsequent time-steps. Hence, in our simulator, the possibility of expanding an installation after its initial deployment is not permitted.

Modelling the investment decision-making process in such fashion ensures the deployment of some DRE units even when the viability of the DRE installations lie at the economically feasible limit (for instance when the PV prices are high or the retail electricity tariff is low), representing the behaviour of those users who are eager to invest. Likewise, this investment decision-making mechanism will prevent some agents from investing even under favourable conditions, representing those agents more reluctant to invest.

A.2.3 Computation of the distribution tariff

Finally, in our multi-agent system, an overall demand reduction in the DN might occur as a result of the progressive deployment of DRE units, which self-consume part of their electricity needs. Assuming that the revenues obtained by the DSO are computed as a monotonically non-decreasing function of the energy charged to the users, this overall demand reduction will cause a loss in revenue, inducing a need for adjusting the distribution tariff to offset the losses.

To adjust the distribution tariff, the following inputs are required: the net consumption of all the agents of the DN (groups A and B), and the retail electricity tariff at every time-step of the dynamical system. Then, we represent the cost recovery scheme of the DSO at every time-step by computing the potential economic imbalances created by the DRE installations deployed within the DN. If the revenue of the DSO at a particular time t does not match its incurred costs (assumed constant over the simulation horizon), an economic imbalance appears (which can be positive or negative). Thus, the adjustment of the distribution tariff must account for both the potential imbalance and the gradual aggregated net demand reduction in the system, this is calculated according to equation (A.2):

$$\Pi_{t+1}^{(dis)} = \frac{C + \Delta_t}{\widehat{D}_{t+1}} \quad \forall t \in \{1, \dots, T\} \tag{A.2}$$

where $\Pi_{t+1}^{(dis)}$ is the distribution tariff of the next period, C are the incurred costs of the DSO, Δ_t represents the imbalance between costs and revenues at period t, and $\widehat{D}_{t+1}$ is the expected aggregated demand (kWh) of the next period.

A.3 Test Case

To illustrate the functioning of our multi-agent system, an example inspired by the current regulation policy in the Walloon region of Belgium is presented in this section. Hence, a tariff design based on volumes of energy traded (paid in €/kWh) is considered. Moreover, to test different environments, we use three distinct incentive schemes, based on the choice of compensation mechanism (the manner electricity traded between the DRE and the grid is recorded). The compensation mechanisms considered are: (a) net-metering (NM): this system consists of one meter that records imports (DRE $\leftarrow$ Grid) by running forwards, and exports (DRE $\rightarrow$ Grid) by running backwards, therefore, this means that both directions are assigned with the same monetary value, namely the retail electricity tariff; and (b) net-purchasing (NP): this option consists of two independent meters for imports and exports, in this setting imports are paid for at retail electricity tariff, and exports are paid at a selling price (SP). With NM the total exports are upper bounded by the total imports, however, with NP there is no upper limit. The three evaluated cases are: *(i)* NM, *(ii)* NP SP=0.04 €, and *(iii)* NP SP=0.08 €. In the three cases the retail electricity tariff is initially set to 0.22 €.

At every time-step of the multi-agent system simulation, we keep track of the deployed DRE units, and of the distribution tariff adjustment. Thus, we can compute the evolution of the system in terms of rate of DRE deployment and distribution tariff evolution. The results of the testing of the multi-agent system with the three different environments are summarised in Figure A.2.

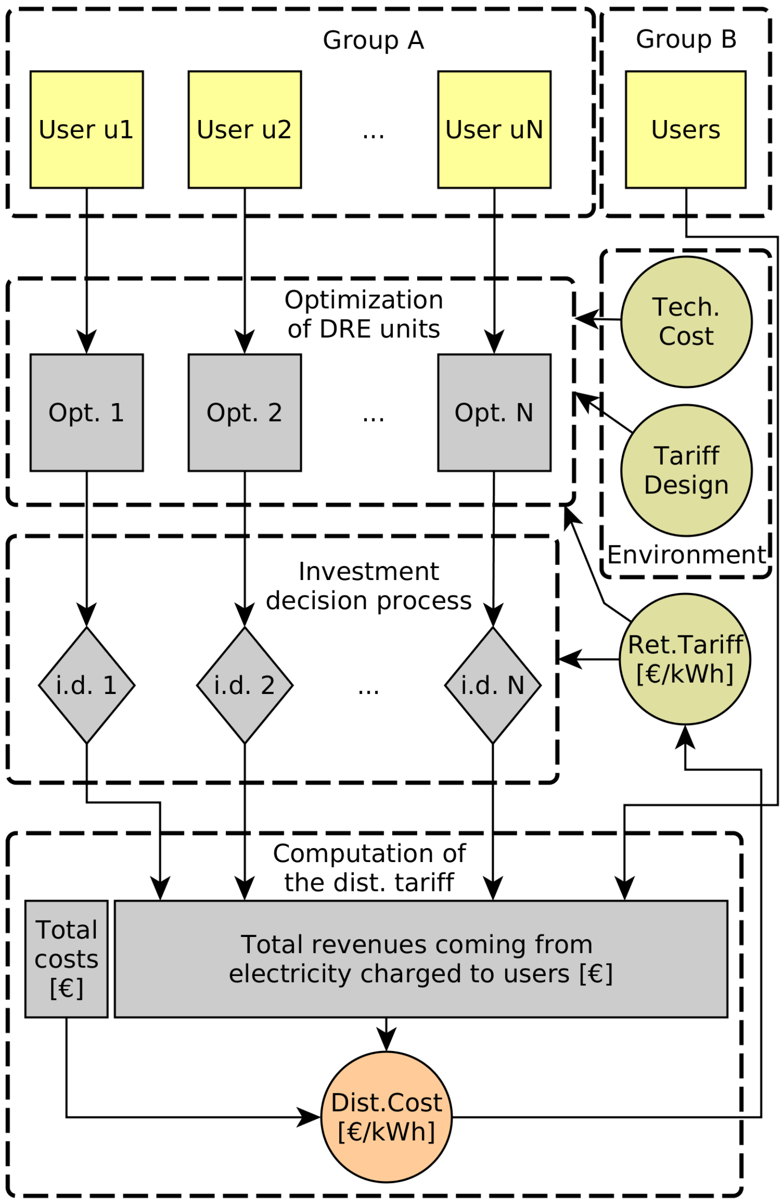


FIGURE A.1: Data flow diagram of the proposed multi-agent system. The flow of actions occurs from top to bottom. The individual users of group A, characterised by their load, undergo an optimisation. The optimisation requires the technology costs, the tariff design, and the retail electricity tariff, as well as the user load. The individual results of the optimisation are used by the investment decision model, which compares the LCOE of the individually optimised installations with the retail tariff, yielding a positive or negative investment decision for each potential installation. Finally, the revenues derived from the aggregated net consumption of all users of group A and of group B are compared with the (fixed) DSO costs, and the distribution cost is updated.

This figure depicts the two metrics considered: evolution of distribution tariff (left axis) and evolution of DRE deployment (right axis), for the three cases. Regarding the distribution tariff, we observe a similar 0.02 € increase for cases *(i)* and *(ii)* after 10 years, due to the loss of revenue of the DSO in both cases, derived from

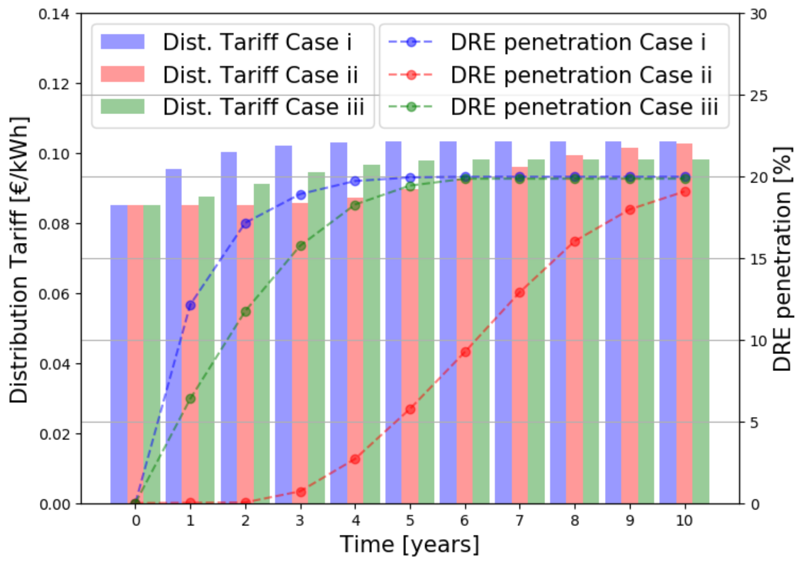


FIGURE A.2: Evolution of the distribution tariff (left axis) and evolution of DRE deployment (right axis). The deployment of DRE units induces an increase in the distribution tariff. Such an increase features a different extent depending on the environment (composed of tariff design, incentive scheme, and technology cost).

the DRE deployment. This indicates that both cases are more inefficient distributing the DSO costs than case *(iii)*. As for the DRE deployment, we can observe a greater deployment for cases *(i)* and *(iii)* both in the trend and in the final outcome after the simulated period, than for case *(ii)*. This suggests that case *(ii)* is outperformed in terms of DRE deployment fostering by cases *(i)* and *(iii)*. These distinct behaviours can be explained, case by case, by the optimal solution identified by the *optimisation of DRE units* component of the multi-agent discrete-time dynamical system:

- Case *(i)*: with this environment, it results optimal to import and export the same volume of electricity so that the electricity bill is reduced (netting 0 kWh consumed). This leads to installations without batteries (since storage and grid are perfect substitutes). Eventually with this setting the DRE owners will not compensate the DSO for their grid use.

- Case *(ii)*: with this environment, imports must be reduced to decrease the bill, leading to highly autonomous installations (large PV + battery capacities). Eventually with this setting the DRE units will become completely independent.

- Case *(iii)*: by increasing the SP with respect to the previous case, the DRE owners business case is to become electricity producers, selling it to offset their electricity bills. This leads to installations with large PV capacites as well as some storage. With this setting the DRE owners still pay the DSO for their grid use, since they rely on it during periods with low PV production.

A.4 Conclusion

This paper has presented a multi-agent discrete-time dynamical system to describe the interaction between the distribution networks and the consumers. In such a system: (i) electricity consumers interacting with a single distribution network are modelled as rational agents that may invest in optimised distributed renewable energy installations; and (ii) the distribution tariff is adapted according to the evolution of the DSO's revenues, depending on the distributed renewable energy that is produced and consumed in the distribution network.

To illustrate the performance of the multi-agent system, we have designed and simulated three different scenarios, starting with the current regulation in the Walloon region of Belgium, and further exploring other incentive schemes. The simulator allows to illustrate the impact of the regulation policies on many aspects: (i) the evolution of the electricity distribution tariff, and with it, the evolution of the retail electricity tariff; (ii) the evolution of DRE deployment; and (iii) the optimised configurations of distributed renewable energy installations in terms of production and storage capacities.

Appendix B

Exploring Regulation Policies in Distribution Networks through a Multi-Agent Simulator

This paper presents a multi-agent simulator that describes the interactions between the agents of a distribution network (DN), and an environment. The agents are the users of the DN and the electricity distribution system operator. The environment is the set of rules (tariff design, technology costs, or incentive schemes) that impacts the agents interactions. For a given environment, we can simulate the evolution of the agents and the environment itself. We assume the electricity consumers are rational agents that may deploy distributed renewable energy installations if they are cost-efficient compared to the retail electricity tariff. The deployment of such installations may alter the cost recovery scheme of the distribution system operator, by inducing a change in the way the user use of the grid. By modelling the cost recovery mechanism of the distribution system operator, the system simulates the evolution of the retail electricity tariff in response to such a change in the aggregated consumption and production.

B.1 Introduction

Over the last few decades, proactive policy making has supported a major paradigm shift in the power generation sector, resulting in a progressive energy transition from fossil fuels to renewable energy sources [156]. Such an energy transition is shaping the future of the electricity system: in this context, numerous incentive mechanisms are fostering a notable integration of **d**istributed **r**enewable **e**lectricity (DRE) generation technologies, such as solar photovoltaic panels (PV), into the distribution networks (DN). However, those incentive mechanisms might have been used without the adequate understanding of the underlying problems they may entail: since DN are not engineered to absorb large amounts of distributed electricity generation [86], the inclusion of a vast volume of DRE may cause severe technical problems [25]. Additionally, regulatory problems may appear also as a result of DRE adoption [36]. In our work we focus on the latter, which range from the over-compensation of DRE owners to the potential failure of the cost recovery mechanisms of the distribution system operators (DSO) [33].

This paper aims at presenting a methodology for assessing the potential regulatory problems stemming from a set of regulation rules (including the incentive mechanisms) that stimulates a heavy DRE adoption. Thus, with this methodology we may take any set of regulation rules as inputs, and compute their impact on a DN. Such an impact is measured with two metrics: (i) the evolution of the retail electricity price (simply retail price from now on) over time, and (ii) the evolution of the proportion of DRE-owners and non-DRE owners in the DN over time. The set of rules that drives these evolutions is known as an environment, and consists of three elements, as explained in [42]:

- *tariff design*: this consists of the type of charges applied to the customers for their grid use (e.g. volumetric tariffs, or capacity tariffs);
- *technology costs evolution*: this includes the prices for generation and storage technologies; and
- *incentive mechanism*: this is the combination of technologies and/or support schemes that help DRE become economically competitive, (e.g. a monetary aid awarded to the DRE owners over the lifetime of the DRE).

To simulate the impact of a given environment on a DN, we need to introduce a set of agents who will interact with it, over a finite time horizon. There are three types of agents:

- *DRE owners*: users of the DN that own a DRE installation (also known as prosumers);
- *non-DRE owners*: users of the DN that do not own a DRE installation (also known as consumers); and
- *distribution system operator (DSO)*: operator of the DN.

As a result of the agents interactions with the environment, the DN will evolve in a dynamical system. At every time step of this system, the two mentioned metrics will be computed, enabling the observation of such an evolution.

The methodology presented in this paper is based on a multi-agent discrete-time dynamical system formalisation that models the interactions of a some agents with an environment, and computes the resulting evolution of the DN. From this evolution, we may compare different environments. Our main contributions are:

- We provide a description of our multi-agent discrete-time dynamical system formalisation. Such a formalisation allows us to test different environments, in particular we introduce (i) two tariff designs, and (ii) two incentive mechanisms. This is detailed in Section B.2.
- We show the simulator functioning by testing different environments. This is presented in Section B.4.

B.2 Methodology

In our multi-agent discrete-time dynamical system, we model the electricity users as rational agents who are —in principle— exposed to retail prices, and that may invest in optimally sized DRE installations, provided that these are cost-efficient compared to the retail price. As a result of users deploying DRE installations, the DSO cost recovery mechanism may be altered, inducing a change in the distribution component of the retail price (distribution tariff from now on) for the subsequent time-step of the dynamical system. These two effects (DRE adoption and distribution tariff evolution), are computed at every time-step of a discrete-time dynamical system in which the interactions of the agents with the environment will drive the evolution of the DN. Thus, in this methodology we: (*A*) start by explaining how the interactions between the agents and the environment occur, (*B*) elaborating then on the different introduced environments, and (*C*) and finalising by providing a description of the agents modelling.

B.2.1 Interactions

The interactions between the agents and the environment are computed at every time-step of our dynamical system. These interactions depend on the nature of the agent, namely:

- the DRE owners interact by trading electricity with the DN. These trades occur in the form of imports: DN $\rightarrow$ user, and/or exports: DN $\leftarrow$ user;
- the non-DRE owners interact also by trading electricity with the DN. In this case these trades occur only in the form of imports: DN $\rightarrow$ user.
- the DSO interacts by computing a distribution tariff that allows it to break-even.

Through these interactions, the agents incur costs and collect revenues. The relation between costs and revenues will drive the evolution of the DN. Computing these interactions, at every time-step, involves calculating: (1) the yearly electricity costs of the users, (2) the yearly electricity revenues of the users (if any), and (3) the new distribution tariff determined by the DSO according to its cost recovery mechanism. These calculations depend on the environments, which are defined next.

B.2.2 Environments

In the presented multi-agent system, we introduce a number of options to build an environment:
Depending on the *tariff design*:

- *a1* - Volumetric: electricity trades are paid for/collected according to volumes of energy [€/kWh].

- *a2* - Volumetric and capacity: two terms, the first one is volumetric [€/kWh], and the second one is based on a fixed charge per capacity contracted by the user [€/kWp].

Depending on the *technology costs*:

- *b1* - Linearly decreasing trend over time.

Depending on the *incentive mechanism*: in particular we focus on the compensation mechanism. By compensation mechanism we refer to the manner the electricity trades between the users and the DN are recorded [73]. We consider two distinct compensation mechanisms, as described in [33]:

- *c1* - Net-metering (NM): system consisting of one meter that records the imports by running forwards, and the exports by running backwards, this entails that both directions be assigned with the same monetary value, namely the retail tariff. Furthermore, the total exports are upper bounded by the total imports for a determined billing period, per user.

- *c2* - Net-purchasing (NP): system consisting of two separate meters for the imports and the exports respectively, this implies that the imports are paid for at retail tariff, whereas the exports are paid at a selling price.

Constructing an environment necessitates choosing one element per option. Consequently, with these settings we can create four different families of environments:

- *e1 = a1+b1+c1*
- *e2 = a1+b1+c2*
- *e3 = a2+b1+c1*
- *e4 = a2+b1+c2*

Each of these families depends on the retail price, the capacity price, and/or the selling price. Consequently, it is possible to create any number of environments by setting different values of these three prices.

The three calculations introduced in subsection B.2.1 (costs of the users, revenues of the users, and cost recovery mechanism of the DSO) depend on the family of environments. Let $\mathcal{N} = \{1, \ldots, N\}$ denote the set with the time-steps of our discrete-time dynamical system. And let $\mathcal{I} = \{1, \ldots, I\}$ denote the users of the DN.

Family of environments e1 the electricity costs of the users are computed according to equation (B.1). The revenues of the users are $\phi_{i,n} = 0$ for this environment, since under net-metering the produced electricity is not sold to the grid. Finally the

DSO computation of the new distribution tariff for the following time-step is computed according to equation (B.2).

$$\psi_{i,n} = \max\left\{0, \left(\rho_{i,n}^{(-)} - \rho_{i,n}^{(+)}\right) \cdot \Pi_n^{(in)}\right\} \quad \forall i,n \in \mathcal{I} \times \mathcal{N} \tag{B.1}$$

$$\Pi_n^{(dis)} = \frac{\Omega_n^{(d)} + \Delta_{n-1}^{(d)}}{\widehat{D}_n} \quad \forall n \in \mathcal{N} \tag{B.2}$$

with $\Delta_{n-1}^{(d)} = \widehat{R}_n^{(d)} - R_n^{(d)}$, where $R_n^{(d)}$ are the actual measured revenues, and $\widehat{R}_n^{(d)}$ are the expected revenues computed (before the period) according to equation (B.3).

$$\widehat{R}_n^{(d)} = \Pi_n^{(dis)} \cdot \sum_{i=1}^{I} \rho_{i,n}^{(-)} \quad \forall n \in \mathcal{N} \tag{B.3}$$

Family of environments e2 the electricity costs and the revenues of the users are computed according to equations (B.4) and (B.5) respectively. The DSO computation of the following distribution tariff is performed as in environment *e1* (see equations (B.2) and (B.3)).

$$\psi_{i,n} = \rho_{i,n}^{(-)} \cdot \Pi_n^{(in)} \quad \forall i,n \in \mathcal{I} \times \mathcal{N} \tag{B.4}$$

$$\phi_{i,n} = \rho_{i,n}^{(+)} \cdot \Pi_n^{(sp)} \quad \forall i,n \in \mathcal{I} \times \mathcal{N} \tag{B.5}$$

Family of environments e3 the electricity costs of the users are computed by means of equation (B.6). The users revenues are $\phi_{i,n} = 0$ (same rationale as before). The DSO computation of the distribution tariff follows equation (B.7). Furthermore, in this case there is a capacity tariff which the DSO may adjust at every time-step (see equation (B.8)).

$$\psi_{i,n} = \max\left\{0, \left(\rho_{i,n}^{(-)} - \rho_{i,n}^{(+)}\right) \cdot \Pi_n^{(in)}\right\} + \Pi_n^{(cap)} \quad \forall i,n \in \mathcal{I} \times \mathcal{N} \tag{B.6}$$

$$\Pi_n^{(dis)} = \frac{\Omega_n^{(d)} + \Delta_{n-1}^{(d)}}{\widehat{D}_n} \quad \forall n \in \mathcal{N} \tag{B.7}$$

$$\Pi_n^{(cap)} = \frac{\Omega_n^{(c)} + \Delta_{n-1}^{(c)}}{\widehat{C}_n} \quad \forall n \in \mathcal{N} \tag{B.8}$$

with $\Delta_{n-1}^{(c)} = \widehat{R}_n^{(c)} - R_n^{(c)}$ and $\Delta_{n-1}^{(d)} = \widehat{R}_n^{(d)} - R_n^{(d)}$, where $R_n^{(c)}$ and $R_n^{(d)}$ are measured once the period is completed, $\widehat{R}_n^{(c)}$ is determined by means of equation (B.9), and $\widehat{R}_n^{(d)}$ is computed as in the family of environments *e1* (see equation (B.3)).

$$\widehat{R}_n^{(c)} = \Pi_n^{(cap)} \cdot I \quad \forall n \in \mathcal{N} \tag{B.9}$$

Family of environments e4 the electricity costs of the users are computed with equation (B.10). The revenues of the users are computed as in the family of environments *e2* (equation (B.5)). The distribution tariff is computed as in environment *e3* (see equations (B.3), (B.7), (B.8), and (B.9)).

$$\psi_{i,n} = \left(\rho_{i,n}^{(-)} \cdot \Pi_n^{(in)}\right) + \Pi_n^{(cap)} \quad \forall i, n \in \mathcal{I} \times \mathcal{N} \tag{B.10}$$

TABLE B.1: Notation

$\rho_{i,n}^{(-)}$	total imports of user i at period n
$\rho_{i,n}^{(+)}$	total exports of user i at period n
$\psi_{i,n}$	electricity costs of user i at period n
$\phi_{i,n}$	revenues of user i at period n
$\Omega_n^{(d)}$	costs of the DSO (volumetric) at period n
$\Omega_n^{(c)}$	costs of the DSO (capacity) at period n
$\Delta_{n-1}^{(d)}$	imbalance of the DSO (volumetric) of period $n-1$
$\Delta_{n-1}^{(c)}$	imbalance of the DSO (capacity) of period $n-1$
$\widehat{R}_n^{(d)}$	expected revenues of the DSO (volumetric) at period n
$\widehat{R}_n^{(c)}$	expected revenues of the DSO (capacity) at period n
$R_n^{(d)}$	actual revenues of the DSO (volumetric) at period n
$R_n^{(c)}$	actual revenues of the DSO (capacity) at period n
$\widehat{D}_n$	expected demand of the users at period n
$\widehat{C}_n$	expected peak demand of the users at period n
$\Pi_n^{(sp)}$	users selling price at period n
$\Pi_n^{(cap)}$	capacity price at period n
$\Pi_n^{(in)}$	retail price at period n *
$\Pi_n^{(dis)}$	distribution tariff at period n *
λ_n	costs of energy, transmission, and taxes *

* The relation between $\Pi_n^{(in)}$ and $\Pi_n^{(dis)}$ follows this equation: $\Pi_n^{(in)} = \Pi_n^{(dis)} + \lambda_n \quad \forall n \in \mathcal{N}$.

All of the presented equations depend on different parameters: $\rho_{i,n}^{(-)}$, $\rho_{i,n}^{(+)}$, $\Omega_n^{(d)}$, $\Omega_n^{(c)}$, $\widehat{D}_n$, and $\widehat{C}_n$. These parameters are computed when modelling the agents of the system. The other parameters in table B.1 ($\Pi_n^{(sp)}$, and λ_n) are inputs of the model. The rest of table B.1 are variables whose computations have been presented in this section ($\psi_{i,n}$, $\phi_{i,n}$, $\Delta_{n-1}^{(d)}$, $\Delta_{n-1}^{(c)}$, $\widehat{R}_n^{(d)}$, $\widehat{R}_n^{(c)}$, and $\Pi_n^{(in)}$).

B.2.3 Agents of the system

Once we have introduced the different environments, and how the interactions with these occur, we can describe how the agents are modelled. In our system we have three types of agents: DRE owners, non-DRE owners, and DSO. The first two are the users of the DN, whereas the third one is the operator of the DN.

DRE owners

these users are modelled relying on an optimisation framework instantiated in the form of a linear program (LP). This LP minimises the levelised cost of electricity (*LCOE*) of the DRE installation. The *LCOE* is the average total cost to deploy and operate a DRE installation, divided by the total energy consumed by the user over the project lifetime. With this LP we can extract, at every time-step, the values of $\rho_{i,n}^{(-)}$ and $\rho_{i,n}^{(+)}$. The LP formalisation is presented in the next section (Section B.3).

non-DRE owners

at the initialisation of the system, we assume zero installed DRE capacity for all the users (i.e. all users are non-DRE owners). Then at every time-step, the system updates the proportion of users who have deployed a DRE installation. Thus, we define two groups of non-DRE owners: *group A*: denoting the users who may deploy a DRE installation, and *group B*: comprising the users who cannot invest in a DRE installation due to technical or economic constraints. We model these two groups differently:

Group *A* we resort to the same LP we use to model the DRE owners. However, in this case we use it to extract the *LCOE* of the potential DRE installation a user of this group could deploy. By comparing this *LCOE* with the retail price, a gradient-like driver is created: if the *LCOE* is lower than the retail price, the user will have a probability $p > 0$ of actually deploying the DRE installation that leads to such an *LCOE*. Once a user from group A deploys a DRE installation, it is modelled as a DRE owner until the end of the simulation. If a user *group A* does not deploy a DRE installation at a particular time-step, it is modelled in the same fashion as *group B* users, for this particular time-step. However, at the subsequent time-steps, this user will have a new opportunity of deploying a DRE installation.

Group *B* we compute the yearly electricity demand of every user, which is covered entirely by the DN.

DSO

the last of the agents is modelled by computing, at every time-step, its cost recovery mechanism, as introduced previously. Then, the DSO will calculate a new distribution tariff for the subsequent time-step that allows it to break-even. To compute this cost recovery mechanism, the following parameters are required: $\Omega_n^{(d)}$, $\Omega_n^{(c)}$, $\widehat{D}_n$, and $\widehat{C}_n$.

$\Omega_n^{(d)}$ costs of the DSO related with the volume of energy distributed to the users of the grid. At the initialisation of the system, we assume a balanced system where the costs of the DSO are fully recovered by its revenue. Thus, we assume the initial costs equal to the initial revenues (aggregated demand of all users times the distribution tariff). At every time step the revenues may decrease due to the DRE deployment. Hence, we measure the total actual revenues of the DSO ($R_n^{(d)}$). Assuming that the cost recovery mechanism recovers all the previous economic imbalances, we use these revenues as costs of the DSO for the subsequent time-step ($R_{n-1}^{(d)} = \Omega_n^{(d)}$).

$\Omega_n^{(c)}$ costs of the DSO related with the capacity required by the users of the grid. Similarly to the previous case, we assume a balanced initial state where the costs of the DSO are fully recovered by its revenue. Thus, we assume the initial costs equal to the initial revenues (aggregated capacity fees of the users). At every time step, the DRE deployment may cause the fees to vary, altering the actual revenues from capacity fees ($R_n^{(c)}$). These revenues are used as DSO costs for the subsequent time-step ($R_{n-1}^{(c)} = \Omega_n^{(c)}$).

$\widehat{D}_n$ expected volume of energy distributed at every time-step. It is computed before the initialisation of the period, and corresponds to the last observed aggregated demand (D_{n-1}) of the users, thus $D_{n-1} = \widehat{D}_n$. Hence, this does not take into account the DRE installations that may have been deployed from $n-1$ to n.

$\widehat{C}_n$ expected aggregated peak demand of the users at every time-step. As in the previous case, it is computed before the initialisation of the period, and corresponds to the last observed aggregated peak demand (C_{n-1}) of the users, thus $C_{n-1} = \widehat{C}_n$. The DRE installations potentially deployed at the previous period are not taken into account.

B.3 LP Formalisation

In this section we formalise the optimisation framework in the form of an LP, used to model the DRE owners and the *group A* of the non-DRE owners. On the one hand, the DRE owners are modelled to compute their electricity trades, which were introduced in the previous section as imports and exports. On the other hand, the non-DRE owners of *group A* are modelled to determine their minimised $LCOE$, obtained for an optimally sized DRE installation.

The optimisation horizon is set to $Y \in \mathbb{N}$ years which are divided into 8760 time-steps ($Y \times 8760$). Let $\mathcal{T} = \{0, \ldots, T-1\}$, with $T = 8760$, represent a time discretisation of one year (in hours). Moreover let $\mathcal{Y} = \{0, \ldots, Y-1\}$, represent the years of the optimisation. All of the parameters and variables presented in this section depend on $\mathcal{N}$. Furthermore, this LP runs for every individual user in set $\mathcal{I}$.

Let χ represent the investment costs as a linear function of technology prices and sizing configuration. These costs are computed according to the following equation:

$$\chi = p \cdot P^{(pv)} + \frac{Y}{B} \cdot b \cdot P^{(bat)} \tag{B.11}$$

where p represents the optimal PV size in kWp, b is the optimal battery size in kWh, $P^{(pv)}$ and $P^{(bat)}$ are the technology prices (PV and battery respectively), and B is lifetime of the battery.

The yearly costs of operation are represented by ξ_y, and computed by means of the following equation.

$$\xi_y = \mu_y + m_y + \zeta_y \quad \forall y \in \mathcal{Y} \tag{B.12}$$

where μ_y are the yearly electricity costs, m_y represents the yearly costs of operation and maintenance, and ζ_y stands for the recovered costs. The electricity costs depend on the family of environments: for family *e1* we use equation (B.13), for *e2* we use equation (B.14), for *e3* we use equation (B.15), and for the family of environments *e4* we make use of equation (B.16):

$$\mu_y = \max\left\{0, \sum_{t=0}^{T-1} \left(\rho_t^{(-)} - \rho_t^{(+)}\right) \cdot \Pi^{(in)}\right\} \quad \forall y \in \mathcal{Y} \tag{B.13}$$

$$\mu_y = \sum_{t=0}^{T-1} \rho_t^{(-)} \cdot \Pi^{(in)} \quad \forall y \in \mathcal{Y} \tag{B.14}$$

$$\mu_y = \max\left\{0, \sum_{t=0}^{T-1} \left(\rho_t^{(-)} - \rho_t^{(+)}\right) \cdot \Pi^{(in)}\right\} + \Pi^{(cap)} \quad \forall y \in \mathcal{Y} \tag{B.15}$$

$$\mu_y = \left(\sum_{t=0}^{T-1} \rho_t^{(-)} \cdot \Pi^{(in)}\right) + \Pi^{(cap)} \quad \forall y \in \mathcal{Y} \tag{B.16}$$

where $\rho_t^{(-)}$ are the hourly imports, and $\rho_t^{(+)}$ represents the hourly exports. $\Pi^{(in)}$ and $\Pi^{(cap)}$ are the retail and the capacity price. These prices are fixed across the entire LP horizon, and correspond to the n^{th} prices determined by the discrete-time dynamical system. The operation and maintenance costs m_y are computed according to equation (B.17) [97].

$$m_y = \frac{1}{200} \cdot p + \frac{1}{100} \cdot b \quad \forall y \in \mathcal{Y} \tag{B.17}$$

Finally, the recovered costs are also environment dependent. In light of this, families of environments *e1* and *e3* have $\zeta_y = 0$, whereas for families *e2* and *e4* we use equation (B.18).

$$\zeta_y = -\left(\sum_{t=1}^{T} \rho_t^{(+)} \cdot \Pi^{(sp)}\right) \quad \forall y \in \mathcal{Y} \tag{B.18}$$

The energy balance of the system depends on the imports $\rho_t^{(-)}$, exports $\rho_t^{(+)}$, the electricity produced by the PV array k_t, the hourly demand $U_t^{(d)}$, the maximum hourly production $U_t^{(p)}$, the energy flow into the battery $j_t^{(-)}$, the energy flow out of the battery $j_t^{(+)}$, the efficiency of charge η^c and discharge η^d the batteries, and the depth of discharge of the batteries *dod*. The energy flows into and out of the battery also depend on the variation of the state of charge (*soc*) between $t-1$ and t. Thus, the following equations control the energy balance, taking into account the state of charge of the batteries:

$$\rho_t^{(+)} - \rho_t^{(-)} = k_t - U_t^{(d)} - j_t^{(-)} + j_t^{(+)} \;\; \forall t \in \mathcal{T}, \tag{B.19}$$

with:

$$k_t = p \cdot U_t^{(p)} \;\; \forall t \in \mathcal{T} \tag{B.20}$$

$$j_t^{(-)} \leq b \cdot F^{(-)} \;\; \forall t \in \mathcal{T} \tag{B.21}$$

$$j_t^{(+)} \leq b \cdot F^{(+)} \;\; \forall t \in \mathcal{T} \tag{B.22}$$

$$b \cdot dod \leq soc_t \leq b \;\; \forall t \in \mathcal{T} \tag{B.23}$$

$$soc_t = \begin{cases} soc_{t-1} - \dfrac{j_t^{(+)}}{\eta^{(d)}} + j_t^{(-)} \cdot \eta^{(c)} \;\; \forall t \in \mathcal{T} \setminus \{0\} \\ soc_0 \in [b \cdot dod, b] \text{ for } t = 0 \end{cases} \tag{B.24}$$

Finally, let *LCOE* denote the general objective function that represents the levelised cost of electricity. This objective function is minimised in this optimisation.

$$LCOE = \frac{i_0 + \sum_{y=0}^{Y-1} \dfrac{\xi_y}{(1+r)^y}}{\sum_{y=0}^{Y-1} \dfrac{d_y}{(1+r)^y}} \tag{B.25}$$

where the yearly demand of the system is defined as $d_y = \sum_{t=0}^{T-1} U_t^{(d)}$, and r represents the discount rate.

B.4 Test case

To illustrate our multi-agent discrete-time dynamical system, an example is presented. In this example, we simulate one environment of each family of environments. Thus, we create four environments, according to the four described families:

- Env. A: corresponds to the family of environments *e1*. We propose a volumetric tariff with a compensation mechanism consisting of net-metering. In this case, the distribution tariff is initially set to $\Pi_0^{(dis)} = 0.09$ €/kWh.

- Env. B: corresponds to the family of environments *e2*. This case is based on a volumetric tariff with a compensation mechanism consisting of net-purchasing. As in the previous case, the distribution tariff is initially set to $\Pi_0^{(dis)} = 0.09$ €/kWh. The selling price is fixed to $\Pi_n^{(sp)} = 0.08$ €/kWh (constant over the simulation).

- Env. C: corresponds to the family of environments *e3*. We create this case with a distribution tariff with two components: volume and capacity. The first component represented with a volumetric fee conveyed to the users by means a distribution tariff which is initially set to $\Pi_0^{(dis)} = 0.045$ €/kWh. The second component is a capacity fee, set initially to $\Pi_0^{(cap)} = 223$ € for installations up to 10 kWp, this term will not evolve in our simulation, since we do not let the users adjust their peak demand.

- Env. D: corresponds to the family of environments *e4*. As in the previous case, there are two terms. The capacity term is the same as case C ($\Pi_0^{(cap)} = 223$ € for installations up to 10 kWp which cannot evolve in our simulations). The distribution tariff term is initially set to $\Pi_0^{(dis)} = 0.045$ €/kWh. Furthermore, the selling price is fixed to $\Pi_n^{(sp)} = 0.08$ €/kWh.

The value of λ_n is fixed to 0.13 €/kWh for all cases. The technology costs are initially set to $P^{(pv)} = 1500$ €/kWp and $P^{(bat)} = 300$ €/kWh; they are assumed to evenly decrease at every period n by 0.07%. The optimisation horizon Y is set to 20 years. The efficiencies are set fixed to $\eta^{(c)} = 0.95$ and $\eta^{(d)} = 0.95$. Finally the *dod* is fixed to 10%.

At the initialisation of the system, all the users are non-DRE owners. Hence, to represent every agent in the proposed multi-agent tool, the model includes two groups of medium size residential users (peak demand of around 3 kW). *Group A*: modelling the heterogeneity of DN users involves the representation of every user as an individual agent. To introduce them in the simulation, the multi-agent model necessitates their electricity demand profile and their production profile. In the analysed test case, we create different synthetic demand profiles with the help of the CREST model [98]. As for the production profile, we count on real PV measurements expressed in kW/kWp. *Group B*: the remaining customers of the DN must be modelled only in terms of net energy off-take.

At every time-step of the multi-agent system simulation, we keep track of the deployed DRE units, as well as of the distribution tariff adjustment. Thus, we can determine the evolution of the deployed capacities of PV and battery. Moreover, it is possible to compute the evolution of the distribution tariff for each case. Two figures depict the two metrics considered: the evolution of DRE deployment and optimal size: Figure B.1; and the evolution of the distribution tariff: Figure B.2, for the four distinct environments.

Regarding the size of the installations, we observe two different behaviours of the four environments:

- A and C do not deploy batteries, these two environments rely on NM as incentive mechanism, therefore not deploying batteries since, with this system, batteries and imports are perfect substitutes. Since there is no incentive to sell electricity (see equations (B.13) and (B.15)), the PV capacity is adjusted to simply cover their peak demand.

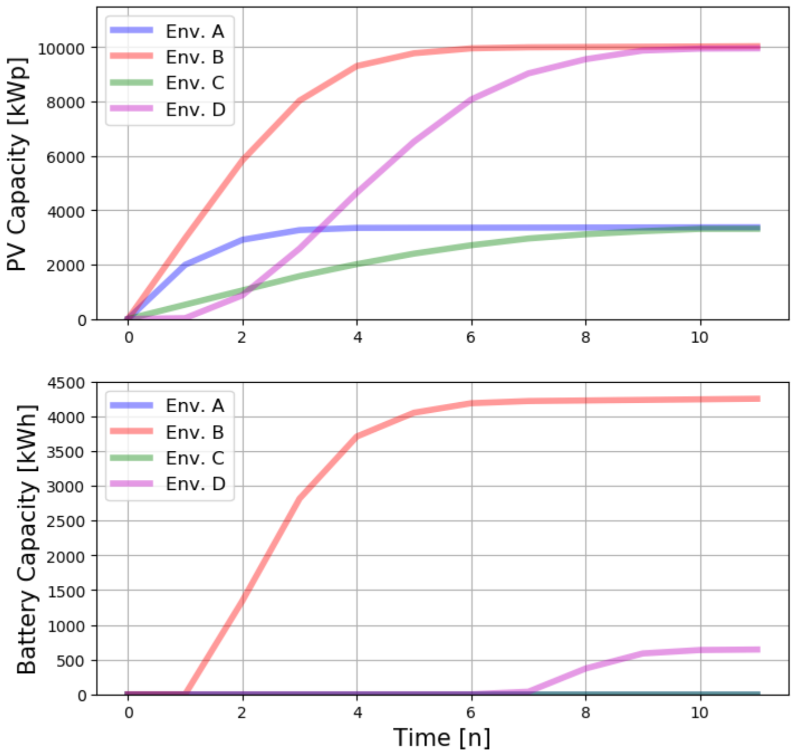


FIGURE B.1: Cumulative PV and battery capacities of the deployed DRE, over the presented discrete-time dynamical system. The economically optimal size of the deployed DRE installations is influenced in a large extent by the environment. In this figure, we observe these different users behaviours under four distinct environments.

- B and D deploy some batteries to become more self-sufficient, reducing the imports. PV deployment results 2.5 times larger than in the other two environments, since there exists an incentive to sell electricity (see equations (B.14) and (B.16)). The difference between B and D lies in the fixed capacity term, which makes difficult the recovery of the installation costs for case D.

Regarding the distribution tariff, the upper sub-figure in Figure B.2 indicates that introducing a capacity term (Env. C and D) will considerably reduce the effect of an increasing distribution tariff, induced by the DRE deployment. However, when inspecting the lower sub-figure in Figure B.2 (change in distribution tariff relative to the initial state), we can observe that the increase in the distribution tariff occurs predominantly in those environments with NM as incentive mechanism (Env. A and C), demonstrating the unfitness of this compensation mechanism to cope with DRE deployment.

B.5 Conclusion

This paper has presented a multi-agent simulator to describe the interaction between distribution networks and consumers, for any regulatory technical environment. In this system, electricity consumers interacting with a single distribution network are

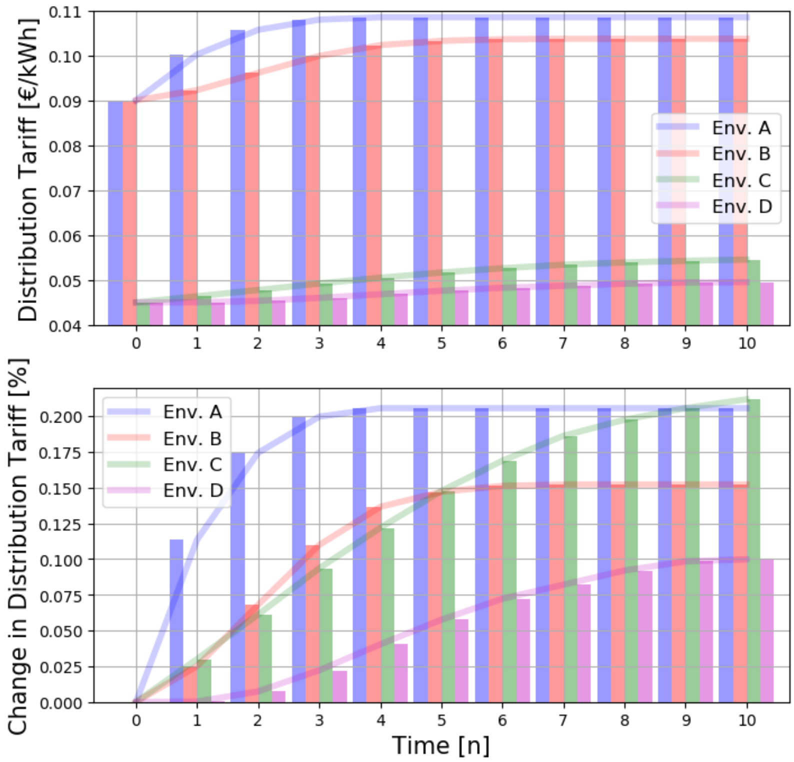


FIGURE B.2: Evolution of the distribution tariff. The deployment of DRE units induces an increase in the distribution tariff. Such an increase features a different extent depending on the environment.

modelled as rational agents that may invest in optimised distributed renewable energy installations. The distribution tariff is adapted according to cost recovery mechanism of the DSO (must break-even), that depends on the distributed renewable energy that is produced and consumed in the distribution network.

To illustrate the performance of the multi-agent system, we have designed and simulated four different examples based on the four families of environments introduced in this paper. The simulator allows to illustrate the impact of the regulation policies on many aspects: (i) the evolution of the electricity distribution tariff; (ii) the evolution of DRE deployment; and (iii) the optimised configurations of distributed renewable energy installations (production and storage capacities).

Preliminary results show a more volatile distribution tariff when net-metering is chosen as incentive mechanism, as a result of the deployment of distributed renewable energy units. This remains true also when a capacity term is added to the distribution costs. These results can be further explored in a future work, by scaling up the simulator introducing a larger user diversity.

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