Operation Strategies for Energy Communities and Evaluation of their Impacts on Power Systems Using an ABM Model

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To My Wonderful Wife

Acknowledgments

I would like to express my heartfelt gratitude to be writing these words. This achievement was only possible through meticulous organization, time management, and unwavering focus. Balancing a professional career while pursuing a doctorate is no easy feat.

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Abstract

Power systems are rapidly evolving, particularly in terms of electricity generation technologies, diverse commercial relationships among various agents, and the increasing empowerment of consumers. This has led to the emergence of Renewable Energy Communities, encouraged by new legislation in many countries. This new paradigm enables citizens to take on roles as energy producers, consumers, or prosumers, thereby increasing choices and flexibility at the household level. Because of all these aspects, Local Energy Markets are emerging to enable local energy trading mechanisms in Renewable Energy Communities. As also supported by the European Directives, Energy Communities business models can include, not local generation, trading, and aggregation, but also storage systems. It is another flexibility option, that has the advantage of being able to act on both demand and supply sides as well as providing a wide range of system services. Integrated in Renewable Energy Communities, and during periods with surplus generation from renewable resources, namely Photovoltaic generation, excess of energy supply can be absorbed by storage systems. Contrary, during times with low contribution from renewable generation, the deficit can be compensated by discharging the storage devices.

However, the requirements, limitations, and opportunities under these new frameworks require much more than analysing only technical and economic aspects. Incorporating new actors and managing coordination among stakeholders requires innovative or adaptive approaches to handle the complexity. This thesis proposes the use of Agent-Based Modelling, employing a Machine Learning procedure - Q-Learning - as a decision support tool for energy transactions between the Local Energy Market and Wholesale Market in the day-ahead electricity market. This research also analyses different storage system architectures' integration within Renewable Energy Communities. The obtained results confirm that modelling the agents with learning capabilities leads to more profits results when compared with the ones without learning strategy. For that reason, we consider that the developed Agent-Based Model can be used as a valuable simulation tool namely for complex systems when compared with other traditional optimization models. Furthermore, an economic assessment is also included, in order to get insights if some level of exemption, for instance associated with some components of the Access Tariffs, have to be considered in order to induce the massification of Renewable Energy Communities.

Keywords: Renewable Energy Communities, Agent-Based Models, Local Energy Markets, Q-Learning, Storage Systems.

Resumo

Os sistemas de energia estão evoluindo rapidamente, nomeadamente através das diferentes tecnologias de geração de eletricidade, das diferentes relações comerciais entre diferentes agentes e pelo crescente empoderamento dos consumidores. Este facto, incentivado também pelo aparecimento de nova legislação que induz esta mudança, levou ao aparecimento das Comunidades de Energia Renovável. Esse novo paradigma permite que os cidadãos assumam papéis como produtores de energia, consumidores ou produtores-consumidores. Desta forma, os Mercados Locais de Energia estão a emergir e a possibilitar mecanismos de negociação de energia em Comunidades de Energia Renovável. Também apoiado pelas Diretivas Europeias, os modelos de negócios das Comunidades de Energia podem incluir, não só a geração local, a negociação e a agregação, mas também sistemas de armazenamento. Este facto representa uma outra opção de flexibilidade, que tem a vantagem de atuar tanto na procura como na geração de energia. Durante períodos em que há excedente de enegia elétrica, nomeadamente de origem renovável, como por exemplo a geração fotovoltaica, este excesso pode ser absorvido pelos sistemas de armazenamento. Por outro lado, durante períodos com pouca geração renovável, o consumo pode ser garantido pela descarga das baterias.

No entanto, os requisitos, as limitações e as oportunidades destes modelos, exigem muito mais do que analisar apenas aspectos técnicos e económicos. É necessário também considerar a participação de novos atores bem como gerir e coordenar a interação entre os demais envolvidos. E este facto, considerando a sua complexidade, requer abordagens inovadoras ou adaptativas. Assim, esta tese propõe o uso de agentes (*Agent-Based Model*) utilizando um procedimento de aprendizagem, *Q-Learning*, como ferramenta de apoio à decisão para transações de energia entre os Mercados Locais de Energia e o Mercado Grossista. Este trabalho analisa também a integração de diferentes arquiteturas de sistemas de armazenamento incorporadas dentro das Comunidades de Energia Renovável. Os resultados obtidos confirmam que a modelização dos agentes com capacidades de aprendizagem, permitem melhores resultados económicos quando comparado com sistemas sem estratégia de aprendizagem automática dos agentes. Neste trabalho também é apresentado um estudo económico com o propósito de avaliar o impacto da consideração de isenções, nomeadamente aplicadas a regimes tarifários e que podem contribuir para a massificação das Comunidades de Energia Renovável.

Palavras-chave: Comunidades de Energia Renovável, *Agent-Based Model*, *Q-Learning*, Mercados Locais de Energia, Sistemas de Armazenamento.

Everything you've ever wanted is on the other side of fear.

George Adair

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List of Abbreviations

ABM	Agent-Based Models
ACER	Agency for the Cooperation of Energy Regulators
AI	Artificial Intelligence
AMES	Agent-Based Modeling of Electricity Systems
AOSE	Agent Oriented Software Engineering
CEC	Citizens Energy Community
CEP	Clean Energy Package
CIEG	Custos de Interesse Económico Geral
CSC	Collective Self-Consumption
DER	Distributed Energy Resources
DGEG	Direção Geral de Energia e Geologia
DP	Dynamic Programming
DR	Demand Response
DSO	Distribution System Operator
EGAC	Entidade Gestora do Autoconsumo
EMCAS	Electricity Market Complex Adaptive Systems
EMD	Electricity Market Directive
ENTSO-E	European Network of Transmission System Operators for Electricity
ERSE	Entidade Reguladora dos Serviços Energéticos
ESS	Energy Storage Systems
EU	European Union

EV	Electrical Vehicles
GA	Genetic Algorithms
ICT	Infrastructure and Communications Technology
IoT	Internet of Things
IRR	Internal Rate of Return
ISO	Independent System Operator
KQML	Knowledge Query and Manipulation Language
LEM	Local Energy Markets
LCOE	Levelized Cost of Electricity
LCOS	Levelized Cost of Storage
LP	Linear Programming
LV	Low Voltage
MASCEM	Multi Agent Simulator of Competitive Electricity Markets
MCP	Market Clearing Price
MDP	Markov Decision Process
MIBEL	Mercado Ibérico de Energia Elétrica
MILP	Mixed Integer Linear Programming
MIP	Mixed Linear Programming
MV	Medium Voltage
MVPP	Multi-Energy Virtual Power Plant
NEMSIM	National Electricity Market Simulation System
NEMO	Nominated Electricity Market Operators
NLP	Non-Linear Programming
NPV	Net Present Value
OO	Objected Oriented
OSS	Open-Source Software
O&M	Operation and Maintenance

P2P	Peer-to-Peer
QL	Q-Learning
RE	Roth and Erev algorithm
REC	Renewable Energy Community
RED	Renewable Energy Directive
RESP	Rede Elétrica de Serviço Público
RL	Reinforcement Learning
SEPIA	Simulator for Electric Power Industry Agents
SME	Small and Medium-sized Enterprises
STEMS-RT	Short-Term Electricity Market Simulator-Real Time
TSO	Transmission System Operator
UPAC	Unidade Produtora para Auto Consumo
VPP	Virtual Power Plant
WSM	Wholesale Market

List of Symbols

Indexes

n	Index of actions
m	Index of states
t	Index for time period of agent's simulation

Parameters and Variables

λ	Learning rate
γ	Discount factor
ε	Greedy policy
r	Reward associated to state
C^{PV}	Price paid to the renewable PV generation (bilateral contract price)
C^{agg}	Retailor/Aggregator tariff (WSM Price)
C^{Bid}	LEM Bid Price
$W_{B,t}^{i}$	Stored energy at time slot *t*
$W_{B,t-1}^{i}$	Stored energy at time slot *t-1*
$\sigma_{SD,t}^{i}$	Self-discharge rate
$P_{BC,t}^{i}$	Battery charging power
$P_{BD,t}^{i}$	Battery discharging power
$\eta_{BC,t}^{i}$	Battery charging efficiency
$\eta_{BD,t}^{i}$	Battery discharging efficiency
α	Battery charging parameter
β	Battery discharging parameter

SOC	State of Charge of the battery
$P^i_{PV,t}$	Prosumer *i*, PV generation at time slot *t*
$P^i_{L,t}$	Prosumer i, demand at time slot *t*
$P^i_{C,t}$	Consumer *i*, demand at time slot *t*
$P^i_{Grid,t}$	Power exchanged with the grid at time slot *t*
ΔE^e_t	Energy change at the battery at time slot *t*
E_m	Rated energy capacity of the battery
NP^i_t	Net load of a prosumer *i* and consumer *i*, at time slot *t*
$Profit^e_t$	LEM hourly revenue
$Cost^{total}_t$	Battery total cost
$C_{O\&M,t}$	Battery operation and maintenance costs
$C_{loss,t}$	Battery charging and discharging costs
C_{BCloss}	Battery charging losses
C_{BDloss}	Battery discharging losses
C_a	Battery annual maintenance cost
C_{PV}	Photovoltaic cost
C_{Mod}	Photovoltaic modules cost
C_{inv}	Inverter cost
C_{ins}	Photovoltaic installation cost
p^e_t	LEM electricity price at time slot *t*
$p_{e,t}$	Power of the ESS
$b_{e,t}$	Energy quantity of the ESS
h_e	Trading period of the energy market
ρ_{min}	Minimum efficiency operation rate
ρ_{max}	Maximum efficiency operation rate

Arrays

Q ($s_m; a_n$)	Q-Learning matrix for state-action ($s_m; a_n$) pair

Functions

U_t^{ag}	Utility function for agent *ag* for time period *t*

Sets

A	Set of all actions
S	Set of all states

Chapter 1

1. Introduction

1.1. Energy Transition – Opportunities and challenges

In the last decades, the share of renewable sources in the energy mix has considerably increased. Since 1990, their share in the primary energy supply has more than tripled and its contribution for electricity generation has more than doubled [1]. All global and European decarbonization scenarios agree that these shares will continue to increase rapidly. With these changes and developments, electricity becomes an important actor towards a carbon-neutral economy.

The rapid improvements of renewable technologies and distributed energy resources, as well as climate change initiatives and policies to promote clean energy, are now prompting the reconfiguration of participant roles in the energy supply chain. In particular, the industry´s traditional centralized electricity supply structure and utility-dominated decision-making regime is being challenged by energy users [2]. In this sense, the European Union (EU) introduced new regulatory frameworks and requirements on the energy market design for new energy initiatives.

The Clean Energy Package (CEP) for all Europeans [3] boosts this transition by acknowledging the role of consumers and citizens in this new energy paradigm. It aims at ensuring an unbiased energy transition at all levels of the economy – a wide transition from a top-down to a bottom-up perspective. It gives new roles and opportunities for citizens, acting as energy producers and consumers, or prosumers [4]. It also gives consumers more choices in their homes and more flexibility to reduce their energy use when it is expensive and consume or store it when it is cheap [5].

New provisions on the energy market design and frameworks for new energy initiatives were introduced with CEP, specifically the recasts of the Renewable Energy Directive EU 2018/2001 [6] and the Electricity Market Directive EU 2019/944 [7]. CEP opens the path for new types of energy initiatives aiming at increasing the empowerment of smaller actors in the energy market as well as an increased decentralized renewable energy production. Some authors term this process as the "democratization of energy" where most of the energy needed to meet household consumption requirements will be produced at local level, with only backup needs to be supplied by the grid [8].

The collective self-consumption, renewable energy communities and citizens energy communities are now new concepts introduced in the energy regulatory frameworks. They are fostering the progressive migration of current centralized market models to new concepts and business models, such as Virtual Power Plants, Microgrids, Smartgrids and Peer-to-Peer trading mechanisms. In this context, Local Energy Markets (LEM) become appropriate for the development of Energy Communities as they allow end users and producers to participate in the electricity trading systems. They can also help the increase of the penetration of renewable energy sources into the energy matrixes. The main objectives of LEMs are to provide a platform for the local economy and to reduce electricity costs since supply fees and grid tariffs are excluded or strongly reduced [9]. This type of market also contributes to the appearance of new agents, although that leads to a new operational paradigm since they should not only interact locally but also be integrated with conventional markets. However, while it is increasing the participation of these new actors, consumers and small-scale producers, the complexity and the uncertainty of the electricity markets has been rising. This is why it is important that electricity markets have the necessary tools and resources to support decision-making processes.

A wide range of research programs involving Artificial Intelligence (AI) tools are being conducted in the field of Energy. These studies aim to develop systems that can perform various tasks such as analyzing and making decisions. One of the most common techniques used in the development of AI systems is Machine Learning. This type of approach is commonly used to solve complex problems in real-world systems. One of the fields of Machine Learning refers to the concept of Reinforcement Learning. This method helps agents perform at their best in an unpredictable setting. It involves an agent interacting with its environment in order to learn the best action to take based on the given situation. In this scope, an Agent Based-Model (ABM) using a Reinforcement Learning mechanism is a suitable approach to modeling and simulating complex systems, such as electricity markets.

An ABM allows agents to make more informed decisions by taking into account their past experiences and the environment. This allows them to improve their strategies and make better decisions. The goal of an ABM is to provide market participants with the opportunity to develop their own adaptive strategies and preferences. This process can be carried out either individually or in combination with other agents. Agents benefit from the learning process of an ABM since it allows them to develop their own strategies and preferences. Since ABM can simulate actions and interactions of independent agents, they have been widely used in the simulation process of the electricity markets. They are a suitable approach to modeling and manage this kind of complex systems [10].

Accordingly, the main focus of this thesis is the development of a simulation architecture to support and validate energy transactions between Energy Communities and among their members. In order to achieve this goal, all the technical limitations, regulatory challenges and opportunities behind Energy Communities will be assessed. The framework presented in this work and its strategy optimization is based on ABM using Artificial Intelligence.

1.2. Motivation and Research Questions

The electricity sector is constantly evolving due to the increasing number of factors that affect its design and operation, such as the technological advancements that are being made in the generation of electricity. Despite the political situation in Europe, which can affect the electricity sector, it is still expected that countries will continue to move toward the decarbonization of their power systems. This includes the reduction or even elimination of the use of coal units and the sharp increase of the installed capacity in PV and wind parks. The various technical and regulatory changes that are being implemented in the electricity sector impose various challenges to power systems.

Several countries have recently enacted legislation aiming at promoting the installation of Renewable Energy Communities. These are designed to encourage the growth of distributed renewable energy sources and provide end consumers with more self-sufficiency. In this sense, new mechanisms are emerging, such as LEM, that are enabling local energy trading in Renewable Energy Communities. The requirements, limitations, and opportunities under these new frameworks require much more than analyzing only technical and economic aspects. Communities themselves, regarding their behaviors, interactions and organizational dimensions should also be exploited. From the point of view of electricity networks, a scenario of massification of Renewable Energy Communities can be translated technically as an increase in the penetration of distributed generation units, especially in low voltage levels, as well as other energy equipment such as Energy Storage Systems.

The regulatory contexts, specifically incentive schemes, must be considered in investment decisions. Besides the legal framework and the various incentives that are being implemented to encourage the deployment of Energy Communities, it is also important to analyze the impact of the different charges and exemptions on the financial viability of these projects. The economic viability of these investments (namely in Storage Systems) and the operation of RECs, specifically considering different tariff and charge exemption designs, should therefore be studied in order to get conclusions on the breakeven of the investments.

The goal of this research is to develop a new approach to simulate the energy trading between the wholesale and local energy markets. In order to understand the dynamics of the electricity markets, it is necessary to first study the interaction between the conventional electricity markets and LEM. Besides this, it is also important to study the impact of the regulations on the participants' behavior. This means that the main research questions to be addressed in this work are as follows:

1. Are the Agent-Based Models capable of handling Energy Communities’ main purposes?
2. How should the Energy Communities’ actors be organized, regarding integration with conventional electricity markets?
3. What is the influence of including not only generation trading and aggregation in Energy Communities, but also storage systems?
4. Can the regulatory context induce the massification of Energy Communities?

1.3. Thesis Objectives

The main goal of this work is to develop a computational tool, using an Agent-Based Model, as a decision tool to support energy transactions between the LEM and the Wholesale Market (WSM). In order to achieve this general objective, it is necessary to study the behavior of participants in local electricity markets, the energy policies in force and use adequate simulation tools considering competition. The developed model will be applied to a realistic case study, in the context of the Portuguese regulatory framework. The proposed market design will be implemented considering a day-ahead market on a one-hour basis.

Research objective 1: To develop a new decision tool to support energy transactions among Energy Community agents and between the communities themselves and the WSM, using an Agent-Based Model.

Research objective 2: To assess the impact of different optimization parameters in the agents’ learning capabilities.

Research objective 3: To analyze the impact of the integration of storage systems in Local Energy Markets, with focus on different architectures, by comparing the obtained market strategy and the profits that can be obtained.

Research objective 4: To assess the economic feasibility of Energy Communities regarding Agents-Based models bidding strategies as well as different levels of exemptions regarding specific terms of the Access Tariffs.

The scientific contributions of this thesis span the aspects of Energy communities, namely Regulatory contexts and optimization models considering the utilization of an Agent-Based Model. A literature review of the application of this kind of models applied to Power Systems is presented in [**Paper A]** included in Annex A. [**Paper B**] also available in Annex A, describes the strategy and the interactions between the LEM of a Renewable Energy Community and the WSM on an hourly basis.

The energy trading between LEM and WSM was simulated with an ABM as a decision tool. [**Paper C**] (available in Annex A) extends the decision tool considering an Energy Storage System. Specifically, [**Paper C**] investigates the Energy Communities' self-consumption profile considering different storage system architectures. This work proposes two types of storage architectures. The first one is a decentralized architecture, where storage, constituted by batteries, is located at the building level, while the second one is centralized within the community. To understand the value of local markets and battery flexibility, [**Paper C**] compares the outcomes of the two proposed market designs, against a reference case, that was described in [**Paper B**].

Besides the implemented legal framework and the incentives for the deployment of Energy Communities and Local Energy Markets, the economic viability of the investments, namely in Storage Systems, should be studied. For that purpose, [**Paper D**] (accessible in Annex A) presents a design and an optimization model to increase the self-sufficiency level, and to better manage the energy produced locally, also admitting the installation of battery storage systems. This paper also includes an economic assessment, considering different tariff and charge exemptions designs, namely the payment of grid tariffs. This allows us to draw conclusions on the breakeven of the investments.

1.4. Structure of the Thesis

This thesis is structured in seven chapters covering the Literature Review, the models that were developed and the adopted solution approaches and their assessment using a realistic case study.

Chapter 2 provides a general overview of electricity markets, considering nowadays legislation frameworks. Section 2.1. presents the electricity market evolution and its classification. A review on European Climate and Energy policies is provided in Section 2.2. and Section 2.3. includes an overview of different national frameworks. Section 2.4 presents an overview on Peer-to-Peer markets. Finally, Section 2.5. introduces the concepts of Microgrids and Virtual Power Plants (VPP).

Chapter 3 presents a Literature review on Electricity Market Simulation. Section 3.1 presents several modelling methods to simulate electricity markets. Section 3.2 introduces the concept of Agent Based Models and provides a review of the various development steps involved in its implementation. Section 3.3 provides a categorization of Machine Learning techniques and finally, Section 3.4 details some ABM electricity markets simulators.

Chapter 4 details Energy Communities business models and presents the structure of the model that will be simulated in this thesis. Section 4.1 details Energy Communities' business models. Its main ideas will be replicated in the proposed market design, which will be presented in Section 4.2. The developed ABM, which incorporates the LEM concept is detailed in Section 4.3. The interactions between the community aggregator and the WSM are exposed in Section 4.4. Hereafter, the defined environment, as the part of the system within which the agents operate, is presented in Section 4.5. followed by the Utility Function considered in this work and detailed in Section 4.6. The Q-Learning procedure used in the proposed model as well as the modelization considered using this optimization strategy, are presented, respectively in Sections 4.7. and 4.8.

Chapter 5 details other models that are integrated in the developed Agent-Based Model, namely the incorporation of Energy Storage Systems. In this purpose, Section 5.1 provides a framework with Energy Community Business Models followed by Section 5.2., where the enhanced market design considering storage systems is explained. Regarding general considerations and Energy Storage Systems' modelization and bidding strategies, Section 5.3. details its main considerations. Following the previous approaches, the modelization of the operation of ESS in the LEM and WSM, using an ABM, is detailed in Section 5.4. This chapter ends in Section 5.5, with the main considerations regarding the economic viability analysis of Energy Communities business models, namely the economic value of the investments and operation of Renewable Energy Communities.

Chapter 6 presents the results obtained using the developed models to a set of scenarios. Section 6.1 presents a general consideration about the Chapter while Section 6.2 details the global characterization of the system that is studied in this work and termed as Reference Case. Section 6.3. describes a scenario only considering a PV system, without storage and which is addressed using the Q-Learning strategy. In this section, it is also assessed the impact on the global results of using different learning parameters. The results, using decentralized and centralized storage systems are detailed in Sections 6.4. and 6.5. The final comparisons and sensitivity analysis for different input data are detailed in Section 6.6.

Finally, Chapter 7 summarizes the contributions of this research and presents the most relevant conclusions. This document ends with a discussion and an outlook about future work and other related research opportunities.

1.5. List of Publications

The next paragraphs present the published and submitted papers that are related to this work. Papers A and B are associated with the model presented in Section 4.2. Papers C and D are related to the model described in Section 5.2., and include a modification on the previous model, now considering the impact of different storage architectures. Paper B was presented to an audience through oral presentation in the 18th European Energy Markets Conference, that was held in Ljubljana, Slovenia 13-15 September 2022. Papers D and C were submitted, accepted and presented to an audience through oral presentation, respectively in the 19th International Conference on the European Energy Market (EEM), Lappeenranta and in the IEEE Belgrade PowerTech, Belgrade, both in June 2023.

[**Paper A**] A. Ferreira dos Santos, J. T. Saraiva, "Agent Based Models in Power Systems – A Literature Review," in University of Porto Journal of Engineering, vol. 7, no. 3, April 2021.

[**Paper B**] A. Ferreira dos Santos, J. T. Saraiva, "An Agent Based Model to Simulate Local Electricity Markets, LEM, and their Interaction with the Wholesale Market, WSM," in Proceedings of the 18th International Conference on the European Energy Market (EEM), Ljubljana, September 2022, pp. 1-5.

[**Paper C**] A. Ferreira dos Santos, J. T. Saraiva, "Decentralized and Centralized Storage Architectures in Local Energy Markets (LEM) and their interaction with the Wholesale Market (WSM)," in Proceedings of the IEEE Belgrade PowerTech, Belgrade, June 2023, pp. 1-6.

[**Paper D**] A. Ferreira dos Santos, J. T. Saraiva, "Simulation of the Operation of Renewable Energy Communities Considering Storage Units and Different Levels of Access Tariffs Exemptions," in Proceedings of the 19th International Conference on the European Energy Market (EEM), Lappeenranta, June 2023, pp. 1-6.

All these papers are available in Annex A.

Chapter 2

2. Background and State of the Art

This chapter presents a background and the state of the art about the main topics approached in this thesis. The electricity market evolution and its classification, according to the type of good and service that is traded and according to its temporal basis, is presented in Section 2.1. A review on European Climate and Energy policies is provided in Section 2.2. The Clean Energy Package (CEP) is described and contextualized with new rules and models for citizens. An overview of some of the national frameworks for Energy Communities in the European Union (EU) is provided in Section 2.3. The advent of the CEP opens the path for new types of energy initiatives and provides new roles and opportunities for citizens, which can act as energy producers and consumers, or prosumers. Within this context, Peer-to-Peer (P2P) models are considered as one of the key elements of the next generation of power systems market and will be described in Section 2.4. Finally, in Section 2.5. the concepts of Microgrids, Smart Grids and Virtual Power Plants (VPP) will be introduced since they allow to manage and coordinate the aforementioned decentralized and distributed new energy business models.

2.1. Electricity Markets

2.1.1. Restructuring of power systems

The electricity sector restructuring originated the unbundling of the traditional vertically integrated companies and lead to the separation of generation property from transmission, distribution and retailing activities. This new desegregated model, presented in Figure 2.1., includes several competitive activities namely, Generation (G), Financial Intermediation (FI) and Retailing (R). The Distribution Network (DN) operates as a regulated monopoly since it is not economically feasible to duplicate the distribution networks in the same geographical area. A similar regulated monopoly approach applies to the Transmission Network (TN) activity. Bilateral Contracts (BC) and Organized Markets (OM) represent the mechanisms available to trade electricity. The Independent System

Operator (ISO) stands for the operation and real time monitoring of the systems and finally Ancillary Services (AS) correspond to a number of products usually bought or contracted by the ISO to ensure the secure operation of the system.

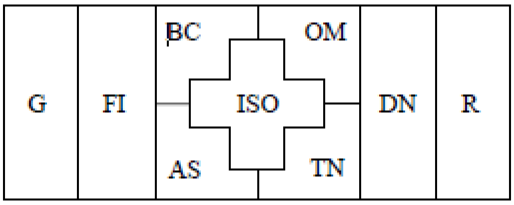

Figure 2.1. Electricity model sector (Source [11])

The central part of this figure corresponds to a set of functions that were usually assigned to the transmission entities in terms of operating and managing power systems. They are:

a) **Bilateral contracts** are a type of contractual arrangement that involves the establishment of physical or financial relations between electricity generation entities and retailers or large consumers. These contracts cover various aspects, such as the price and energy required to be supplied and produced.

b) An **Organized Market** is a type of financial transaction that involves the execution of various activities, such as day-ahead and intraday market activities. If these activities and bilateral contracts come together, then a mixed model might be presented [12]. The operation of organized markets is usually carried out through the purchase and sale of electricity. Market operators receive bids from different entities for every hour or half hour of the next day. These bids are usually accompanied by energy and price values. These markets then build a supply and a demand curve for each trading period, which is used to provide a complete economic dispatch. The market design can also include complex bids that have additional information, such as minimum profit requirements, ramps and hours of operation [11]. Another type of market is the forward markets which involve the trading of electricity blocks to be delivered in future periods.

c) The **System Operator, ISO,** is an organization that has the technical capabilities to manage the power system operation. It is also responsible for collecting information related to the economic activity generated by the bids that are submitted in the organized markets. The ISO should also perform a technical evaluation of the dispatch for each period of the next day, to ensure that it is feasible, namely, to evaluate the network constraints and the potential impact of congestion on the system. If there are no limitations, the ISO sets the amount of ancillary services that are required and contracts the providers of these services. In some cases, the ISO and the Transmission Network (TN) functions are under the responsibility of the same entity, taking the name of Transmission System Operator (TSO). This is the case of REN, Redes Energéticas Nacionais, in Portugal and REE, Red Eléctrica de España, in Spain.

d) The **Transmission Network** company which is an entity that owns or has the concession of the assets of the electricity transmission system. It operates in a monopoly position in the geographical area where it is located. Like other companies, it is regulated by the Regulatory Authorities.

e) Besides the primary, secondary and tertiary reserves, it is also necessary to contract other **Ancillary Services** such as reactive power and voltage control, black start and the solution of violated network constraints. These services are provided by different entities, such as network or generation companies. In most systems, the amount of ancillary services that are required are determined by the System Operator. The System Operator then accepts bids for the provision of some of these services. The primary reserve is composed of the Frequency Containment Reserve, which is a type of reserve that is designed to maintain a steady power balance in the system. The secondary reserve, which is denominated as Frequency Restoration Reserve, is designed to restore the frequency to its nominal level. Finally, the tertiary reserve, called Replacement Reserve, includes reserves with activation time from 15 minutes up to some hours in order to replace secondary reserve generators if that becomes necessary [13]. In several systems some of these services are mandatory and not paid (as it is the case of primary reserve in Portugal) while others are contracted in specific markets (as it occurs with secondary and tertiary reserves in Portugal).

2.1.2. Market Types

Considering the organization previously detailed, markets can be classified according to the type of good and service that is traded and according their temporal basis [14]. In this scope, the Electricity Market is where electricity is traded between sellers and buyers, through a centralized mechanism, operating as a spot market (usually known as Pool markets) and/or through contracts established directly between buyers and sellers (Bilateral Contracts). These are different types of trading mechanisms that are designed to provide a central and transparent platform for the trading of electricity. In addition to these, some ancillary services are also traded in specific markets to ensure that the power system operates in a secure and reliable way.

The different types of electricity markets can be classified as:

- Spot market, which is a daily market that aims to negotiate the energy supply typically for each hour of the next day (also known as Day-Ahead Market);
- Intraday Markets, that can be used by market agents to purchase or sell usually small quantities of electricity. This type of market is designed to address the potential imbalance between the supply and demand of electricity;
- The Derivatives and Forwards market is composed of future contracts and options. It is designed to address the volatility of the daily electricity price by providing financial instruments that are designed to protect investors from the effects of the short-term market;
- Long-term Investment market, which is focused on investing in new infrastructure projects.

If retail agents, eligible consumers and generation agents submit their bids in an anonymous way to a Market Operator, it corresponds to a centralized spot market, commonly referred to as **Pool market**. It features short-term mechanisms designed to balance the demand and supply of electricity. These markets are usually referred to as **Day-ahead markets** and are designed to work for the next day. They can be symmetrical or asymmetrical, voluntary, or mandatory.

The implementation of this dispatch design must deal with the physical properties of power system networks (Figure 2.2.). The Market Operator matches the bids from an economic point of view and the System Operator verifies if transmission grid limits are not surpassed. If congestion occurs on the transmission grid both the System and Market Operators need to work together in order to solve the problem. If it cannot be resolved, for any kind of reason, the System Operator has the authority to change the initial dispatch in order to regain feasibility.

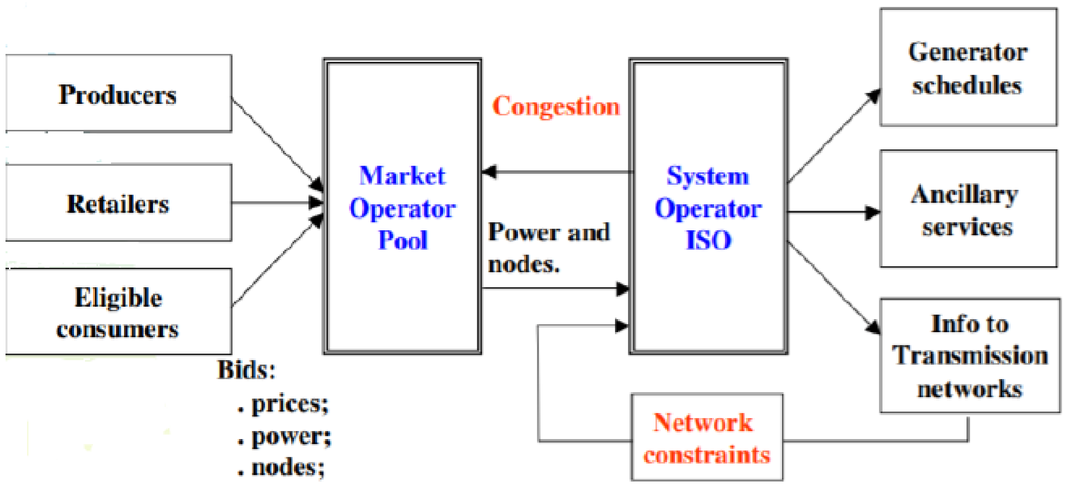

Figure 2.2. Poll based Electricity Market Model (Source [11])

The **Symmetrical** markets allow market participants to make buying and selling bids. After the bids have been received, the Market Operator builds the aggregated curves according to the increasing and decreasing bid prices. The demand bids are ordered by descending price order and cumulative quantity, and they form the aggregated demand curve. The supply bids are ordered by the ascending price order and cumulative quantity, and they form the aggregated supply curve. The point of intersection between the supply and demand curves defines the clearing price and quantity. All the market agents buy and sell energy at the clearing price. These markets are also known as Uniform Price Auctions. After the bid process has ended, the Market Operator uses the Market Clearing Price to settle the traded electricity quantities. The power plants that bid above the market price and the demand that bids below it will not be cleared in the market. The symmetrical model is illustrated in Figure 2.3.

The **Asymmetrical** model is another type of market that can be designed to operate on a day-ahead basis. It allows the generation agents to participate in the market and the demand is normally modelled by forecasts for each trading period. In practice, this model assumes that the demand is inelastic and ready to pay the market price. The selling bids are then used to determine the final prices. Figure 2.4. illustrates this market mechanism, in which selling bids are organized in ascending order of the bid price together with the forecasted demand levels. In this case, three demand levels (Q1, Q2 and Q3) determine three distinct market price levels (MP1, MP2 and MP3) [11].

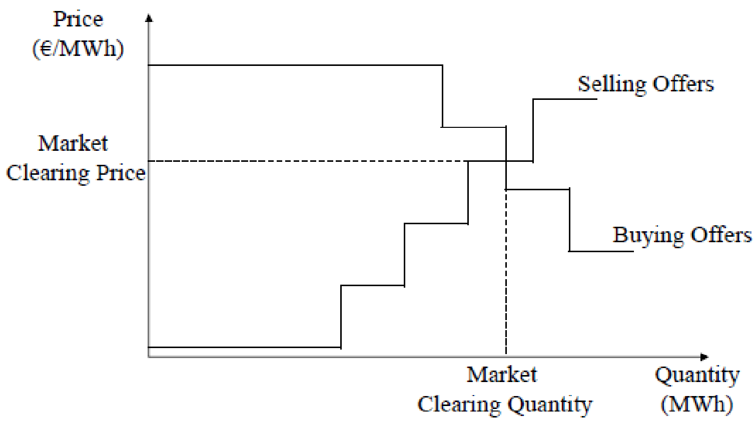

Figure 2.3. Symmetrical Poll Spot Market (Source [11])

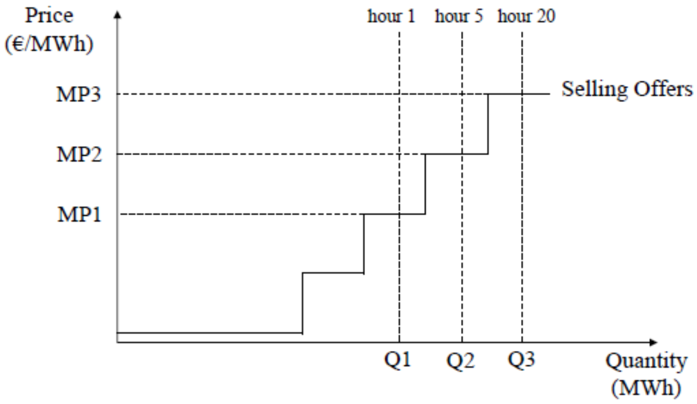

Figure 2.4. Asymmetrical Poll Spot Market (Source [11])

Another type of relationship between market agents is the **Bilateral Contracts**. The previous Pool Model is based in short term marginal costs which are very volatile, being influenced by the demand, generators, and their operation costs and the transmission grid line capacity. To overcome the usual pool model price volatility, in the Bilateral Contracts model the generation and retailing companies, as well as eligible consumers, are free to establish between themselves contracts to buy and sell electricity. Duration, amount of generation and demand as well as their agreed price, are freely negotiated in these kinds of contracts. The responsibility of technically validate these bilateral agreements is done by the System Operator. If they originate unfeasibilities regarding the operation of the network, the ISO/TSO must activate mechanisms in order to introduce changes and consequently make the system feasible.

In most countries in which there was a reorganization of the electricity sector, a mixed structure (**Mixed Models)** was adopted allowing market agents, producers, consumers and retailers to participate in the day ahead market or to establish bilateral contracts. The technical validation of the global dispatch will be carried out by the ISO or TSO for each period of the next day. This process will gather information about the various bilateral agreements and the bids that have been cleared by the Market Operator [11]. Figure 2.5. illustrates this type of mixed structure.

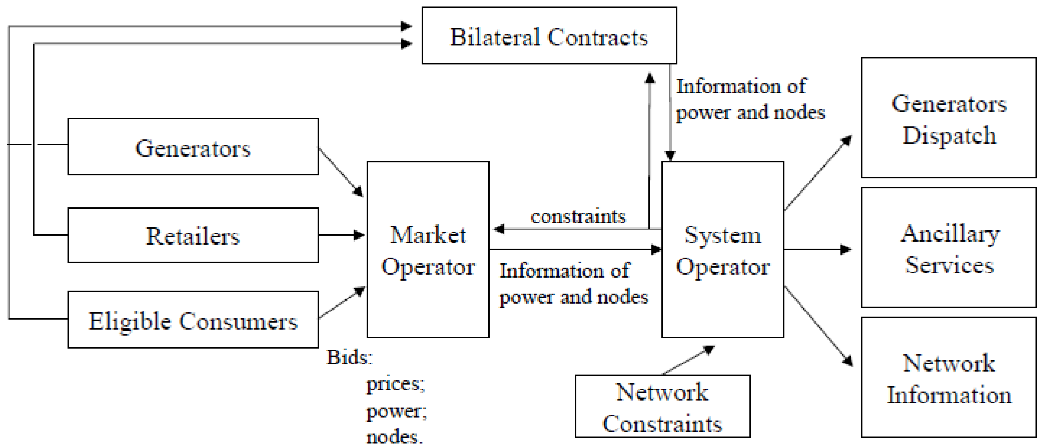

Figure 2.5. Mixed Model including a Spot Market and Bilateral Contracts (Source [11])

System Operators use a set of operational services to control the power system and to balance supply and demand. They are usually termed as **Ancillary Services** and aim to stabilize the system and to maintain security of supply and system reliability. As mentioned in Section 2.1 these include the frequency control and active power reserves, voltage control and reactive power, black start capability, emergency control actions, and grid loss compensation.

The frequency control service is designed to maintain the system's frequency within a certain interval. It can also be used to control the active power to ensure that the system is balanced. The voltage control service manages the reactive power to maintain the voltage level within the specific ranges. When there are contingencies and unpredictable deficits caused by factors such as the failure of generators and transmission lines, different types of reserve services are utilized. These include primary reserve which is an on-line resource that can be immediately available. On the other hand, secondary and tertiary reserves have longer activation times and can be used to supplement the primary reserve. The black start service is an emergency response that can be utilized by a generating unit to restore power supply after a large blackout has occurred. Other services that can be obtained by the ISO include remote generation, emergency control actions, and grid loss compensation [15].

The different approaches to procuring ancillary services can be determined depending on the type of power system and the country where they are located. The first one involves requiring the TSO to set a mandatory provision, for instance for primary reserve. Other services, as secondary and tertiary reserves can be contracted by the ISO in specific daily markets or using long term contracting established with generation agents.

In a recent report [16], the European Network of Transmission System Operators for Electricity (ENTSO-E) presents a vision of what would be necessary to achieve a Power System fit for a Carbon Neutral Europe. Regarding the increasing operational challenges and the rapidly changing of market actors, ENTSO-E refers that new products for both balancing and non-frequency ancillary services are required, to support for example, voltage control, inertia and fast frequency response. In this scope, the demand response namely using electrical vehicles and distributed resources will have an important role, as well as the presence of fast service providers.

The **intraday markets** are similar to day-ahead energy markets and the main difference is the gate closure. They follow the day-ahead session and work as adjustment markets, i.e. the market agents can correct accepted bids from the day-ahead market or from previous intraday sessions. The rapid emergence and evolution of smart grids and renewable sources are expected to have a huge impact given the variability if several primary resources.

Two structures of intraday energy markets can be found [17]:

- Discrete: fixed number of trading sessions with a pre-defined period and with a gate closure of one hour before the physical delivery;
- Continuous: the trading is continuous and starts after the day-ahead market with a gate closure of one hour before physical delivery.

The Iberian Electricity market, MIBEL, comprises a day-ahead and an intraday market. The latter was initially characterized by 6 consecutive auctions, to take adjusted network constraints and unforeseen events into account. Currently, MIBEL also includes a continuous Intraday Market mechanism.

The European Commission has set out its objectives for the development of continuous energy trading in Europe. This is done through the allocation of transmission capacity between different zones. The XBID, or Cross-border Intraday Coupling, is a project that was launched in 2012 to create solutions for intraday continuous trading across Europe and to increase overall trading efficiency within a single intraday EU electricity market. The goal of the system is to link the orders placed by electricity market participants in different countries using a central IT system. This system also allows the exchange of information between different sectoral trading platforms and the transmission capacity of the participating regions.

2.2. Clean Energy Package for all Europeans

2.2.1. Legal documents

In May 2019, EU institutions concluded the final legislative files for the Clean Energy for All Europeans Legislative Package (CEP) [3]. It is a legal framework that defines European climate and energy policy and sets the EU ambitions on this topic for the 2030 horizon. It is composed of eight different pieces of legislation aimed at accelerating the energy transition in Europe. The CEP for Europe introduces three new concepts that are designed to help consumers and the public to participate in the development of a new energy paradigm. These include the Collective Self-Consumption, the Renewable Energy Communities, and the Energy Communities of Citizens. The objective of the package is to ensure that the transition to a decarbonized and decentralized energy system is carried out in an unbiased manner. The main objective of this new energy paradigm is referred to as the democratization of energy so that most of the energy that households need to meet their consumption requirements is produced at a local level [8].

Several new frameworks and provisions for the design and implementation of new energy programs were also introduced. These include updated versions of the Electricity Market Directive EU 2019/944 [7] and Renewable Energy Directive EU 2018/2001 [6]. The updated Electricity Regulation 2019/943 [18] provides a framework for addressing the various changes that are happening in the electricity market. These include cross-border flows, customer participation, and market-based pricing.

All the documents under the CEP are available in [19] and will be summarized in the following paragraphs:

- Energy Performance of Buildings Directive (EU) 2018/844 [20]

The Energy Performance of Buildings Directive [20] aims at achieving a highly energy efficient and decarbonized building stock by 2050 and to create stable investment conditions to foster investments into the renovation of buildings. This Directive encourages the deployment of automation and control systems in buildings for a more efficient operation as well as the rollout of charging points for electric vehicles (EVs).

- Renewable Energy Directive (EU) 2018/2001[6]

The original Renewable Energy Directive [21] already set the basis for the promotion of energy from renewable sources. As the use of renewables has significantly increased and new technologies allow for a more flexible integration into the grid, the new Renewable Energy Directive [6] was recast as part of the CEP. The Renewable Energy Directive was also updated to provide a binding target of 32 percent of the energy from renewable sources that the European Union will require by 2030. The updated regulations also provide targets for renewable energy in the transportation and heating sectors.

One of the key objectives of the CEP is to put consumers at the heart of the energy transition. To facilitate achieving this goal, the new Renewable Energy Directive [6] gives citizens, who produce their own energy from renewable sources, a clear right to consume, store and sell their generated energy, including through power purchase agreements. In addition, this Directive enables the participation of consumers in the so called 'Renewable Energy Communities'. These communities are autonomous legal entities based on the open and voluntary participation with the purpose of providing environmental, economic or social community benefits for its shareholders or members rather than financial profits.

Like individual citizens, such communities are entitled to generate, consume, store and sell energy from renewable sources. Member States can allow Renewable Energy Communities to be open for cross-border participation.

- Energy Efficiency Directive (EU) 2018/2002 [22]

Putting energy efficiency first was one of the main objectives of the CEP. The updated Energy Efficiency Directive [22] provides a target of 32,5 percent of Energy Efficiency by 2030. It extends the obligation of Member States to reduce their energy consumption by 0,8 percent annually until 2030. Metering and billing rules, especially for multi-apartment and multi-purpose buildings, have been amended to provide clearer rights for consumers on their billing information.

- Governance of the Energy Union and Climate Action Regulation (EU) 2018/1999 [23]

The Governance of the Energy Union Regulation [23] establishes a transparent and predictable governance mechanism to ensure that EU meets its 2030 climate targets as well as international climate commitments. The Governance Regulation of the Energy Union applies to the different dimensions of the organization, such as the internal market, decarbonization, innovation, and competitiveness. Member states can contribute to the overall goals of the Union in different ways.

- Electricity Regulation (EU) 2019/943 [18]

One of the main components of the CEP is the updated electricity market rules, which are designed to reflect the new market realities. They are also designed to ensure that the security of supply is not compromised. The increasing role of consumers in the clean energy transition is also highlighted by enabling their active participation in the electricity markets.

The recast Electricity Regulation [18] sets out general principles for the operation of the electricity markets, including market-based prices, more flexibility, customer participation and cross-border electricity flows. Several specific topics regarding the redesign of electricity markets are:

- Balancing

  The Regulation establishes that generally all market participants are responsible for imbalances in the system. Balancing capacity must be procured separately from balancing energy. Transmission System Operators (TSO) have to procure balancing capacity based on market-based principles. Balancing energy has to be settled at marginal pricing and must reflect the real-time value of energy.

- Short-term and long-term markets

  The new rules also harmonize trade intervals and gate closure times for day-ahead and intraday markets. In order to enable the participation of all market participants, minimum bids of 500 kWh or less are allowed. In forward markets, TSOs shall issue long-term transmission rights to incentivize cross-border trading.

- Dispatch and redispatch

  The new Electricity Regulation establishes that dispatching priority is given to renewable energy sources and high-efficiency cogeneration facilities with an installed capacity of less than 400 kW or demonstration projects using innovative technologies subject to approval by the regulatory authority, provided that such priority is limited to the time and extent necessary for achieving the demonstration purposes. From 2026, dispatching priority shall apply only to power-generating facilities that use renewable energy sources and have an installed electricity capacity lower than 200 kW. Sources that were subject to priority dispatch before the entry into force of the new Regulation continue to benefit from priority dispatch until there is a new connection agreement or an increase in generating capacity or any other substantial modification.

- Congestion management and capacity allocation

  The revised Electricity Regulation reinforces rules on capacity allocation and congestion management, including through a review of bidding zones. Member States must put in place action plans to remedy congestions based on non-discriminatory and market-based solutions. Transactions may only be curtailed in emergency situations. Revenues generated from congestion management can be used to maintain the availability of allocated capacity or to optimize and develop new interconnections.

- Capacity mechanisms

  The recast Electricity Regulation establishes new rules on capacity mechanisms to ensure resource adequacy by remunerating resources for their availability. Member States shall only use capacity mechanisms as a last resort while implementing measures such as removing regulatory distortions and price caps, enabling scarcity pricing, energy storage or demand side measures. Before introducing a capacity mechanism, Member States also have to coordinate with other directly interconnected Member States. Capacity mechanisms shall be temporary, non-distortive, and non-discriminatory and opened to all types of resources, including storage and demand side management.

- European Network of Transmission System Operators for Electricity, Transmission System Operators and Distribution System Operators

  The roles of TSOs and the ENTSO-E are strengthened and clarified. In addition to their already existing tasks, TSOs established regional coordination centers since 1 July 2022. The regional coordination centers are responsible for the coordination of capacity calculation, security analysis, restoration support, adequacy forecasts or for facilitating the regional procurement of balancing capacity.

  The recast Electricity Regulation also establishes new tasks for Distribution System Operators (DSOs), including the creation of a European entity for EU DSO. The EU DSO will promote operation and planning of distribution networks, facilitate the integration of renewables, distributed generation and storage resources and increase the presence of flexibility resources. Further tasks include the support of the development of data management, cyber security, and data protection. The EU DSO shall also cooperate with the ENTSO-E on the development and implementation of network codes as well as in identifying best practices relevant for the distribution networks.

- Network codes and guidelines

  The revised Electricity Regulation refines the rules for developing network codes and guidelines and extends the areas for which the European Commission can require the preparation of network codes. In this regard, new network codes can be established for non-frequency ancillary services, demand response, storage, curtailment, data management and cybersecurity.

- Electricity Directive (EU) 2019/944 [7]

The recast Electricity Directive of the CEP aims at developing and completing the internal electricity market and to address new market challenges. To facilitate the completion of the internal electricity market, Member States have to remove barriers to cross-border electricity trade and consumer participation. Prices will be set using market-based criteria and Member States shall facilitate flexibility and ensure third-party access in a non-discriminatory manner. In this scope this Directive addresses the following issues:

- Empowerment of consumers

  One of the main features of the new electricity system design is the ability of consumers to actively participate in the markets. Member states are required to implement measures that allow them to participate in the electricity market through aggregation or direct participation. Customers can also sell their own electricity and participate in energy efficiency programs. In addition, active consumers are required to pay the network charges and accept responsibility for any imbalances that they may cause. Customers who own energy storage facilities are not required to pay double charges or license fees.

  The revised Electricity Directive further provides the possibility to establish Citizen Energy Communities (CEC). They are based on the open and voluntary participation. Member States must enable CEC to access electricity markets without discrimination and DSOs have to cooperate with CEC to facilitate electricity transfers within the CEC. Member States can also grant CECs the right to manage distribution networks in their area of operation. CECs are also subject to network charges and costs for the imbalances they cause.

- Demand response

  The new Electricity Directive indicates that Member States may allow and facilitate the use of demand-side management measures through Aggregation. This aggregation allows customers to purchase and sell electricity as well as provide and trade flexibility products.

Market access for all participants must not be discriminatory. Aggregation participants are responsible for the various imbalances that they cause in the electricity market. They are also liable for the costs that other market participants incur due to the demand response activities.

- Dynamic electricity pricing, metering, and billing

  The updated electricity directive requires Member States to carry out cost-benefit analyses on the implementation of smart meters. They should also allow customers to request their devices' installation. These devices should be able to provide consumers with reliable and accurate readings on their electricity usage. Customers who have installed smart meters are entitled to request a dynamic electricity pricing contract.

- DSO, TSO, and National authorities

  The recast Electricity Directive establishes new tasks for DSOs, in particular in what concerns the procurement of non-frequency ancillary services, flexibility, data management and the integration of electromobility. Procurement of ancillary services shall be market-based, transparent and non-discriminatory. For the procurement of other relevant services effective participation of all market agents shall be made possible, including for those participants engaged in storage, demand response or aggregation. Member States shall incentivize DSOs to procure flexibility services, including the procurement of distributed generation, demand response or energy storage. Regarding the integration of electromobility, DSOs shall facilitate grid connection and can only own, develop, manage, or operate recharging points for EVs subject to strict conditions.

  The tasks of TSOs have been slightly extended to include the procurement of ancillary services, the digitalization of transmission systems and data management.

• Regulation on Risk-Preparedness in the Electricity Sector (EU) 2019/941 [24]

The Risk-Preparedness Regulation aims to establish a framework to prevent, prepare for and manage electricity crises. In order to achieve these objectives, Member States are required to cooperate. The Regulation also aims at establishing an effective monitoring system for the security of supply in the Union.

- Regulation on the European Union Agency for the Cooperation of Energy Regulators (EU) 2019/942 [25]

The Agency for the Cooperation of Energy Regulators (ACER) was established through the Third Energy Package passed in 2009 [26]. Originally, ACER's role was limited to coordination, advising and monitoring. With the increase in cross-border cooperation under the new electricity market design of the CEP, ACER has been given additional responsibilities in the areas where uncoordinated national decisions with cross-border relevance could impact the functioning of the internal electricity market. The new ACER Regulation [25] establishes ACER's responsibility to supervise the ENTSOs for electricity and gas, the regional coordination centers, the EU DSO, TSO and Nominated Electricity Market Operators (NEMOs) and it assists the competent national regulatory authorities in performing their tasks. ACER will also be involved in the development of network codes, guidelines and methodologies and in monitoring their implementation.

2.2.2. Self-Consumption, Collective Self-Consumption and Energy Communities

The CEP aims to place consumers at the center of the energy transition by including the definition of new models and rules for citizens. This will help for the definition of new rules and models for citizens, which could act as energy consumers or producers, or prosumers [4]. The definitions of Self-Consumption, Collective Self-Consumption and Energy Communities are based on the legal framework set by CEP. Their legal concepts and main regulatory characteristics are defined in a report provided by the Council of European Energy Regulators [27]. A diagram showing their characteristics is provided in Figure 2.6 and their definitions and features are detailed in the next paragraphs.

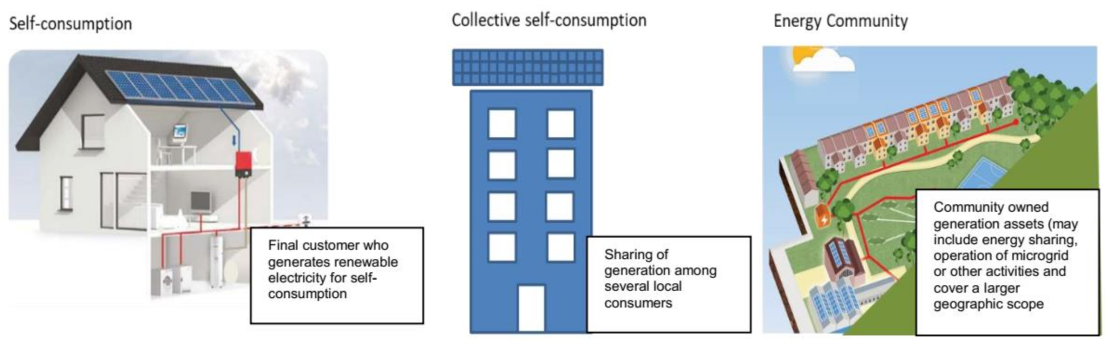

Figure 2.6. Diagram illustrating self-consumption, collective self-consumption and energy community.(Source: [27])

- Individual Self-Consumption

Self-Consumption stands for final customers that consume the energy they produce on site. Both, the recast Renewable Energy Directive [6] and Electricity Market Directive [7], introduce new definitions formally recognizing self-consumers:

- Electricity Market Directive (2019) Article 2/8 [7]

  "Active customer means a final customer, or a group of jointly acting final customers, who consumes, or stores electricity generated within its premises located within confined boundaries or, where permitted by a Member State, within other premises, or who sells self-generated electricity or participates in flexibility or energy efficiency schemes, provided that those activities do not constitute its primary commercial or professional activity".

- Renewable Energy Directive (2018) Article 2/14 [6]

  "Renewable self-consumer means a final customer operating within its premises located within confined boundaries or, where permitted by a Member State, within other premises, who generates renewable electricity for its own consumption, and who may store or sell self-generated renewable electricity, provided that, for a non-household renewables self-consumer, those activities do not constitute its primary commercial or professional activity".

  Final consumers, who are the ones who produce and consume electricity, are allowed to store and sell the electricity they have used within their installations. Member States may also extend this scope beyond the consumers' own premises. However, these activities are not allowed in cases in which these are the actors' primary professional or commercial activities.

  Although the definition of renewable self-consumers is different from that of active customers, the CEP also allows them to participate in various energy efficiency schemes and flexibility programs.

- Collective Self-Consumption

The increasing financial viability of installing small renewable generation units and the emergence of a sharing economy have led to an increase in the number of people who are interested in directly sharing their electricity with other consumers. This concept is now formally recognized at the EU level legislation.

In the Electricity Market Directive [7], the concept of active customers includes groups of jointly acting customers, whereas the Renewable Energy Directive [6] defines jointly acting renewable self-consumers in a separate definition:

- Renewable Energy Directive (2018) Article 2/15 [6]

  "Jointly acting renewable self-consumers means a group at least two jointly acting renewable self-consumers (…) who are located in the same building or multi-apartment block".

  This definition only applies to renewable self-consumer groups that are located in multi-unit residential buildings. Member States can't extend this concept beyond these buildings [27].

  The primary difference between the two definitions of renewable self-consumers (Table 2.1) is that renewable self-consumption is about a single consumer generating renewable electricity on its premises for its own individual consumption, while jointly acting renewable self-consumers implies that multiple consumers come together to generate renewable energy on their same building or multi-apartment to meet their collective consumption needs.

Table 2.1. Renewables self-consumption definitions under the Renewable Energy Directive (Adapted from [28])

Article 2(14) REDII: 'renewables self-consumer'	Article 2(15) REDII: 'jointly acting renewables self-consumer'
A final customer operating within its permises located within confined boundaries or, where permitted by a Member State, within other premises who generates renewable electricity for its own consumption and who may store or sell self-generated renewable electricity, provided that for a non-household renewables self-consumer, those activities do not constitute its primary commercial or professional activity.	A group of at least two jontly acting renewables self-consumers in accordance with point (14) who are located in the same building or multi-apartment block.

- Energy Communities

The Clean Energy Package contains two definitions for Energy Communities: CEC which is contained in the recast Electricity Market Directive [7], and Renewable Energy Communities (REC), which is included in the recast Renewable Energy Directive [6].

The concept of CEC is defined in the Electricity Market Directive (2019) Article 2/11 [7]:

"Citizen Energy Community means a legal entity that: (a) is based on the voluntary and open participation and is effectively controlled by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises; (b) has for its primary purpose to provide environmental, economic or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits; and (c) may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for EVs or provide other energy services to its members or shareholders";

The Renewable Energy Directive (2018) Article 2/16 [6] states the REC model:

"Renewable Energy Community means a legal entity: (a) which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity; (b) the shareholders or members of which are natural persons, Small and Medium-sized Enterprises (SMEs) or local authorities, including municipalities; (c) the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits";

Table 2.2. The Energy Communities definitions in the CEP (Adapted from [28])

Article 2(16) Recast Renewable Energy Directive Renewable Energy Community'	Article 2(11) Recast Electricity Directive Citizen Energy Community'
A legal entity: which in accordance with the applicable national law; is based on open and voluntary participation; is autonomous; and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity;	A legal entity: is based on voluntary and opne participation and is effectively controlled by members, local authorities, including municipalities, or small entreprises.
the shareholders or members of which are natural persons. SMEs or local authorities, including municipalities.	has for its primary purpose to provide environmental, economic or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits, and
the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits.	may engage in generation, including from renewable sources, distribution, supply, cinsumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders.

The two definitions are based on principles-based elements that must be met in order for a set of installations to be considered an energy community. This first criterion requires the creation of a legal entity that is organized around certain governance and ownership principles. Both definitions imply that collective ownership can be organized around a specific energy-related activity. This is because some of the elements of the CEC and REC definitions are similar.

In CEC, no proximity or geographic limitation to the energy project is required. According to Electricity Directive (Art. 16.2a) [7], Member States may provide in the enabling regulatory framework that CEC "*are open to cross-border participation*". Accordingly, this type of community can correspond to a virtual network since participation is not restricted to a specific location. The primary resource that is used is not necessarily renewable energy, however it is limited to activities in the energy sector.

On the other hand, a proximity requirement needs to be defined for REC and shareholders or members do not include large companies. The activity is open to all sources of renewable energy (e.g., also heat), but it is restricted to renewable energy technologies.

Both concepts are summarized in Table 2.3, where EMD is the acronym for Electricity Market Directive and RED stands for Renewable Energy Directive.

Table 2.3. Overview of conceptual dimensions regarding the Citizen and the Renewable Energy Communities (Adapted from [29])

	EMD		RED II	
Energy Sector	Electricity market (technology-neutral)		Renewable energy market (heat and electricity based on renewable energy)	
Legal form	Any		Any	
Participation	**Structure**	**Actors**	**Structure**	**Actors**
	Open and voluntary	Any	Open and voluntary	Natural persons, local authorities and SMEs whose participation does not constitute their primary economic activity
Control	**Structure**	**Actors**	**Structure**	**Actors**
	Effective control	Natural persons, local authorities and smal and micro-sized enterprises	Effective control	Natural persons, local authorities and SMEs whose participation does not constitute their primary economic activity
Autonomy	Large energy companies cannot exercise any decision-making power		Explicitly mentioned	
Geographical limitation	No		Those in control need to be located proximity of projects owned and developed by the community	
Activities	Generation, distribution, supply, consumption, sharing, aggregation and storage of electricity. Energy-efficiency services, EV charging-services, other energy-related services (commercial)		Generation, distribution, consumption, storage, sale, aggregation, supply and sharing of renewable energy. Energy-related services (commercial)	
Purpose	Social, economic and environmental benefits for members/shareholders or the local area in which it operates		Social, economic and environmental benefits for members/shareholders or the local area in which it operates	

2.3. Overview of National frameworks for Energy Communities in the EU

Since a few years ago, the discussion and the initial implementation of Collective Self-Consumption (CSC) schemes has been ongoing in some EU Member States while the legislative processes on Energy Communities is in its early stage in most countries. A working paper developed in 2019 [30] provides an overview of the status quo of national approaches for CSC and Energy Communities and assesses their relation to the EU directives. A cooperation group of Smart Grids and Energy Storage H2020 projects (BRIDGE – horizon 2020) also developed a report whose main objectives were to provide an overview of the existing legal developments regarding energy communities in the EU and to build recommendations for the European Commission [29]. This section provides an overview of different European countries' frameworks based on the previously mentioned documents.

For CSC, the national approaches mostly refer to multi-family houses and mixed use with offices and-or Small and Medium-sized Enterprises (SMEs). Partly, CSC is also enabled between different buildings. In this context, storage is also an important element to maximize the self-consumption rate of locally produced electricity and is partly specifically considered in the legislation e.g., through incentive schemes. In some countries, CSC is currently allowed only in a limited way (e.g., via private grids) or tolerated within a regulatory grey zone. In the field of Energy Communities legislation is much less advanced. The heterogeneity of national legislation in the analyzed countries is very large apart from being continuously changing.

In 2016 and 2017 important legal changes were introduced in Austria [31], France [32] and Germany [33], related to the direct use of locally generated electricity by the tenants in multi-family houses or commercial buildings via a private grid. In 2016, Greece passed a law on virtual net metering which was complemented by a law on energy communities in 2018 [34]. Slovenia [35] and the Wallonia region of Belgium [36] adopted laws on CSC and Energy Communities, while Luxembourg has drafted a law in 2018 [37].

Table 2.4 gives an overview of CSC and Energy Community schemes in the EU Member States [30]. In the case of Energy Communities, full transposition of the EU provisions is not yet the case in EU Member States. However, specific elements or framework legislation with further need for specification are in place in some cases. Because legislation on energy communities is not clearly attributed to either REC or CEC, Table 2.4 makes no distinction regarding this point.

Table 2.4. Collective self-consumption and energy community frameworks in selected EU MS and Switzerland (June 2019) (Source: [30])

Country	Collective Self-consumption	Energy Communities
AT	✓ ElWOG 2017	Legislative process started (Renewables expansion law)
BE	✓ Wallonia, decrees in 2018, 2019	✓ Wallonia, framework legislation; decree in 2019
DE	✓ Tenant power model 2017	-
DK	PG only	-
EE	PG only, Electricity Market Act	-
ES	✓ Royal Decree 244/19	- (multi-building CSC)
FI	PG only	-
FR	✓ Law 2017-227, decree 2017-676	Legislative process started
GR	✓ 2016 law on virtual net metering	✓ Law N4513/2018 on energy communities 2018
LU	Draft electricity market bill 2018	Draft electricity market bill 2018
NL	PG only	-
PT	Legislative process started	-
SI	✓ Regulation on self-supply 2019	✓ Framework within regulation on self-supply 2019
SE	PG only	-
UK	PG only	-
CH	✓ Energy law and decree 2016/2017	✓ Energy law and decree 2016/2017

The next paragraphs detail the situation on CSC and Energy Communities in some EU countries.

Austria's amendment of the Electricity Act in 2017 [31] supports private and commercial CSC (in e.g., multi-apartment buildings) which previously was hardly possible. This amendment defined specific aspects of these models on building scale such as the role of the different involved actors and the required contractual relationships between them. Neighboring buildings so far are not covered.

The renewable energy legislation extends the scope of the CSC framework to energy communities. This includes REC according to the Renewable Energy Directive [6] that may have cooperative structures for generating, storing and delivering renewable electricity across different real estate boundaries. Current discussions on local grid tariffs between the regulator and market agents include the idea that consumers only using the Low Voltage (LV) grid also only pay the LV grid related term of the grid tariff. The spatial and regulatory boundary of an energy community would be MV/LV substation.

On April 5th 2019, the **Spanish** government approved the Royal Decree 244/19 [38] that regulates the administrative, technical and economic conditions of self-consumption in Spain. This Decree completes the regulatory framework on this issue, driven by Royal Decree-Law 15/2018 [39], which repealed the so-called sun tax (the term solar tax or "*impuesto al sol*" was a toll or tax that Spanish authorities asked to be paid for the costs of distribution and maintenance of the electricity network in Spain [40]), and provides increased certainty and security to users. Among other measures, the royal Decree – Law 15/2018 [39] enables CSC by groups of apartment owners or in industrial estates; it reduces administrative procedures, especially in the case of small self-consumers, and establishes a simplified mechanism for compensation of energy fed into the public grid. Self-consumption was previously allowed with generation facilities located in the same dwelling only. According to the new rules, power surpluses may be shared with nearby consumers also in other buildings or fed to the grid. The generation facilities are connected to the internal network of associated consumers (direct lines) or to the LV network derived from the same MV/LV substation. Self-consumed energy from renewable sources, cogeneration or waste will be exempted from all kinds of charges and taxes.

The law distinguishes between:

a) Modalities for self-consumption without surpluses. In these cases, an antifouling mechanism must be installed to prevent the injection of surplus energy into the distribution network. In this case there will be a single type of subject, who will be the consumer;
b) Modalities of supply with self-consumption and surpluses. In these cases, production facilities that are close to and associated with consumption facilities may, in addition to supplying energy for self-consumption, inject excess energy into the distribution networks;
c) Production facilities not exceeding 100 kW associated with surpluses will be exempted from the obligation to register as an electricity production unit and will be subject only to technical regulations;
d) Regulations may be developed for production facilities below 100 kW for a simplified compensation mechanism between deficits of self-consumers and surpluses from its associated production facilities. For installations above 100 kW, surplus energy is sold on the electricity market.

In **Wallonia/Belgium** in May 2019 a legislative framework promoting CSC and REC was adopted [36]. According to this framework, the specific purpose of a REC is to produce, consume, store, and sell renewable electricity for the benefit of participants at the local level using the public network or a private grid. Several entities (natural or legal persons) within a “local perimeter” can agree to share and store their production and electricity consumption based on electricity exclusively produced from renewable sources or high-quality cogeneration (cogeneration with a specific efficiency). The law defines such a local perimeter as a grid segment whose connection points are located downstream of one or more MV/LV substation units. Thus, as opposed to proximity definitions using a predefined distance, local perimeters can have different extents, taking into account in particular the technical characteristics of the network.

Citizen participation in the energy transition has a strong tradition in **Germany**. Ownership of renewable energy units by single owners or communities dates back to the early 70s. A survey developed on March 2020 [41], refers that exist over 800 energy cooperatives operational in Germany (e.g EWS Schsönau eG [42], Isarwatt eG [43] and UrStrom eG [44]). The legal concept of CSC was introduced in Germany in 2017 [33] and it allows the plant operator in a multifamily house to sell locally produced electricity to the tenants in direct proximity. However, it has an unclear definition of proximity [45]. Citizen Energy Companies should contain at least ten natural persons who are members eligible to vote, in which at least 51 per cent of the voting rights are held by natural persons with a permanent residency in the administrative district of the project location. Further, no member or shareholder of the undertaking shall hold more than 10 per cent of the voting rights.

Self-consumption in **France** is detailed in the Law 2017-227 [46] and in the Decree 2017-676 [32] which contain provisions for individual and collective self-consumption. These provisions are included in the French Energy Code. The definition of the two forms of self-consumption includes that individual self-consumption does not involve the public grid for sharing the produced electricity while collective self-consumption does. CSC is allowed if electricity is produced and consumed by several consumers and producers linked together through a legal entity. According to the French PACTE law adopted in April 2019 [47], the geographical scope no longer relates to a transformer MV/LV but refers to proximity within the LV grid.

A law on energy communities was introduced in **Greece** in 2018 [34] and expanded the scope of virtual net metering to energy communities. This law defines energy communities as civil law partnerships with the exclusive aim of promoting the social economy, encouraging solidarity and innovation in energy, responding to energy needs, promoting energy sustainability in the production, storage, self-consumption, distribution and supply of energy and increasing energy efficiency in final consumption on the local and regional level. The proximity requirement is transposed through the requirement that 50% plus one of the members need to be located in the same District as the headquarters of an Energy Community.

A regulation on self-supply with electricity from renewable energy sources was adopted in **Slovenia** on May 1st 2019 [35]. It allows two forms of CSC:

- CSC in multi-apartment buildings, where the inhabitants can share energy from a renewable energy source generation unit connected to the LV network of the building. The renewable energy source production unit is located on the building and is connected through its own metering point to the point of common coupling of the building network with the LV distribution grid;
- CSC in renewable energy source communities that can be formed by customers in various types of dwellings. The renewable energy source production unit can be located at a separate

building and is connected to a dedicated production metering point on the LV distribution grid. The consumers participating in the renewable energy source community can consume electricity through two or more consumption metering points that are connected to the LV distribution grid of the same LV transformer station as the metering point of the renewable energy source production unit.

Inn **Portugal** the 2014 Decree-Law [48] introduced the definition of *Small Production Units for Self-consumption* (in Portuguese termed as UPACs), which were limited to individual or collective persons, with each production unit being associated only to one single meter, thus rendering impossible any form of collective renewable Energy prosumer initiative.

As a response to the recast of Renewable Energy Directive [6], a new Decree-Law was issued on the 25th of October 2019 (DL 162/2019) [49]. This Decree-Law came into force on January 1st, 2020 for self-consumption and Renewable Energy Communities with intelligent metering system and installed at the same voltage level, and in 2021 for other self-consumption activities. This Decree-law allows self-consumers to group together, and the same unit of energy production may have several self-consumers (collective self-consumption). This new regime allows direct exchange between two or more prosumers and sets the ground for the development of various collective self-consumption business models (including P2P schemes). It is also allowed that self-consumers and other participants in renewable energy projects constitute legal entities (the Energy Communities) for the production, consumption, sharing, storing and selling of renewable energy.

The main objective of this Decree-Law is to create the conditions for Portugal to achieve the goals defined within the scope of the National Energy-Climate Plan for 2021-2030 [50], namely to achieve a share of 47% regarding the energy from renewable sources in the gross final consumption in 2030, as well as to reduce the price of electricity for those who adhere to self-consumption.

This legal text aims at inducting greater efficiency from an energy and environmental point of view and ensures that the benefits from energy transition (e.g., costs of the national electricity system) are shared in a fair and impartial way, both by companies and by citizens interested in participating, without public subsidies.

For the first time, there was a legal framework for jointly acting self-consumers and REC, which is a copy of the recast of the Renewable Energy Directive definition. The mentioned legal framework does not clearly set spatial limits for the proximity between prosumers (i.e. in km), although DL 162/2019 Art.5 states that members of the community should be located within the proximity of the renewable energy installation. For each case, neighborhood relation or project proximity should be assessed by the National Directorate for Energy and Geology (DGEG) considering the project physical and geographic continuity, and jointly acting self-consumers and REC. The definition of the proximity criterion can also consider the project connected substation, different voltage levels or other legal and technical issues.

There were no legal provisions for CEC. However, DL 162/2019 offers equally a legal basis for aggregators and the use of Guarantees of Origin (producers and energy suppliers may use this mechanism), allowing the setting up of new business models and new networks and social innovations that may further develop CEC in Portugal.

Administrative procedures for UPACs registration and licensing are also simplified by the DL 162/2019:

- Capacity equal or under 350 W: no previous control was required;
- Capacity between 350 W and 30 kW: it was required a previous communication to DGEG;
- Capacity between 30 kW and 1 MW: they needed a previous registration and an operation certificate;
- Capacity higher than 1 MW: it was required to have a production and operation licenses.

Concerning the remuneration, DL 162/2019 stated that collective self-consumption and REC should receive a remuneration for surplus energy supplied to the grid that reflected the market value of that electricity and which can be commercialized by an independent aggregator or utility company. It also recognized a new actor, Entidade Gestora do Autoconsumo (EGAC), which is a legal entity that represents collective self-consumption participants.

It was also stated in Decree Law 162/2019 Art. 18 (n. 4), that charges associated with CIEG (Custos de Interesse Económico Geral), a subsidiary tariff named Costs of General Economic Interest, could be totally or partially deducted from the grid access tariffs. In 19th June 2020, a government dispatch, n.º 6453/2020 [51], stated that self-consumption and CER projects, starting operation till the end of the calendar year 2021, benefited from an exemption from charges corresponding to CIEGs network access charges for seven years.

On 20th March 2020, the Portuguese regulatory agency Entidade Reguladora dos Serviços Energéticos (ERSE) approved the Regulation for implementing the new self-consumption regime, n. 266/2020 [52]. In May 2021, ERSE replace the former Regulation 266/2020 with new regulation regime, n. 373/2021, that includes storage pilot projects [53]. Specifically, the designation of consumption, production or storage facility is adopted. On the other hand, EGAC is the entity that must interact with the DSO, so that energy sharing by collective self-consumption communities can be managed. It also needs to cooperate with aggregators for selling exceeding energy purposes.

In 14th January 2022 it was published in Diário da República the Decree-Law n. 15/2022 [54], that establishes the organization and functioning rules of the National Electric Systems, incorporating in a single legislative instrument a wide range of diplomas. It revokes and refreshes Decree Law 162/2019 and details the scope for control procedures for electricity production and storage. The main amendments introduced details for Self- Consumption, the concept of proximity between the UPACs and the utilization installations, with the law establishing the maximum distance between them (Art. 81-90) [54]. In Art. 187-191 it is also included the concept of CEC and REC (art. 187-191) [54]. Overpowering and Repowering (Art. 62-73) [54] are considered non-substantial changes and can be requested after the production license is issued and shall not lead to autonomous procedure of modification title and, in the case of wind or solar plants, no new environmental impact evaluation will be required. In wind farms already in operation, it is accepted that they may inject into the grid the additional energy resulting from prior control titles (operating licenses), maintaining the connection power unchanged, with the energy being remunerated in accordance with the remuneration system in force and for the applicable period. For all generating plants, with the exception of hydroelectric projects with a connection capacity exceeding 10 MVA, it is accepted that they may increase the installed power up to a limit of 20% of the connection power, with the connection power remaining unchanged. In this Decree Law, it is also defined the concept of hybridization (Art. 74-78) [54] corresponding to the inclusion of a new renewable energy plant into an existent generation plant. Unlike overpowering, it may be granted to a different owner of the generating plant or UPAC without the need for a dominance relationship.

It is foreseen the exemption from the RESP operator's intervention, provided the requirements laid down by law are met, being applicable until the injection capacity of the RESP, established by an annual quota set by the Government member responsible for the energy sector, is reached.

2.4. Peer-to-Peer markets

The Clean Energy Package provides a framework for new energy initiatives that are aimed at increasing the participation of small and medium-sized energy producers in the energy market. It also allows consumers to play a more prominent role in the energy transition. Through the CEP, consumers can now have more options when it comes to their energy consumption and their choice of home appliances. It allows them to take informed decisions regarding the use of their electricity. Passive energy consumers can also become prosumers by actively investing in and participating in renewable energy initiatives [5]. This new framework, called by some authors as the democratization of energy, aims to provide a more decentralized and open energy market. This new approach also paves the way for the establishment of new electricity markets. One of these is the P2P mechanisms, which are designed to provide a more direct and transparent connection between small consumers and energy producers. Consequently, P2P electricity trading has become the next generation of smart grid energy management schemes that allows prosumers to participate in electricity trading activities [55].

The Renewable Energy Directive [6] recognizes prosumers as entities which have the right to consume, store or sell renewable energy generated on their premises:

- individually, that is, households and non-energy SMEs and collectively, for example in tenant electricity projects ([6], Art. 21), or
- as part of Renewable Energy Communities organized as independent legal entities ([6], Art. 22)

On the other hand, the 2019 Electricity Directive (recast) of the European Commission [7], described in Section 2.2.2, is aligned with the concept of P2P since it allows prosumers to participate in electricity trading activities.

So, both directives expressly place the consumer at the heart of the energy markets [56], where they have the right to consume, to generate renewable energy, including for their own consumption and to store or sell excess electricity production. This could be done via bilateral trading, aggregators and P2P trading, receiving a market-based remuneration and guarantying the access to all suitable energy markets directly or via aggregation.

The electricity market was typically settled in a unidirectional way, where generation companies sell large amounts of electricity to retailers in the wholesale market, and retailers then sell electricity in smaller amounts to end users in the retail market. However, the P2P energy trading encourages multidirectional trading within a local geographical area. To address some of these challenges, P2P electricity trading emerged as a new alternative to foster the deployment of distributed generation technologies. It allows a direct interaction between market participants without considering a third party involvement [57]. Through P2P, customers can benefit from lower energy costs by sharing their surplus generation with other people in need. This provides both the consumer and the energy producers with a win-win situation [58].

An overview of key aspects of P2P energy trading was made by Zhou el al [58]. It includes a description of market designs, different trading platforms, physical and information and communication technology (ICT) infrastructures. These aspects are illustrated in Figure 2.7 and summarized in the following sections.

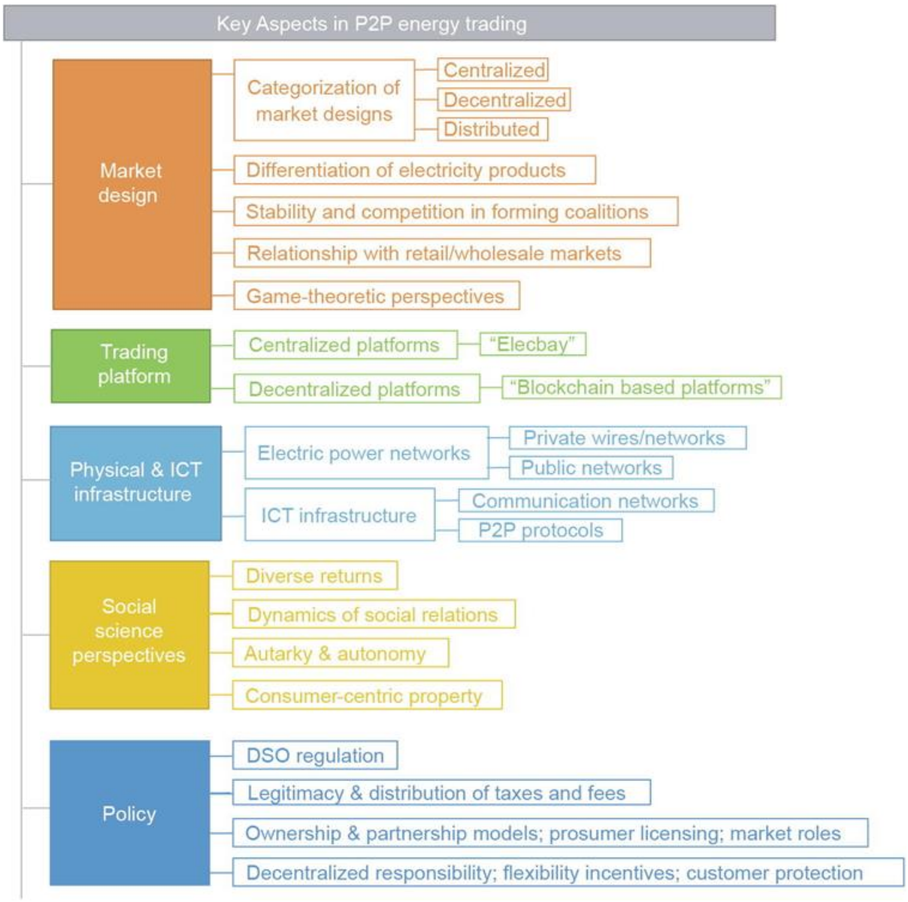

Figure 2.7. Overview of key aspects in P2P energy trading (Source: [58])

2.4.1. Market Design

The decentralization of energy markets, taking into account the increase of DER units, led to innovative market arrangements in P2P energy trading:

a) Centralized, decentralized and distributed

Based on the level of centralization, market design models for P2P energy trading can be organized into 3 categories: centralized, decentralized and distributed markets as illustrated in Figure 2.8.

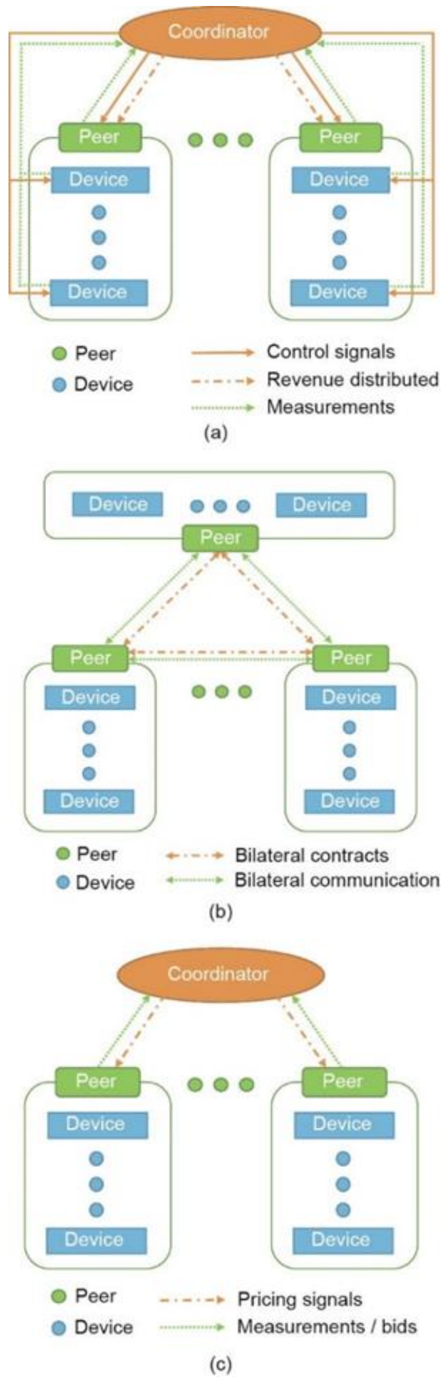

Figure 2.8. Categorization of markets for P2P energy trading. (a) Centralized markets; (b) Decentralized markets; (c) Distributed markets (Source: [58])

In a **centralized market**, a coordinator communicates with each peer and collects information from them. With the obtained information, the coordinator directly decides the energy transactions of the peers or the operational status of the devices among the peers. The revenue generated by the

P2P community is then distributed to the members by the coordinator according to predefined principles.

One of the main advantages of a centralized market is its ability to maximize the social welfare of the whole P2P community. It allows the coordinator to set the goals of the community and ensure that the members are satisfied with the services that they receive. [59]. One of the main disadvantages of this type of market is its complexity due to the amount of computational work involved in managing the various Distributed Energy Resources (DER) units. This kind of markets are vulnerable to single-point failures at the coordinators.

A number of studies have been conducted on the potential advantages and disadvantages of centralized markets for P2P electricity trading [59-62].

Unlike a centralized market, **decentralized P2P** trading platforms do not have centralized coordinators. Instead, they allow peer-to-peer transactions. This type of market does not explicitly maximize the social welfare of the whole P2P community [63]. The advantages of a decentralized market are its scalability and ability to allow its members to easily plug-in and out.

However, one of the biggest issues of decentralized markets is their lack of predictability, which can impact the operation of electricity distribution systems [64]. Thus, it becomes more complex to manage network constraints and more difficult to improve the operational efficiency of the power systems [64].

In decentralized markets, peers are exposed to significant uncertainties, which can affect the interests of their vulnerable customers. For instance, load and generation curtailments can occur under the continuous double auction mechanism described in [65]. A more detailed overview on decentralized P2P energy markets is provided in [64, 66-69].

Distributed energy markets are a type of design where the coordinator influences the other participants in the market by sending price signals. This type of system does not directly instruct the other participants on the status of their devices [70-72]. Unlike a fully decentralized market, a distributed market still has a coordinator to ensure that the other participants' behavior is coordinated. This type of market does require some information from its peers, but it does not directly control the devices of its participants. Due to the decentralized nature of its design, distributed markets provide a higher level of autonomy and privacy for their participants. They also combine the features of a central and a decentralized market [58]. A number of studies have proposed distributed markets for P2P energy trading as the ones described in [73-79].

Electricity products are typically **differentiated** from one another due to how they have varying prices and values. The wholesale market typically has different prices for electricity delivered over different time periods. Retail markets also utilize various pricing mechanisms such as time-of-use tariffs, real-time pricing and critical peak pricing [80]. In addition to these, electricity also has different pricing mechanisms based on the accumulated consumption. For instance, in some countries, such as China [81], Canada, and South Africa [82], it is adopted the incline block tariffs where electricity prices are divided into several levels based on the accumulated electricity consumption in a month.

Through P2P energy trading platforms, electricity products can also be differentiated from one another. This is because these markets operate in local energy systems that have specific characteristics. They are more flexible when it comes to implementing their settings.

A number of studies have been conducted on the potential of electricity products to be differentiated from one another in P2P energy trading platforms. For instance, in a study conducted by Morstyn et al. [77], it is proposed a multi-class management framework for electricity trading. This type of system would allow users to choose which type of electricity product they want to use (green energy, subsidized energy, and grid energy) which are preferred by different types of prosumers. These researchers proposed a consensus-based approach that would allow electricity products to be differentiated from their peers. For instance, in a case study, they noted that certain costs would be imposed on trades involving a different distance between the peers.

In the future, different designs for electricity trading will be developed and adopted. These will allow for the development of products that can be differentiated based on supply reliability or power quality. The differentiation of electricity products is summarized and illustrated in Figure 2.9.

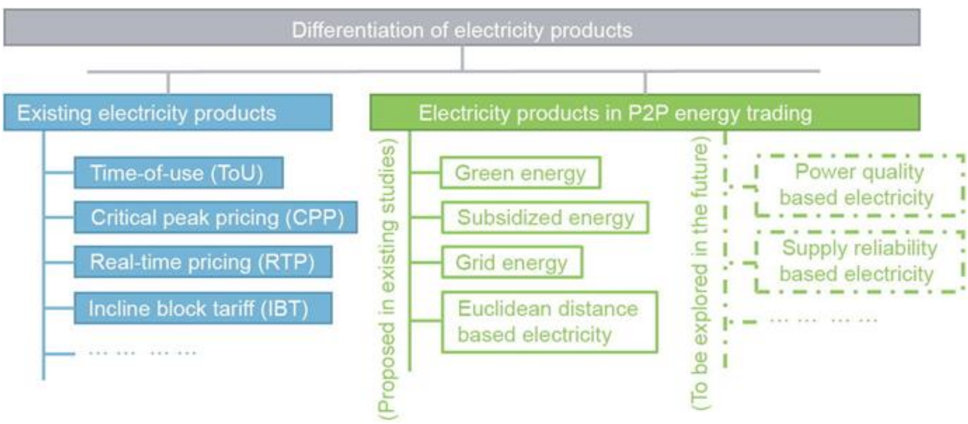

Figure 2.9. Differentiation of electricity products (Source: [58])

The **stability** in P2P energy trading markets can be defined as the ability to keep peers within the market. Zhou et al. [58] mentioned several studies, such as the ones presented in [57, 61, 62, 64, 66-68, 70, 71, 73-79, 83], which assumed that there was only one uniform P2P energy trading market for the considered area. Nevertheless, it is possible to have several P2P market service providers in an area, which compete with each other to recruit peers for the markets they have established. In such cases, the stability would become an important dimension for evaluating a P2P energy trading market design. In order to access the impact of P2P energy trading, on both individual peers and wider society, Zhou et al. [58] proposed an evaluation on how peers will be grouped for a certain area when they are free to form P2P coalitions.

Despite the various opinions about the potential of electricity trading, the evolution of power system markets is still not clear. As indicated in [84-86] the conventional wholesale and retail markets will continue to exist for a long time. This is why it is important that the studies on the **relationship between the emerging P2P** and existing energy trading platforms are conducted. Detailed discussions on the relationship between the retail and P2P markets can be found in [59, 61, 68, 75, 76, 78, 87]. Although the relationship between the two is examined in detail in [57, 77, 83], in most studies peers are assumed to first trade with each other, and then trade with the wholesale [60, 77, 83] or retail market [59, 61, 87] individually or in aggregate (depending on the scale of the peers and the design of the market for P2P energy trading) in order to deal with the energy imbalance. In other words, the conventional wholesale or retail market acts as the "residual balancer" for the peers in P2P energy trading. This allows the P2P trading system to maintain a steady supply of electricity while ensuring that the consumers are satisfied with the overall performance of the market. The “community-based market”, presented in [88], is an example of this type of relationship as illustrated in Figure 2.10.

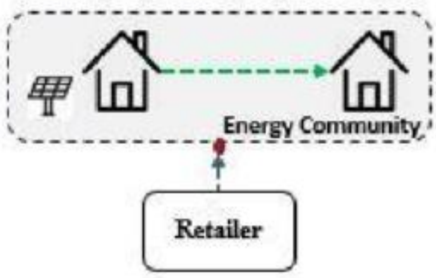

Figure 2.10. Community-Based P2P structure (Source:[88])

Another type of market design that is proposed for electricity trading is the direct energy trading between retailers and small producers. This type of system can be used to allow both the retailers and the generators to participate in the market. Sousa et al. [89] presents an example of this type of market design. Moreover, the proposed bilateral contract arrangements could be applied to enable direct energy trading among prosumers, retailers, and generation units as well [64].

The modeling of decision-making processes of entities with conflicting interests can be done with game-theoretic approaches. It can also motivate entities to compete or cooperate in order to achieve certain goals. Thus, game-based models have a large potential for application in P2P energy trading [90].

Simulations of the potential outcome of P2P markets have been conducted through non-cooperative game frameworks. The Nash equilibrium[1] of a microgrid, in which prosumers with onsite PV systems and flexible demand trade with each other, was calculated in order to assess the outcome of P2P energy trading [91]. Non-cooperative game-based approaches were also used in [78] to model the behavior of the peers. Furthermore, non-cooperative auction-based approaches have been used as the core mechanisms of distributed P2P energy trading markets.

Stackelberg game-based[2] approaches have been used in some studies for establishing pricing mechanisms in distributed P2P energy trading markets. In [74], the coordinator acted as the “leader” and the peers acted as the “followers” while in [78], the sellers acted as the “leaders” and the buyers acted as the “followers”.

A variety of game-theoretic approaches have been proposed, as summarized in [90], although only a few have been used for P2P energy trading in existing studies. Game-theoretic approaches are valuable models and techniques to be utilized in the future for modeling the trading behavior of peers and for designing and assessing P2P energy trading markets.

2.4.2. Trading platforms

Through P2P platforms, electricity users can easily trade their energy supply while following the market rules. Moreover, they can monitor the energy consumption of their peers. Its underlying technology can be distributed across decentralized or centralized platforms.

[1] In game theory, the Nash equilibrium is a solution concept of a non-cooperative game involving two or more players, in which each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only its own strategy.

[2] The Stackelberg model is a strategic game in economics in which the leader firm moves first and then the follower firms move sequentially.

Regarding the centralized trading platforms Long et al. [75] developed a microgrid-based P2P energy trading system. It allows electricity producers to list their products and consumers to place orders. Each order includes when and how much electricity needs to be supplied between the producers and consumers. The DSO and the electricity suppliers also share information with the platform to balance electricity excess/deficit and determine whether the P2P trading would violate the network limits. In reference [92] it is also proposed an electricity trading system which enables prosumers to sell electricity to peer.

Due to the increasing number of concerns about the security and reliability of P2P platform transactions, more emphasis is being placed on the use of blockchain technology. This type of technology is a cutting-edge innovation that can help decentralize electricity trading. A comprehensive review on this topic is provided in [93], which establishes an analytical framework for blockchain-based microgrids. The decentralization feature of blockchain is considered to be well matched with the decentralized characteristic of P2P energy trading, where electricity supply is no longer provided by centralized large generators, but rather by small prosumers with DERs.

Blockchain is an emerging technology that has the potential to fulfill security, privacy and payment transaction requirements in distributed energy trading. Blockchain technology was proposed in 2008 and began with cryptocurrencies like bitcoin but since then it has expanded beyond the world of finance and banking. Its application in the energy field refers to the energy blockchain and it combines conventional and renewable energy sources based on blockchain technology. Moreover, apart from promoting a more efficient use of traditional energy, it also accelerates the widespread use of new energy sources as addressed in [94, 95]. In this setting, [74] and [76] utilized blockchain technology to develop platforms for P2P electricity trading based on the industrial Internet of Things (IoT) concept.

Compared with traditional energy technologies, applying blockchain into the energy field has the following technical advantages [96, 97]:

- ability to create a simplified and efficient multi-layer trading system. It eliminates the need for third parties to coordinate the activities of the electricity supply chain. Through its decentralized network, producers and consumers can easily connect and conduct transactions;
- allows consumers and energy traders to perform electronic contracts through a consensus mechanism. This ensures that the transactions are secure, tamper-proof and robust to single point failure;

- ability to create smart contracts, which are easy to execute and can be used to reduce the costs of compliance and contracting. This is particularly beneficial for P2P transactions, which involve low-value transactions between small-scale customers with DERs.

The blockchain technology will not be detailed in this work. However, some details and discussions about blockchain technology are available in [98].

The application of blockchain in the energy field is mainly concentrated on energy trading, EVs charging, security of power information, carbon trading, demand side response, distributed and multi-complementary energy systems (as shown in Figure 2.11). The next paragraphs provide further information on these application areas.

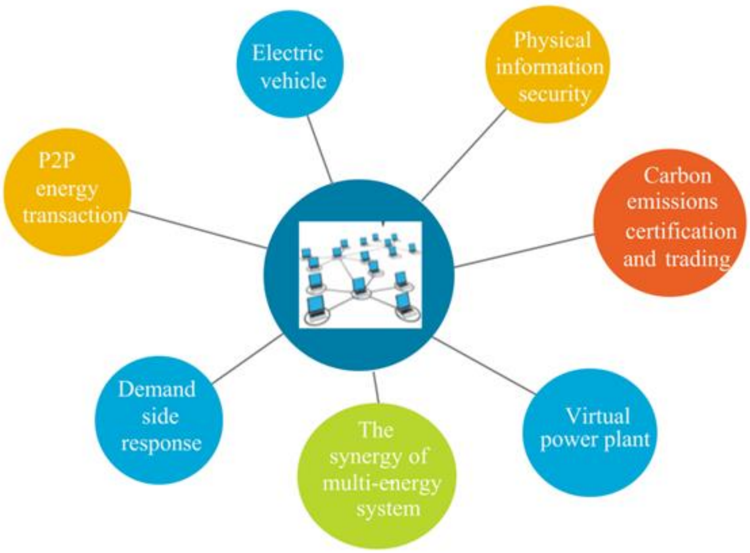

Figure 2.11. Applications of blockchain in energy sector (Source: [94])

a) P2P energy trading

The blockchain based P2P energy trading model can provide an efficient, inexpensive, open and trustworthy trading platform in decentralized energy systems. The power trading process based on blockchain has great potential in decentralized energy systems (Figure 2.12).

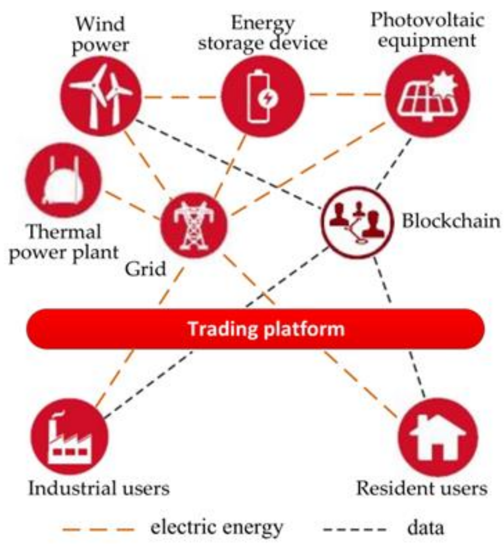

Figure 2.12 Blockchain-based power trading process (Source: [94])

A number of studies have shown how blockchain technology can be used to facilitate P2P energy trading, particularly using IoT. For instance, a blockchain was used to develop platforms for the exchange of energy between producers and consumers [74, 76]. A consortium blockchain was proposed in [74] for supporting P2P energy trading in microgrids, energy harvesting networks, and vehicle-to-grid applications. In [76], a local electricity storage solution was proposed to address the issue of a long chain maintaining many blocks possibly being created during P2P energy trading, and thus reducing the operational overhead. Kang et al. [73] designed a consortium blockchain for P2P energy trading between plug-in hybrid EVs, which could improve transaction security and privacy protection level. Aitzhan et al. [99] developed a blockchain-based platform that allows energy traders and producers to conduct secure and private transactions.

b) Electrical Vehicles, EVs

The rapid emergence and growth of EVs is expected to be induced by various factors such as lower costs, faster charging, and better vehicle performance. However, the lack of charging infrastructure is still a major issue that is preventing many car owners from fully embracing the technology.

Currently, there are a number of electric vehicles charging providers and payment platform operators. Unfortunately, the standards for electric vehicle charging aren't uniform, which makes it very inconvenient for car owners. With blockchain technology being used in these operation platforms, the management of electric vehicle charging will be streamlined, and the security of their system will be improved [100].

c) Physical information security

One of the most common security measures that electricity distribution companies use to prevent unauthorized access to their networks is by building communication lines. However, this method can be costly and can be vulnerable. Instead, they can use the data collected by their equipment in the line transmission system. According to a study conducted by Ding et al. [101], blockchain technology can help addressing some of the security issues that information and physical systems face. These authors discussed about the various factors that can affect the operations of blockchains, such as the loss of private keys and privacy leaks. In the mentioned paper, it is discussed the multiple security measures that can be implemented to protect energy blockchains. These include structural, management, and ontological security.

d) Carbon trading

Due to the complexity of the carbon emission market, it is currently difficult to track and manage multiple transactions in its trading and certification system. Blockchain technology can be used to help solving this issue by providing a central management platform for the trading of carbon rights [102]. On the other hand, consumers can use tokens representing energy production or tradable digital assets to buy, sell or exchange renewable energy with each other. So, the development of P2P financial transactions through blockchain technology can help strengthen the climate financing flows.

e) Virtual Power Plants

VPPs can also benefit from blockchain technology by establishing a central management platform that can operate the distributed generation and energy storage systems. These facilities can then participate in the development of virtual power transactions.

Blockchain technology has the characteristics of decentralization and mutual complementarity, which is aligned with the geographical dispersion and scheduling of VPPs. It also has advantages in transaction applications because of its own characteristics, and can provide a transparent, fair, reliable, and low-cost trading platform for VPPs [103].

Wei and Yue [104] introduced the blockchain technology into VPP. The proposed model proposed an improved VPP operation and scheduling model.

f) Demand side response

One of the most important factors that can be considered when it comes to the development of demand side response services is the availability of a central management platform and the scalability of the solution. The use of blockchain technology in energy management of residential buildings, for instance, is an important option since it will allow to implement a more efficient and cost-effective solution. The use of blockchain technology for the accounting of general ledgers can also help prevent the transmission of false information. This can be done through the establishment of a comprehensive set of traceability systems.

g) Multi energy systems

In a study conducted by Mihaylov et al. [105], it was noticed that blockchain technology could be used to settle the transactions in multi-energy systems. This method allows the recording of real-time production and costs of different energy systems. These authors concluded that this approach could help improving the efficiency of various energy systems by allowing them to monitor and manage the prices of different energy sources in real time. For instance, by implementing automatic scheduling and settling transactions, multiple energy systems can improve their efficiency.

2.4.3. Physical and Information and Communications Technology infrastructure

After reaching trading agreements on P2P energy trading platforms, the agreed amounts of electricity need to be delivered from one peer to another at an agreed period through the electric power networks. To do so, physical and Information and Communications Technology (ICT) infrastructures are essential for energy trading.

The physical distribution of electricity between its peers is necessary in order to deliver the agreed amount of power. There are two types of solution for this purpose: private wire networks or public networks:

- Private electric power networks and associated control strategies

  One way to improve the efficiency of electric power systems is by building private networks between different peer-to-peer entities. Despite the various advantages of this type of approach, it still has a high cost of construction and a low operating margin [106]. Despite the advantages of this approach, building private networks for the trading of energy is not an attractive solution due to the various factors that affect the development and operation of such systems. For instance, the lack of regulation and the uncertainty regarding the future security of supply of energy are still major factors that prevent the private networks from operating successfully [107]. According to Werth et al. [108], a DC nanogrid could be used to connect the houses in a community. These structures are equipped with various components such as a network controller, an external power bus, and photovoltaic panels. These components can be used to exchange power between the houses. However, and despite the technical potential of private networks, they are not expected to expand significantly in the near future.

- Public electric power networks and associated technical arrangements

  A public power network can be used to deliver the agreed amount of electricity to its peer groups. Unlike private networks, the efficiency of the pool allows the consumers and producers to benefit from the same energy. The development of new power routing devices and algorithms could potentially change the way energy trading is conducted in public power networks. Instead of traditional physical energy exchanges, this type of system is designed as a virtual one [109, 110]. Zhou et al. [58] noted that in order to ensure that the physical laws and limits of the equipment's in public power networks are enforced properly, a technical evaluation is needed. In this scope, through a sensitivity analysis, Guerrero et al. [65] were able to determine if a trade could be approved or denied. Aside from this, other factors such as the incentives for the trading of energy have also been taken into account to improve the efficiency of the power networks.

  Nikolaidis et al. [111] proposed a loss allocation framework that would allow the power networks to efficiently manage their financial transactions. This method was able to fit into the financial features of P2P trading. This paper proposed various charging methods that are adequate for P2P energy trading including uniform charging, zone-based charging, and electronic distance charging. Since these methods are all external, they can fit seamlessly into the regulatory and physical configurations of most of the grids.

2.4.4. Peer-to-Peer Trading Projects

As exposed before, the implementation of P2P models will have some impacts and advantages in communities. Because of these benefits, several projects worldwide have focused on P2P energy trading. Notable examples are Piclo in the UK, Vandebron in the Netherlands, sonnenCommunity in Germany, and Yeloha, Mosaic and TransActive Grid in the United States [112].

Piclo was launched in the UK to help electricity consumers find the best possible price for their energy supply. Through its platform users can easily compare multiple generators' prices and monitor their energy consumption. It also allows them to receive premium rates and discounts from the providers. Its main objective is to help consumers reducing their energy demand, and supply cost by increasing the use of renewable energy sources [113].

Vandebron, a company located in the Netherlands, is able to provide its consumers with a way to purchase electricity from independent producers. Like Piclo, this platform acts as a bridge between the generators and their customers [91]. In Germany, a project known as PeerEnergyCloud was launched to develop a technology that would allow generators and retailers to monitor and manage their excessive production. It was established in order to create a virtual marketplace for power trading within a microgrid [114].

In Germany, a company known as sonnenCommunity launched a project that allows individuals to voluntarily share their solar panels' surplus with other people. This project allows them to receive the benefit of the surplus energy they produce. Through its software platform, the company was able to monitor the energy consumption of their members. Like other similar projects, this project highlights the need for storage systems [75].

In the US, projects known as Yeloha and Mosaic allowed people who don't own a solar system to pay a small portion of the electricity generated by the hosts' panels. While these projects are similar to others, they mainly focus on solar energy.

2.5. Virtual Power Plants and Microgrids

2.5.1. Concept, purposes and benefits

The traditional approach to power generation was to have centralized generation in large units with unidirectional power flows. However, with the emergence of DER, power systems now have bidirectional power flows. This means that communities and citizens can act as energy consumers or producers or prosumers. This transition presents various new challenges and opportunities. Some of these include the emergence of smart grids and the increasing number of flexible loads, such as heat pumps and storage systems. The development of Microgrids and Virtual Power Plants can be seen as paving the way to smart grids.

A microgrid is defined as “a group of interconnected loads and DER with clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid and can connect and disconnected from the grid to enable it to operate in both grid-connected or island modes [115]. It can be connected to the DSO through a central management entity [116]. By managing and deploying distributed energy resources the system's reliability can be improved. Figure 2.13 presents the architecture of a grid-connected Microgrid.

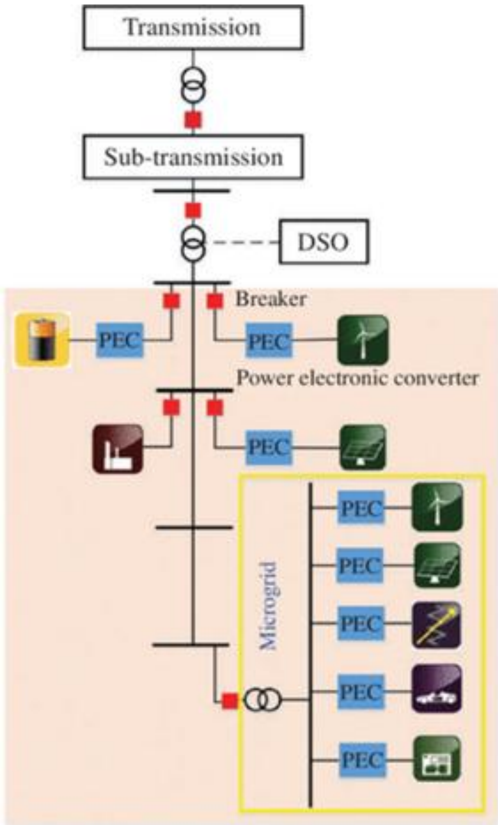

Figure 2.13. Illustration of the grid-connected microgrid architecture (Source: [117])

According to Sabry, a microgrid can be classified into two categories: a pool of distributed generation resources that can be dispersed across different points of the distribution network, or a network of decentralized power generating units [118]. From a market perspective, a microgrid can be viewed as an aggregator of DER and consumers installations operated by a microgrid central controller.

A VPP is a type of DER that can be aggregated and operated as a single flexible structure. It can provide services to the grid and participate in the energy trading market [119]. This concept emerged during the 1990s as a way to address the challenges and issues related to the connection of renewable energy units in the electricity grid [56]. Its main objective is to maximize its profitability through the development of a framework that enables it to make informed bidding decisions. It can also trade energy in the wholesale market and provide services to consumers and to the system operator [120].

As previously referred, a microgrid is an integrated system that can operate connected to the electricity grid or islanded away from it. On the other hand, a virtual power plant is a structure that uses software systems to coordinate the various components of its DER. Although both types of architectures have similar features, they have varying capabilities when it comes to integrating renewable energy and demand response programs. Asmus [116] summarized the main ones as follows:

- microgrids can be connected to the electricity grid or be independent whereas virtual power plants are always in the grid-tied mode;
- microgrids typically require additional storage, however virtual power plants can provide their own storage;
- unlike VPPs, microgrids rely on certain hardware innovations, such as switches and smart inverters. VPPs are heavily dependent on smart metering and information technology;
- unlike a microgrid, a virtual power plant can operate in large geographic areas. This allows it to combine different resources and provide consistent and coordinated operation;
- microgrids are normally used to trade only in the form of retail distribution, while the VPPs can build a bridge to the wholesale market;

According to Ullah et al. [121], the main purposes of VPPs are to provide the following opportunities to the participating partners:

- energy trading: to provide opportunities to their owners in the electricity trading market. Through energy trading, the participantes can benefit from the different opportunities offered by the electricity market;
- network services: to offer system support services to transmission and distribution system operators;
- balancing services: to balance production and consumption demand, utilizing multiple markets simultaneously in real time. This can help improving the efficiency of their operations and provide their partners with environmental and economic benefits;
- optimizing: to optimize the production and consumption of the members of the VPP itself.

A structure of a VPP is presented in Figure 2.14.

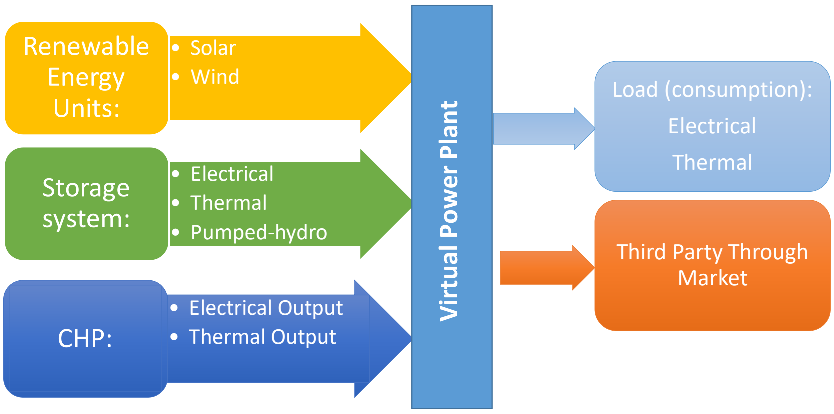

Figure 2.14. VPP structure (Adapted from [121])

According to the VPP concept a set of conventional generating units, renewable energy units and storage systems are managed by a central entity. The demand side management and market operators complete and perform the structure of VPP.

A VPP architecture can be implemented in four steps [121]:

- Forecasting for renewable energy generation and for demand;
- Running of stochastic optimization models to determine market bids;
- On the basis of commitments and updated forecasts, unit commitment optimization adjusts DER operation;
- A controller is used to reach commitment targets.

The concept of VPPs brings benefits which could be identified and grouped among different stakeholders. Othman et al. [122] and Braun [123] organized them considering the point of view of different entities:

- policymakers can benefit from the various advantages of VPPs, such as their ability to contribute to the reduction of global warming and their ability to provide additional choices to consumers. They can also improve the wide deployment of DER units and can open new opportunities for small-scale energy producers;
- benefits to suppliers and aggregators in sense that VPPs can minimize the economic risk of both suppliers and aggregators, by creating new offers and reducing the investment in the electricity distribution grid. They can also increase energy efficiency due to loss reduction on transmission networks;
- benefits to energy consumers such as the ability to improve the reliability of the electricity supply and provide resiliency services during times of outages;

- benefits to DSO and TSO since VPPs can help creating a better coordination between the DSO and the TSO. They can help improving the visibility of the DER units in the network operations;
- benefits to DER owners due to their ability to participate in the energy market. This can help lowering the costs of operation and provide them with a financial support. In addition, they can help minimizing the risk of financial loss for small producers.

One of the main activities of a virtual power plant is providing real-time balanced services. This is done through two different entities that are known as Technical Virtual Power Plant and Commercial Virtual Power Plant. Both operate together in order to achieve the VPP functions detailed in Figure 2.15.

The Technical Virtual Power Plant ensures that the various systems that are part of a facility's operation are completed properly. These include the distribution of energy and storage units, as well as controllable loads. It also collects data about the consumption and supply of electricity from Commercial Virtual Power Plant. This information is then used to develop a comprehensive analysis of the plant's operations and provide its partners with the necessary information to make informed decisions [124]. The Technical Virtual Power Plant ensures the correct and secure operation of the power system considering the physical constraints and system support facilitation services offered by the VPP.

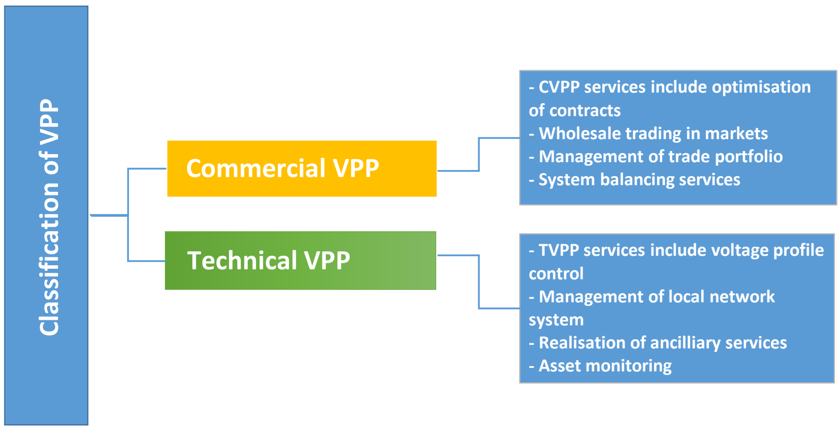

Figure 2.15. Classification of the VPP (Adapted from [121])

The functionalities provided by Technical Virtual Power Plant are [125]:

- to determine fault location;
- to provide maintenance facilitation services;
- to continuously monitor assets;
- to offer balancing services, management of local network and implementation of ancillary services;
- to offer visibility to DER units in energy markets;
- to ensure that the power system is operating in an optimal safe way.

The Commercial Virtual Power Plant is primarily focused on providing the required energy to the electricity markets. It engages in daily market activities through the transmission of bid information and the clearing of the market. The bilateral contract information as well as the clearing of the daily market should be sent to Technical Virtual Power Plants to ensure that the contracted power is generated in each time period. Due to the nature of Commercial Virtual Power Plants, small producers can now participate in the energy markets, thus eliminating a regulatory barrier that existed in many systems [123].

The functionalities of the Commercial Virtual Power Plant can be summarized as:

- to trade in the wholesale electricity markets;
- to prepare DER bids and their submission to the electricity markets;
- to optimize the daily schedule production consumption forecasts of the VPP units;
- to balance trading portfolios;

Trading with VPPs can pose various technical challenges. These include system capacity, voltage drop, and unplanned outages. To minimize these issues, the distribution and transmission network operators should focus on optimizing the power network system. Doing so they can help ensuring that the electricity supply is continuously delivered to the users without interruption [126].

New incentive programs and management methods can help small producers overcoming their commercial challenges. These programs can assist in developing new energy sources and reducing the costs associated with maintaining the distribution network. Incentive strategies need to be implemented in order to rewards, in an adequate way renewable distributed producers [121].

2.5.2. Planning, optimization and operation of VPP

The characterization and technical planning of VPPs are carried out to evaluate their operation and maximize their commercial potential. Optimal planning mainly depends on two aspects: the technical aspects and the commercial objectives. The former involves analyzing the plant's capacity, line loading, voltage profile, and asset monitoring. The commercial objectives of VPPs are usually focused on optimizing the total cost of operation. These processes can be carried out through the implementation of various optimization models [121].

Optimizing VPP operation is a process that aims to reduce the total cost of production. It can be divided into two categories: structural and operational optimization [122]. The optimization of the VPP structure includes the optimal sizing and siting of Distributed Generation units and the energy storage devices, the optimal load control and the optimal measurement device’s location.

On the other hand, if the power system already exists, then this process can be limited. If the power grid is already set up with the necessary parameters, such as the number of storage devices and the production of distributed generation units, then operational optimization can be carried out by determining the production of DG units, energy storage system rate of charge and discharge and how much energy is purchased from the wholesale energy market.

The success of VPP operation depends on various factors such as the stability of the power system, the security of supply, and the cost competitiveness of participating in the market. A customized characterization strategy is then developed to address the varying economic objectives of the VPP [122].

A distributed level VPP can also be equipped with an operational framework that includes the forecast of solar and wind generation, and thermal generators. This framework can be used to determine the optimal strategy for the plant's dispatchable participation in the market. In both real-time and day-ahead periods, an internal market can also be established between the DERs and the VPP [127].

Baringo et. al [128] presented a novel model for the day ahead market trading of a VPP. The model was able to take into account the various uncertainties associated with the plant's operation. As a result, it can be used to predict the reserve requirements of the system operator. In addition, uncertainty in available wind power generation and requests for reserve deployment were modeled using confidence bounds and intervals, respectively, while uncertainty in market prices was modeled using scenarios. The resulting model is formulated as a stochastic Adaptive Robust Optimization problem, which was solved using a Column-and-Constraint Generation Algorithm. The main conclusions of this work [128] were as follows:

- the stochastic Adaptive Robust Optimization approach was used to self-scheduling a VPP trading in the energy and the reserve electricity markets;
- a model relying on intervals was provided to characterize the uncertainty in the requests for reserve deployment;
- the resulting trilevel optimization problem was effectively solved using an enhanced Column-and-Constraint Generation Algorithm. Duality theory was applied in this problem;
- the uncertainty in market prices, available wind power generation, and requests for reserve deployment are key factors in the decision-making problem faced by a VPP trading in energy and reserve electricity markets.

Chapter 3

3. Literature review on Electricity Market Simulation

Since 1980s, power systems have been gradually evolving from monopoly structures into liberalized structures. This brings the opportunity for generation companies to make more profits while embracing more risks of not being dispatched. On the other hand, this “democratization of energy” has created new actors and structures in power systems. Thus, it has become a core interest for all the participants in electricity markets to develop new simulation models in a variety of areas from planning to operation problems. Since Agent Based Models are able to simulate the interactions and actions of autonomous agents, they are widely used in the electricity market simulations field.

Machine Learning Techniques, namely the Reinforcement Learning, are a computational approach to get agents to perform their best actions in an uncertain environment. They are especially suited to model systems influenced by social interactions between flexible, autonomous, and proactive agents. They also allow dealing with Markov Decision Processes where the probabilities and rewards of Markov transition matrix are unknown.

Therefore, Section 3.1. presents some modelling methods to simulate electricity markets. Section 3.2. introduces the concepts of Agent Based Models and provides a review of the various development steps involved in implementing them. A categorization of Machine Learning techniques is presented in Section 3.3, detailing a description of Q-Learning methodology. Finally Section 3.4, details some ABM electricity markets simulators.

3.1. Modeling methods to simulate electricity markets

With the restructuring of the power systems, where new actors and models were introduced to foster competition, better allocation of the resources, cost minimization, and profit maximization become some of the major goals of all the participants.

In terms of electricity market simulation, liberalized electricity markets are generally considered to be imperfect competition and oligopoly mechanisms due to their unique characteristics. In certain cases, market agents can manipulate the price of electricity by conducting strategic bidding behaviors. For instance, generation companies that have different generation mixes, such as wind, hydro, and nuclear power plants, can bid on the electricity market including a number of blocks of energy price together with the corresponding quantity of electricity [129]. On other hand, and with the increase of small-scale producers, prosumers and consumers involved in the electricity market, the need for an intelligent bidding/offering agent, responsible for making all the dynamic decisions involved in this trading paradigm, turns the electricity markets very complex and very specific to simulate.

Various research works have been conducted on the development and simulation of electricity markets. They use different methods and models to get the most realistic and efficient results. This section covers the main areas of research that are related to the electricity market simulation and are summarized in [130]:

- Optimization problems, addressing a single company assuming no market reactions;
- Equilibrium Models from Game Theory economics, considering a larger number of competitors;
- Agent-Based Models (ABM) that simulate the behaviour of the companies and the interactions between autonomous agents;
- Hybrid solutions.

An optimization model focuses on finding the best price for a single firm in the market, often considered as a price-maker, while an equilibrium model considers the market behavior of all participants. ABM are becoming more prevalent when a complex problem cannot be addressed in a traditional framework. Li et al.[130] resume and detail a complete classification of some of the modelling approaches to simulate electricity markets (Figure 3.1).

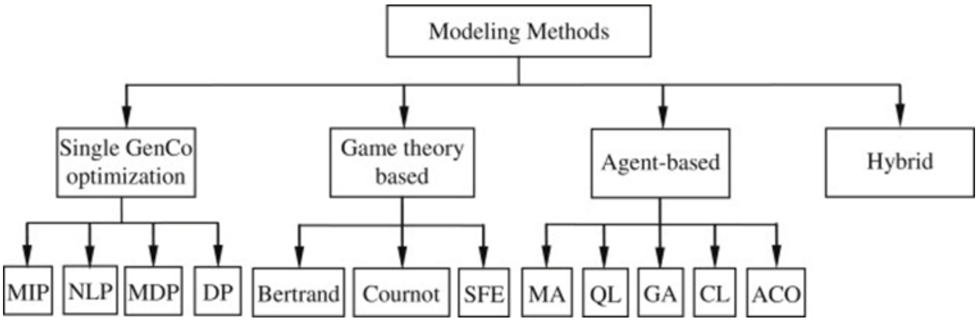

Figure 3.1. Modelling methods to simulate electricity markets (Source: [130])

The main characteristics of these modeling approaches are provided in **Table 3.1**.

Table 3.1 Characteristics of modelling methods to simulate electricity markets (Source [130])

Models	Characteristics
Single Generation Company optimization	• Developing optimization models to describe the entities in the electricity market with the objective of finding an optimal solution: • Well-established and solid mathematical foundation; • Generally focusing on one specific player in the system by simplifying the rest of the system as a set of exogenous variables; • Usually modeling no aspects of players' intelligent behaviors; • Difficult to model the complex, uncertain and dynamic systems or analytically derive the optimal bidding strategy for the Generation Companies in the deregulated electricity markets;
Game theory	• Modeling the electricity market as a game and mathematically capturing the players' behavior in the game where one player's success in making choices depends on the others' choices: • Usually mathematically well-defined, involving a set of game players, a set of bidding strategies, and a specification of payoffs for each possible combination of bidding strategies; • Analyzing the economic equilibria of the electricity market by focusing on the players' interactions; • Capable of providing analytical rationale and explanation on how strategic bidding behaviors affect the Generation Companies market power and profits; • All players are assumed to be rational, which does not generally hold in reality; • Multiple equilibria often occur in solving realistic problems;

Models	Characteristics
Agent-based	• Modeling the complex electricity market as collections of rule-based agents interacting with one another dynamically and intelligently, simulating human beings' behavior to make optimal bidding strategies: • Only a few simple rules are specified for and followed by various agents that are situated in the network and behave intelligently in the system; • Agents usually have and only require imperfect, local information and visibility; • No centralized control or planning is required although random elements often exist either among variable agents or in the system; • Agents can interact with each other directly or through the environment, resulting in complex emergent global behavior of dynamic-equilibrium and adaptation; • More flexible, robust, and easily implemented compared with analytical approaches; • Capable of capturing the details about agents' behaviors, which is helpful in figuring out the relationships between individual decisions and system behavior; • Capable of modeling the dynamics of systems that are not in equilibrium as well; • Usually they require computation-intensive procedures.

The traditional methods for optimizing the bidding process of a generation company were usually used to address the issue of cost minimization [131]. The minimum revenue condition and the use of indivisibility bids can also be considered as viable alternatives to turn the solution more realistic. They can be integrated into the simple quantity-price pool designs to accommodate thermal plants requirements that need to meet a minimum revenue condition.

The goal of a **Single Generation Company Optimization Model** is to find the best price for its single player. Other factors that influence the market are also simplified in this model. Since the market clearing price is considered as an external variable, many programming techniques have been utilized to solve the optimal bidding strategy issue. Some of these include the use of traditional Linear Programming (LP), Mixed Integer Linear Programming (MILP), Mixed Integer Programming (MIP), Nonlinear Programming (NLP), Dynamic Programming (DP) and Markov Decision Process (MDP). Although an optimization model can represent the markets in a quasi-perfect manner, it fails to take into account the firm's decisions regarding the Market Clearing Price (MCP) [130].

A price-maker Generation Company can use a MILP model to solve the issue of self-scheduling and maximize the profit of a pool-based electric market. These models provide the capability of altering the market's prices to their own benefit [132].

A NLP is proposed in [133] to optimize the bids of a Generation Company during a multi-year auction market. It is proposed the use of a Lagrangian relaxation method to deal with the other aspects of the bidding optimization problem.

A self-commitment problem for a generation firm that is affected by the exogenous price uncertainty is presented in [134]. The different generator models take into account the minimum and maximum output energy levels, as well as various other factors such as the ramp rate limits, start-up and shutdown costs, and incremental energy costs. The objective function of the optimization problem is to maximize the firm's profit by taking into account the prices of energy of the different generation units.

Paper [135] presents a stochastic NLP model that takes into account the optimal strategies for power suppliers in an auction-based market. This model assumes that the supplier's bid is accepted at the market's price and that the system's dispatch levels are set by a market operator to minimize customers' payments. The authors show that the competitive levels of power suppliers can be substantially higher than those of the other players if they strategically bid.

The optimal bidding strategies in the context of the generation limits and the market share of the power suppliers are analysed in [136]. The authors of this paper concluded that the MDP framework can effectively optimize the decision over time. However, it does not allow the use of risk attitudes and makes a few strong assumptions such as ignoring the power system operational constraints.

The authors of [137] present a framework that allows generation companies to develop optimal strategies at an annual level in uncertain and competitive markets. They then use a stochastic MILP, combining optimization techniques with the Monte Carlo method to analyze the effects of uncertainty on the decisions. The proposed framework is focused on developing a dynamic strategy that is followed by all participants in the market.

Game theory models, also called equilibrium models, can be used to improve the bidding process by analyzing the interactions between the players and analyzing economic equilibria of the system. It can then reach an optimal solution through the Nash equilibrium. Different game theory models can be adopted for competition rules such as the Bertrand competition, Supply Function Equilibrium and the Cournot competition.

The most common type of competition rule utilized in this framework is the Bertrand competition. It allows the generation company to compete with its counterpart by using prices and ignoring their capacity constraints. In the Cournot model, similar to the Bertrand competition, the participating generation companies use quantities as their strategy choices. The MCP is determined by the intersection of the aggregated supply and market demand curves.

The quantity-setting equilibrium in the electricity market is more realistic than the Bertrand price-setting strategies. For instance, in the Bertrand equilibrium, a firm can capture the entire market by providing a low-price. However, this assumption is not tenable due to the increasing marginal cost of generation and the capacity constraints [130].

The goal of the Cournot model is to maximize the output of each generation company while ensuring that the remaining firms can no longer improve their profitability. The advantage of this model over the price-setting strategy is that it allows the generation companies to make strategic decisions based on the quantity-setting behavior of their units. An empirical simulation framework that calculates the Cournot equilibrium iteratively was developed in [138]. Several models based on the Cournot competition can be found in [139]. This paper summarizes models applied in the analysis of different deregulated markets such as New Zealand, California, and England.

Klemperer and Meyer [140] introduced the concept of the Supply Function Equilibrium, which is a type of competition rule that allows firms to maximize their profits in a competitive market. Instead of competing with each other, the participants choose to set their supply functions instead. The advantages of the Supply Function Equilibrium model are widely debated. It is a better compromise between the Bertrand and Cournot models, and it allows the users to get a more accurate depiction of the behavior of the market participants. A number of studies on the strategic bidding market have also been published using this model [141-144].

Agent Based Models are commonly used in market analysis to complement traditional models and provide a deeper understanding of the energy transition. They were also reported as a potential alternative to the traditional equilibrium models due to their complexity. The main issues with the traditional equilibrium models are that they do not incorporate strategic behavior of market participants and have unrealistic design when assuming that market participants have all relevant information about the characteristics and behavior of competitors. In addition, the traditional equilibrium models neglect the consequences of the knowledge that a participant could get through the daily operation on the electricity market. On other hand, Game Theory is largely limited to specific situations in the markets and which depend on some few factors [145].

ABMs work by allowing the agents to make their own decisions based on their experiences with other agents and through interaction with the environment. The agents usually have local and imperfect information which, combined with their past experiences, help them improving their decisions by modifying their strategies. This type of model allows the market participants to develop their own strategies and preferences as adaptive agents. They can then learn from their past experiences to improve their performance. There are also artifacts, which are components that are passive and are modified or shared by the market participants in order to carry out their operations in a cooperative or competitive manner. For instance, in electricity markets, the Market Operator is involved in the process of receiving bids from the market participants and then setting up a schedule for each trading period. The concept of workspace as a conceptual container for artifacts and agents is useful in defining the environment's topology. It can also help in establishing a locality concept.

Generally, the agent-based modeling procedure can be described as follows [146]:

- define the research questions to be resolved;
- construct a model comprising an initial population of agents;
- specify the initial model state by defining the agents' attributes and the structural and institutional framework of the electricity market within which the agents operate;
- allow the model to evolve over time without further intervention;
- analyze simulation results and evaluate the regularities observed in the data.

The ABM can be categorized in terms of different learning algorithms such as Model-Based Adaptation Algorithms, Genetic Algorithms, Q-Learning, Computational Learning, and Ant Colony Optimization.

The development of agent-based methods of optimization and simulation began with techniques that mimic aspects of natural selection. Holland's Genetic Algorithm (GA) [147, 148] was used as a new kind of optimizing tool for problems intractable by traditional calculus-based tools. The goal of the GA is to test and score the various possible solutions in a population and, based on the "fitness" score of each of them, select pairs of "parents" for a new "offspring" generation of possible solutions. This artificial reproduction uses the genetic operations of "crossover" and "mutation" on the parents. The selection and testing of new populations lead to the improvement of the quality of the population. The process is commonly referred to as an optimization technique, which eliminates the need for exhaustive testing of all possibilities. Since the process is carried out through the genetic operations (selection, crossover, and mutation), the players are able to learn from each other. The goal of the process is to test and score the various possible solutions in a population and improve the adaptation of the population as the simulation evolves.

The populations in the first applications of GAs were seen as trial solutions that would optimize the function under analysis (usually highly non-linear and discontinuous). Later applications, however, treated the populations as comprising agents rather than numbers. Individual agents were immutable, but in each generation the population of agents would change, under selective pressure.

This learning and adaptation process can be performed either within one single agent or in cooperation with two or more agents. In a competitive market environment, agents naturally learn isolated and use the learned knowledge for their own advantage. This modelling process corresponds to an explicit learning procedure.

The probability of choosing a particular action again in the future increases if the feedback is positive and decreases if negative feedback is received. This effect is called reinforcement and it is advantageous in machine learning environments, where it is impossible for the agents to compare the action's result with a specified goal. Instead, the agent receives feedback for a performed action and deduces the coherence of the action and its performance. Generally, a given feedback is assigned not only to one action, but to the action of other agents or earlier performed actions. Q-Learning is one type of reinforcement learning that was originally developed to handle the temporal credit assignment problem.

Since it will be the methodology considered in this work, the Q-Learning approach will be analyzed with more detail in Section 3.3 of this chapter.

Hybrid models combine various modeling methods available in the literature. For instance, a model that combines the Lagrangian relaxation algorithm with the GA for generation companies to build a proper unit commitment scheduling and derive the optimal supply curves to set up a proper schedule for their units was developed by Yamin and Shahidehpour [149]. In another study, Sueyoshi proposed an ABM equipped with Game Theory to analyze the interaction between learning agents and the market participants during the electricity crisis in California (2000-2001) [150].

In 2019, Wang et al. [151] proposed a hybrid model (Figure 3.2) that combines the multiple modeling problems and platforms used in the market. It uses a system dynamic simulation and agent-based approach to analyze the operations of the electricity market, by which the operation of the electricity market is modeled holistically to observe the overall changes of the system. In order to better simulate the trading conditions of the real time electricity market, ABM is applied to the bidding transactions. With the real-time feedback changes of relevant variables, the results are presented accordingly, thus simulating the multilateral bidding process of the electricity market. The agents (Figure 3.2) are classified into five categories: trading agents, government agent, grid company agent, power plants (two thermal power plant agents, a hydro-power plant agent and a wind power plant agent) and consumer agents.

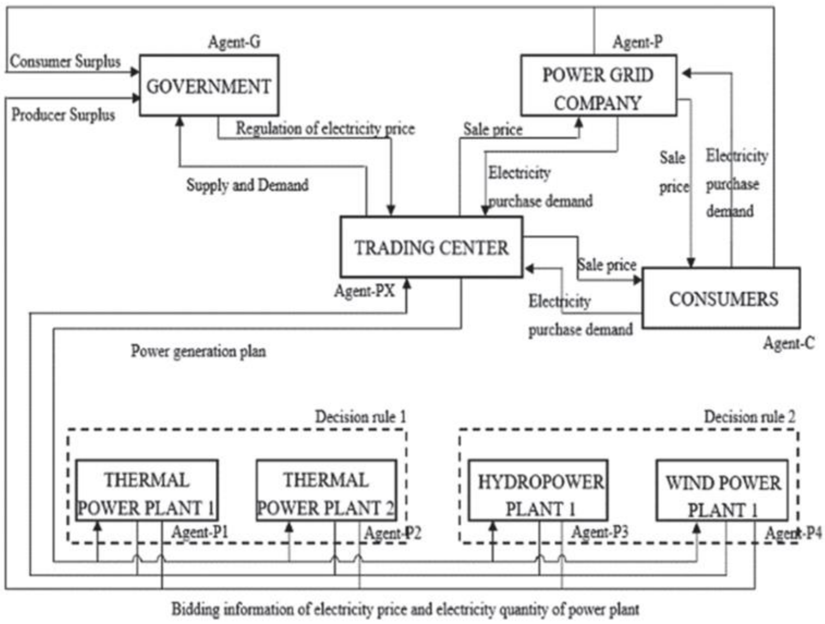

Figure 3.2. Organization of the multilateral bidding model of the electricity market proposed in [151].

The trading center is responsible for the functions typically associated to a Market Operator and separately reports the results of the clearing activity to the power plants. The power plants then adjust their bidding strategy using a learning algorithm. The government agent then monitors the effects of the learning on the social welfare. It takes into account the varying contract power ratios and the supply and demand balance. The grid company agent formulates a power purchase plan for each clearing round according to its own demand function after each clearing. Some consumer agents can purchase electricity directly from the trading center, or purchase electricity from the grid company subsequently.

3.2. Agent Based Models

In a context of new business models such as energy communities, where several challenges for both technical and regulatory issues are addressed, ABM are especially suited to model them. ABM are especially appropriate to model systems influenced by social interactions between agents that are flexible, autonomous, and proactive. In these models, agents are able to collaborate, compete and exchange information with other agents, which gives them a social capacity and are important features to fully address communal potentialities. Moreover, the agent paradigm can be a powerful computational tool that can be used to examine socio-technical system performance over time, wherein system behavior is subject to complex and dynamic individual and social interactions.

A didactic review about agents and Agent Based Models is detailed in Section 3.2.1. Agent architectures and communication are analyzed in Sections 3.2.2 and 3.2.3. Finally, Section 3.2.4 provides information on building and designing ABMs.

3.2.1. Basic Concepts and Definitions

As long as systems are becoming more complex, new tools, simulation and modeling approaches are needed. An alternative to typical simulation techniques (such as traditional optimization techniques, discrete-event simulation and differential equations) are ABM.

The concept of agent-based techniques for optimization and simulation emerged from the study of natural selection. One particular technique that became popular during the 1970s was the GA. It was presented in John Holland's book Adaptation in Natural and Artificial Systems [147]. In late 1990's, ABM emerged and started being used to explain interactive system dynamics [152]. More recently, ABM has received increasing attention since it has advantages in modeling complex systems. It was reported as a better approach to complement equilibrium models when the problem is too complex to be analyzed, as for instance dynamic problems with several parameters and randomness. ABM refers to a category of computational models that invoke dynamic action, reaction and intercommunication protocols amongst the agents in their shared environment [153]. ABM is considered a computational framework for simulating processes that involve autonomous agents. An autonomous agent acts on its own without external direction in response to situations the agent encounters during the simulation.

The following definitions of ABM are provided in [154-156]:

- "Agent-based modeling is a way to model the dynamics of complex systems and complex adaptive systems. Such systems often self-organize themselves and create emergent order. ABM also include models of behavior (human or otherwise) and are used to observe the collective effects of agent behaviors and interactions. The development of agent modeling tools, the availability of microdata, and advances in computation have made possible a growing number of agent-based applications across a variety of domains and disciplines." [156].
- "The ABM approach consists of a decentralized collection of agents acting autonomously in various contexts. The massively parallel and local interactions can give rise to path dependencies, dynamic returns and their interaction. In such an environment global phenomenon

such as the development and diffusion of technologies, the emergence of networks, herd-behavior etc. which cause the transformation of the observed system can be modeled adequately. This modeling approach focuses on depicting the agents, their relationships and the processes governing the transformation." [154].

- "Formally, agent-based modeling is a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment." [155].

Basically, ABM focuses on modeling and to simulating complex systems, at a local level through the definition of their elementary units and at a high level, suited to model adaptive heterogeneous actors – agents.

There is not a universal consensus about the definition of an agent. However, Wooldridge and Jennings' definition [157] is increasingly adopted:

"An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives" [157].

As referred in [158], Wooldridge's classical definition of an agent does not clearly distinguish agents from a few existing software's and hardware systems. There are several points to note about this definition. First, this definition implies that agents have sensors to sense the environment and effectors/actuators to modify and act over the environment. Second, autonomy is not defined. Third, the above definition does not say anything about what type of environment is occupied by an agent.

A top-level view of an agent is provided in Figure 3.3. An agent has well-defined boundaries and interfaces and can monitor the environment through sensors or data access from other sources and modify it by reacting autonomously to changes that occur in it. The two concepts that capture the interface between an agent and its environment are the percept, an item of information received by some sensor, and the action, which is something that the agent does. We can see the action output generated by the agent as an event that affects its environment. In most domains of reasonable complexity, an agent will not have complete control over its environment. It will have at best partial control, in that it can influence it. Hence, the key issue lies in between the sensing and acting activities, where the agent decides how to proceed based on the percepts collected via input sensors [159].

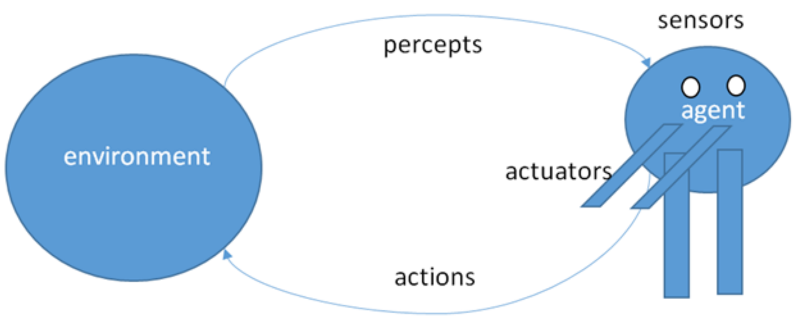

Figure 3.3. Agents and environment (adapted from [160])

Macal [156] listed some criteria, which need to be accomplished in order to think in terms of agents:

- When the problem has a natural representation as being comprised of agents;
- When there are decisions and behaviors that can be well-defined;
- When it is important that agents have behaviors that reflect how individuals behave (if known);
- When it is important that agents adapt and change their behaviors;
- When it is important that agents learn and engage in dynamic strategic interactions;
- When it is important that agents have dynamic relationships with other agents, and agent relationships form, change, and decay;
- When it is important to model the processes by which agents form organizations, and adaptation and learning are important at the organization level;
- When it is important that agents have a spatial component to their behaviors and interactions;
- When the structure of the system does not depend entirely on the past, and new dynamic mechanisms may be invoked or emerge that govern how the system will evolve in the future;
- When arbitrarily large numbers of agents, agent interactions and agent states are important;
- When process structural change needs to be an endogenous result of the model, rather than an input to the model.

The complexity of the decision-making process can be affected by a number of different environmental properties as detailed in [160]:

Fully Observable or Partially Observable: If an agent's sensor gives access to the complete state of the environment at each point of time, then the environment is considered fully observable. Otherwise, it is considered partially observable.

Deterministic or Stochastic: If the next state of the environment is completely determined by the current state and the action executed by the agent, then the environment is considered deterministic. Otherwise, it is considered stochastic.

Episodic or Sequential: In an episodic environment, the agent's experiences are split into atomic episodes, each consisting of the agent perceiving and then performing a single action. The next episode does not depend on the actions taken in the previous ones, and the choice of actions in each episode depends only on the episode itself. On the other hand, in sequential environments, current actions may affect all further decisions.

Static or Dynamic: A static environment is one that can be assumed to remain unchanged except by the performance of the actions taken by the agent. A dynamic environment is one that has other processes operating on it, and which hence changes in ways beyond the agent's control.

Discrete or Continuous: The distinction between discrete and continuous environments can be applied to the state of the environment, to the way the time is handled, and to the perceptions and actions of the agent. All these features can be either discrete or continuous in the environment modeling.

Single agent or Multi-agent: Single agent environments are those where only one agent is situated. Multi-agent environments are those where more than one agent is situated.

The most complex environments are those that are partially observable, stochastic, sequential, dynamic, continuous and multi-agent. In real world applications, agents have at best partial understanding and control the environment. Furthermore, multiple agents can interact with each other, as illustrated in Figure 3.4.

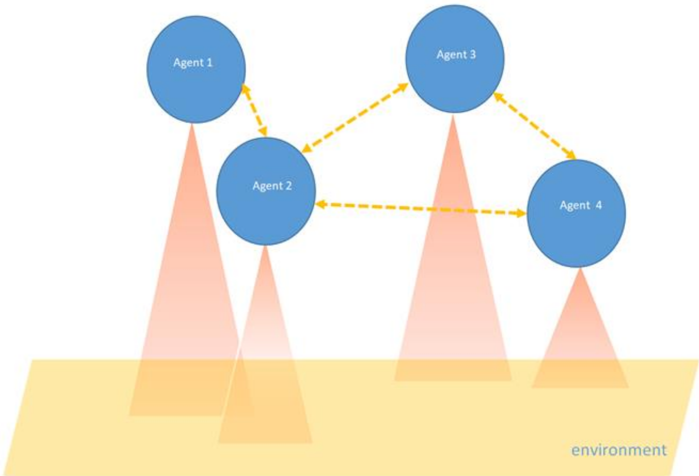

Figure 3.4. Typical structure of a multi-agent system (adapted from [161])

The environment is defined as the part of the system within which the agent operates. It is not the agent itself nor it is any of the other agents, but rather it is everything that has an (external) influence upon it. As visualized in Figure 3.5, environments can be simple, multi-layered, or even change over time.

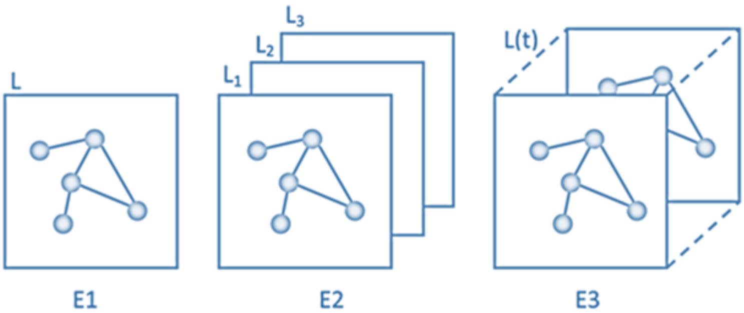

Figure 3.5. Different environments: E1: single layer, E2: multi-layer, E3: continuous changing environment (adapted from [161])

An agent can be interpreted as a computer system that can perform autonomous actions in an environment in order to meet its design objectives. It can sense its surroundings using various sensors, such as software devices and physical ones, and can then provide a variety of actions to modify the environment. However, its actions may not always respond in a predictable manner.

Autonomous agents can also be defined as intelligent agents since the concept of intelligence is often specified in terms of its phenomenological functions as a capacity or ability to solve problems autonomously. Whenever an agent, biological or artificial, possesses this ability, it is considered intelligent, otherwise not [162]. There is an approach to the Artificial Intelligence (AI) where any intelligent system is considered as an intelligent agent or a collection of them [160]. This leads to a very broad definition of an intelligent agent. However, in the field of engineering and computation, intelligent agents typically correspond to software components.

So, when do we consider an agent to be intelligent?

An intelligent agent is one that is capable of flexible autonomous actions in order to meet its design objectives. In line with [157], flexibility means three things:

- **Proactiveness**

  The goal-directed behavior of an agent is shown through its proactive approach, which means that it tries to achieve its goals. If a specific goal is given to it, then the agent should at least try to accomplish it.

- **Reactivity**

  The ability to react to changes in the environment allows agents to perform different tasks in a more efficient manner.

- **Social ability**

  The ability of agents to interact with other agents or entities in order to meet their design goals is known as social ability. This is different from the way they interact with hardware and software entities. Usually, interactions are defined as those that are carried out in terms of verbal communication. They can also be categorized into different types of human interaction such as cooperation, negotiation, and coordination [163].

Other more general attributes of agents have been described in [164] and include:

- **Accuracy**

  An agent's accuracy is determined by its ability to perform the tasks that it is asked to do.

- **Adaptivity**

  Its adaptivity is also evidenced by its ability to improve its performance through experience.

- **Adaptability**

  An agent can adapt to the changes in the environment by providing various actions to modify it.

- **Mobility**

  Agents can also move between different host platforms.

- **Temporal continuity**

  An agent's temporal continuity is also evidenced by its continuous running processes. It can maintain its identity and state over a long time.

- **Reliability**

  The reliability of an agent is also determined by its refusal to pass false information.

- **Inferential capability**

  An agent can act on task specifications that are based on its knowledge of general goals with an inferential capability.

The concept of an intelligent agent is a natural development of other trends of AI, which has relations and differences between agents and other computer science concepts and approaches:

- **Agents and AI**

  The intelligence requirements of AI and agents are usually met by following a certain set of rules. This includes making a reasonable decision regarding their environment when it comes to taking an action. An agent can also interact with other individuals through their interactions within the environment. This is the main mode of interaction that computer science usually focuses on.

- **Agents and Objects**

  Both agents and objects are similar in their capabilities when it comes to performing various actions. An object, on the other hand, is a computational entity which can perform methods and actions on a certain state. The main advantage of an object over an agent is that it has a single thread that can control everything. An agent, on the other hand, is a process-like entity which can simultaneously execute various types of tasks.

- **Agents and Expert Systems**

  During the 1980s, AI was heavily focused on the development of expert systems, which are capable of providing advice in certain knowledge domains [165]. These systems are not directly related to the environment they interact in, and they do not require to interact with other agents in order to perform their tasks.

Some examples of the various applications that can be made using intelligent agents, are:

- An intelligent agent can perform various tasks such as searching the internet for a specific query and gathering information about its users. It can then provide the users with the necessary information on a regular basis.
- Examples of such systems include Amazon's Alexa and Apple's Siri. These assistants use sensors to analyze the data collected by the users after they have made a request. They can then use this information to gather data about their users' perceived environment, such as weather and time [166].
- Autonomous vehicles can also be considered intelligent agents due to the use of cameras, sensors, and GPS to make informed decisions when it comes to navigating through traffic.

A single agent system refers to an agent-based system with only one agent, then comprising a single agent environment. Similarly, a Multi Agent System is used to denote the combination of one or more agents capable of exhibiting their attributes within a co-operative system [167]. Each agent has internal sets of structures and mechanisms which allow them to reason about itself and the environment [159]. These set of structures and mechanisms define the agent´s architecture.

3.2.2. Architectures for Intelligent Agents

An agent decision making function is an abstract function that can be used to determine which actions to perform. It can be implemented in four different architectures: logic-based, reactive, belief-desire-intentions and layered-based agent architectures [168] that are briefly described below:

- Logic-based agents – in which decision making is performed through logical deduction;
- Reactive agents – in which decision making is implemented in some form of direct mapping from situation to action;
- Belief-desire-intentions agents – in which decision making depends upon the manipulation of data structures representing the beliefs, desires, and intentions of the agent;

- Layered architectures – in which decision making is conducted via various software layers, each of which is more-or-less explicitly reasoning about the environment at different levels of abstraction.

In this thesis, we will not make a specific commitment of each kind of agent architecture that is used. However, the Belief-Desire-Intentions model and its associated Procedural Reasoning System, according to [169] is the best known and best studied model.

In the Belief-Desire-Intentions model, the **Beliefs** of an agent represent the informational states of the agent environment. In its logic, Bel$i(\alpha)$ expresses the fact that the agent *i* believes α. In this proposition, the belief is directly associated with the agent, so the agent *i* is omitted from the description of a belief. The content of the belief expresses a state or an activity concerning the agent or its world. For example: Bel(*helicopter1, takeCare, tree12*) expresses that the agent has a belief that agent *helicopter1* will take care of the agent *tree12*. While the expression Bel(*X*, *burning, null*) means that the agent believes that agent *X* is *burning* (i.e. in the state burning), the Bel(*X*, Bel(*tree12*, *burning*, *null*), *null*) declares that the agent believes that the agent *X* believes that the agent *tree12* is *burning* [170].

The **Desires** (options) represent the motivational states of the agent. As desires are also mental states like beliefs, a desire shares with a belief the same content format. Considering that an agent cannot simultaneously pursuit competing desires, two additional attributes to describe a desire were proposed [170]:

- Competing category: each desire belongs to a competing category. Two desires of the same category cannot be considered at the same time;
- Priority: the priority is the degree of importance of a desire. The higher the priority, the more important the desire is. Among the desires of a competing category, the agent chooses the desire with the highest priority.

Events trigger the reactive activity of the agent. In the *AgentSpeak* architecture [171], an agent begins reacting when its mental state changes. In this architecture, events are described as a creation or a deletion of a mental state. It means that when an agent acquires a new belief or a new desire, this agent creates an event.

Rules are what an agent uses to make the logic deduction creating new beliefs and new desires from current beliefs and desires. The modifications of mental states come not only from what the agent perceives but also from its internal reasoning process. That means that an intelligent agent is also capable to reason in order to update its beliefs and desires according to its current mental states.

A **Plan** is a sequence of declared actions that the agent has to apply to reach one (or many) goals. This means that a plan describes the fact that the agent has to execute some particular actions once it gets a specific condition on mental states (beliefs, desires). A plan is composed of goals (desires of the agent), context (conditions on mental states), trigger (events that trigger the plan) and actions (actions to execute).

An **Intention** represents the deliberative state of the agent, i.e. what the agent has chosen to do. According to [172], "intending to do something (or having an intention) and doing something intentionally are not the same phenomenon". Thus, intentions are classified into two types:

- A Future-oriented intention is a specific instance of an applicable plan;
- A Present-oriented intention is the future-oriented intention that the agent has chosen to pursuit.

In terms of implementation, intentions are manifested by means of executing one or more plans, which are developments of actions. So, **Actions** are one of the components of an intention. An intention may contain several actions that will be performed sequentially. Each action describes the agent's behavior and the action conditions. An action is composed of three components corresponding to three situations:

- Normal - it is a situation where the mental condition of the agent meets the intention condition that is inherited from the plan context. At this moment, the action is normally performed;
- Success - it is a situation where the agent's mental condition allows the agent to decide that certain goals are achieved (for example, the agent acquires new desires that allow the agent to satisfy the desires of its intention goals);
- Failure - it is a situation where the agent considers that the action failed and where it decides to stop following the action goal. In this case, the agent removes the corresponding desires or creates new events that trigger the backup plans.

Using these concepts, the key data restrictions in our agents will be beliefs, desires and intentions. How does an agent with beliefs, desires and intentions go from these to actions? The particular model of decision-making underlying the Belief-Desire-Intentions model involves two important processes: deciding what goal we want to achieve, and how we are going to achieve these goals and this process is known as Practical Reasoning System.

From the architecture point of view, the associated Practical Reasoning System, originally developed at the Stanford Research Institute, is a generic architecture to represent and reason about actions and procedures in a dynamic domain [173]. It was perhaps the first agent architecture to explicitly embody the Belief-Desire-Intentions model and has proved to be one of the most durable approaches to develop agents to date [171]. This architecture is shown in Figure 3.6.

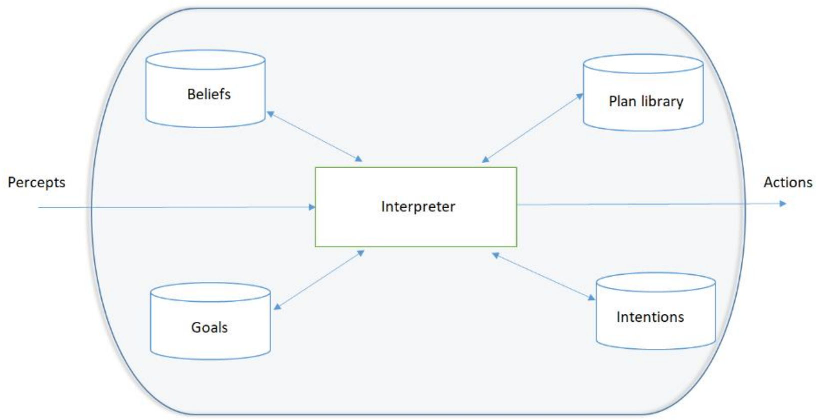

Figure 3.6. The Practical Reasoning System architecture (adapted from [174])

The agent interpreter manages the beliefs, goals, plans and intentions in the Practical Reasoning System agent architecture. It is responsible for updating the beliefs from observations made from the environment, generating new desires (tasks) on the basis of new beliefs, and selecting from the set of currently active desires some subset to act as intentions. Hence, the interpreter must select an action to perform on the basis of the agent's current intentions and knowledge [159].

A Practical Reasoning System agent starts with a set of plans and top-level goals and initial beliefs. These beliefs are then represented by atomic formulas of first-order logic. The goal is then put into an intention stack, and the agent can look through the stack to see what goals are still outstanding. Some of these will have their conditions satisfied according to the agent's current beliefs. This means that the plans that achieve these goals can become the agent's options. The process of selecting a plan can then be carried out through utility ordering or meta-level plans [171].

The Practical Reasoning System architecture only addresses the internal reasoning of agents. However, this has been extended to allow other agents to interact with each other, for example, communication and interaction with each other in order to conceive some social ability.

3.2.3. Agent communication and interaction

One of the most important factors that an agent should consider when it comes to achieving its goals is the availability of communication. This will allow them to perform their duties in a more efficient manner. In this sense, one should have a standardization related with agent communication. The Foundation of Intelligent Physical Agents (FIPA) [175] is an Institute of Electrical and Electronic Engineers Computer Society that promotes agent-based technology and the interoperability of its standards with other technologies.

The ability of agents to communicate with one another has been a central theme in the development of their conceptual frameworks. This allows them to tackle problems that no single individual can solve alone. The concept of agent communication is based on the speech-act theory, which states that language is action. This distinction between actions that are non-speech acts and those that are speech acts is important. Thus, examples of speech acts might be to change your beliefs, desires or intentions. Various types of speech acts were identified by Searle [176].

A speech act's content is different from a Java method's list of parameters. Instead of just having a set of arguments, the content of a speech act is a proposition, which means that it can either be true or false. This is very different from method invocation, as it allows a knowledge-level communication to be carried out. The Knowledge Query and Manipulation Language (KQML), developed in the context of the 'Knowledge Sharing Effort' project [177], was the first attempt to define a practical agent communication language that included high-level (speech act based) communication as considered in the distributed artificial intelligence literature. It defines a number of performatives, which make explicit an agent's intentions in sending a message. For example, the KQML performative tell is used with the intention of changing the receiver's beliefs, whereas achieve is used with the intention of changing the receiver's goals. Thus, the performative label of a KQML message explicitly identifies the intent of the message sender. The KQML language has reserved parameter keywords as detailed in Table 3.2.

The FIPA standard for agent communication is closely based on KQML, differing in its performative set and semantics. The main goal was to simplify and rationalize the performative set as much as possible, and to address the issue of semantics, a somewhat problematic issue for agent communication languages.

Table 3.2 KQML reserved parameter keywords (Source: [177])

Keyword	Meaning
:content	Information about which the performative expresses na attitude
:force	Whether the sender will ever deny the meaning of the performaive
:in-reply-to	Expected lable in a reply
:language	Name of the representation language of the content parameter
:ontology	Name of the ontology, e.g. set of term definitions, used in the content parameter
:receiver	Actual receiver of the message
:reply-with	Whether the sender expects a reply, and if so, a label for the reply
:sender	Actual sender of the message

3.2.4. Building and designing Agent-Based Systems

Developing agent-based model requires specific steps and agent-related tasks that are indicated in Figure 3.7. Several of agent-specific questions before developing an agent-based model should be done. Table 3.3 presents some of them. The answers to these questions help defining the scope, level of detail and granularity that are appropriate to model the system. They imply the resources required for successfully completing the project and can be used to help identifying likely bottlenecks to the development [156].

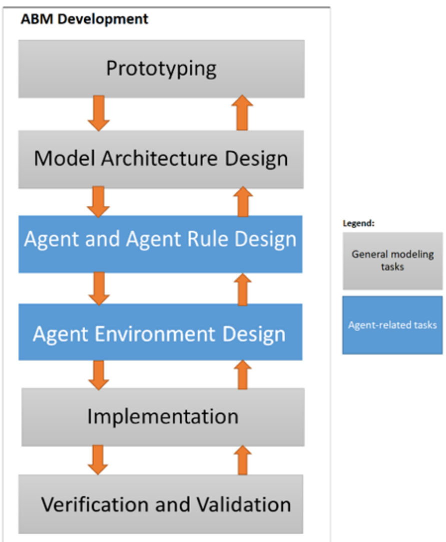

Figure 3.7. Agent-Based Model development process (adapted from [156])

The agent-based modelling follows some steps which are similar to the standard computer simulation procedure. Following [178] these steps are enumerated below.

Formulation of objectives and questions

The formulation of objectives of a simulation or model is first established during the initial step of the process. This step should be carried out in order to ensure that the results of the study are focused on the correct objective.

Design of the model

The design phase is also a crucial part of the development of agent-based models. It involves deciding the level of detail that the system should be built with, as well as the type of cognitive activity that it should perform. The shared environment of the agents should also be addressed.

Table 3.3 Questions to ask before developing an ABM (Adapted from [156])

Model Purpose and Value-added of Agent-based Modeling:
What specific problem is the model being developed to address?
What specific questions should the model answer?
What kind of information should the model provide to help make or support a decision?
Why might agent-based modeling be a desirable approach?
What value-added does agent-based modeling bring to the problem that other modeling approaches cannot bring?
All About Agents:
Who should be the agents in the model?
Who are the decision makers in the system?
What are the entities that have behaviours?
Where might the data come from, especially for agent behaviours?
Agent Data:
What agent behaviour are of interest?
What decisions do the agents make and what information is required to make such decisions?
What are being acted upon?
What actions are being taken by the agents?
How would we represent the agent behaviours? By If-Then rules? By adaptive probabilties, such as in reinforcement learning? By explicit heuristics? By regression models or neural networks?
Agent Interactions:
How do the agents interact with each other?
How do the agents interact with environment?
How expansive or focused are agent interactions?
Agent Recap:
How do design a set of experiments to explore the importance of uncertain behaviours, data and parameters?
How might we validate the model, especially the agent behaviours and the agent interaction mechanisms?

A large number of methodologies have been proposed to design agent-based systems. They can be broadly divided into two groups [167]:

- those that take their inspiration from Object-Oriented (OO) development, and either existing OO methodologies or adapting OO methodologies to the purpose of agent-oriented software engineering (AOSE);
- those that adapt knowledge engineering or other techniques;

The methodologies AAII [179], GAIA [180], Tropos [181], Prometheus [182], MaSE [183] and PASSI [184] have been proposed to design agent-based systems and are described in detail in the above references.

Justification of assumptions

The various assumptions that are built into the model should also be supported by empirical data. This ensures that they are coherent.

Choice of measurements

Once the model has been designed, it is also important that the measurements that are used are defined. These measures will allow the system to evaluate the model's performance.

Choice of software

Developers can create agent-based models using various software components. These include libraries, toolkits, and programming languages. These are commonly used in the development of models and simulations.

In terms of the scale of the software, there are several approaches to build Agent applications [156] as follows:

Desktop Computing for Agent Based Simulations Application Development:

Spreadsheets: Excel using the macro programming language VBA

Dedicated Agent-based Prototyping Environments: NetLogo, Repast Simphony

General Computational Mathematics Systems: MATLAB, Mathematica

Large-Scale (Scalable) Agent Development Environments:

Repast, Swarm, MASON, AnyLogic, Simio

General (Object-Oriented) Programming Languages:

Java, C++, Python

A learning agent model can be created using Desktop Agent Based Simulation, which is a simple and flexible software. It can be used to perform various tasks such as modeling and performing limited analyses. Although spreadsheets are a simple way to create agent models, they generally do not allow a lot of diversity, have poor scalability, and restrict the behaviors of the agents. This is why it is important to use a macro-programming language such as Visual Basic for Applications [156]. Developers can use general purpose mathematical systems such as MatLab and Mathematica to create agent models. However, since there is no dedicated library or module for this type of modeling, the developer should create the model from scratch.

Swarm was the first Agent Based Simulation software development environment, launched in 1994 at the Santa Fe Institute. Swarm was originally written in Objective C and was later fitted with a Java interface [156]. A multi-agent programmable modeling environment is provided by Netlogo and is particularly well suited for modeling complex systems developing over time [156, 185].

Following the original Swarm innovation, the Repast (REcursive Porous Agent Simulation Toolkit) toolkit was developed as a pure Java implementation [186], and Repast Simphony (Repast S) is the latest version of Repast, designed to provide visual point-and-click tools for agent model design, agent behavior specification, model execution, and results examination. Repast Simphony 2.0 also includes ReLogo, a new Logo-like interface for specifying agent models [187]. They are freely available and/or open source.

Anylogic has the capabilities to structure models that combine agent-based, system dynamics and discrete events [188].

As computational capabilities continue to advance in both hardware and software, new capabilities are continuously being incorporated into the latest versions of Agent Based Simulation toolkits. This field is advancing rapidly toward highly scalable, high productivity agent development environments that are easy to learn and use.

Implementation, verification and validation of the model within the selected software

After the model has been designed, it should be implemented in a certain software platform. This step involves ensuring that the model is correct. Doing so can help certify its accuracy. Another step that should be taken is the validation test, which is usually carried out on the model's observed behavior. This validation step is carried out to ensure that the model is accurate. This step should be performed on the individual and systemic scales since ABM can be distributed across different platforms. For instance, in energy systems, the consumer or power plant can be parameterized and evaluated. This step can confirm the validity of the model.

In the case of a population of replicated agents, once having calibrated the individual agents, a calibration of the model at an aggregated level should take place. This is usually possible through the available macro-data (in the case of energy systems, measurements at an aggregated scale such as a transformer or substation) [154].

Sensitivity analysis and results interpretation

A sensitivity analysis is also usually performed after the model has been established as valid. This step involves identifying and avoiding false or local optima. This step can help the developer determining the optimal outcome for the model [178].

3.3. Machine Learning Methodologies

There are several fields of Machine Learning that address the purpose of agents since it is possible to learn from data and to ensure that the knowledge over the problem is constantly updated. Figure 3.8. illustrates a categorization of Machine Learning fields and sub-fields.

The first category belonging to the family of Machine Learning techniques and algorithms is called **Supervised Learning**. It is probably the most well-known branch of Machine Learning and is intended to find patterns in data that can be applied to an analytic process. It refers to situations where the target variable is known and, in this case, the target variable is present in the dataset. The goal of supervised learning is to provide a better understanding of a target variable by learning from its value. Unfortunately, this type of learning is not ideal for developing interactive problems.

This category of Machine Learning is mainly focused on the use of classification and regression techniques. One of the main applications of supervised learning is in forecasting analyses. This type of learning is commonly used in the development of procedures related to medical diagnostics and process optimization [189].

Unsupervised learning is another type of machine learning that is commonly used in developing applications that involve large amounts of unlabeled data. This approach is best suited for problems that require a lot of data to be analyzed. Most of the time, this approach is performed in an iterative manner. The main difference between unsupervised and supervised learning is that the model should learn without having a specific target as a purpose. The most common examples of this category of problems include clustering and dimensionality reduction: detecting potentially useful clusters of input examples [160].

The third and last type of Machine Learning techniques is called **Reinforcement Learning** (RL). This method involves an agent interacting with its environment in order to learn the best action to take based on the given situation. Unlike other techniques, this method does not provide the agent with an advice. Instead, the agent explores the environment to maximize its future rewards. In general, in this type of learning, the objective of the agent is to achieve the highest reward, due to adopting the optimal policy, in the long term. The applications of Reinforcement Learning nowadays are abundant given the data-centric era that is approaching and the number of processes requiring accurate and optimal decision-making [190].

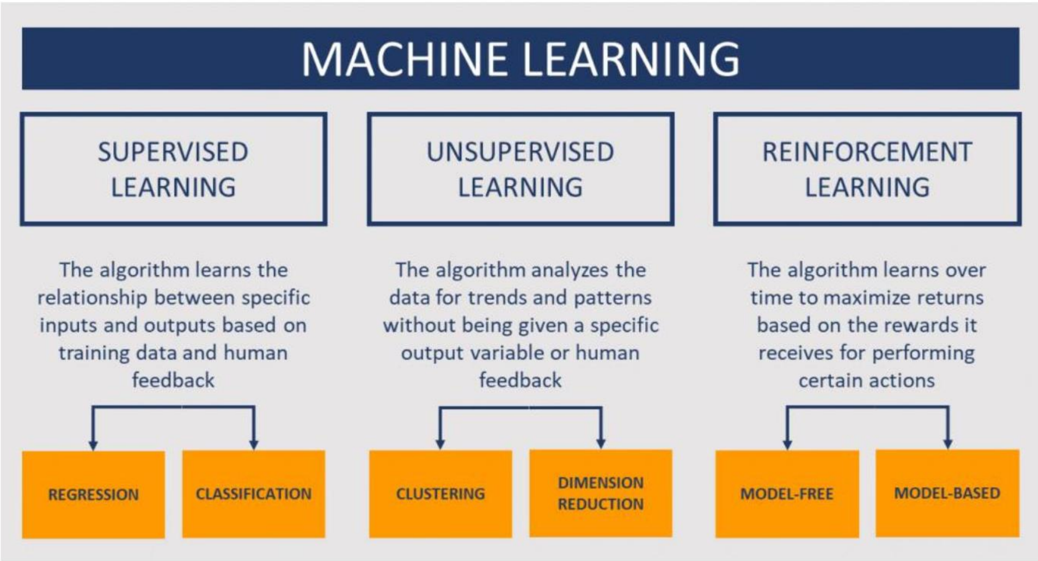

Figure 3.8. Categorization of Machine Learning techniques (source [189]).

There are two main criteria that can be used to classify different RL approaches:

- The first criterion is whether or not there is a perfect model for the environmental behavior. A model-based method can learn how an environment works and predict the outcomes of its actions, allowing agents to anticipate the rewards that will be received. However, most model-based methods are impractical when dealing with large state-action space constraints. On the contrary, model-free approaches do not require knowledge of the environment to perform well. They can learn an optimal policy by repeatedly experiencing the various rewards and states of the environment;
- The second criterion that can be used to classify RL algorithms is whether the algorithms "learn" off-policy or on-policy. On-policy takes into account the expected rewards that will be received by the system based on the current policy. On the other hand, off-policy assumes that the agent follows a greedy strategy.

Learning from interaction and achieving a goal is the main purpose of RL. The process of an agent observing the environment output and taking an action, which is interpreted into a reward in order to select the next state, which is fed back into the agent, is the typical framework of a RL. A Markov Decision Process can be defined as a framework under which an agent observes the environment characterized by a state s, selects an action among the ones available at that state and then the process responds at the next time step by moving the system to a new state and by allocating the agent with the corresponding reward. This reward can be interpreted as the motivation the agent has in choosing a specific action given that he is in a given state.

The **agent** corresponds to the decision-maker of the problem and is the one who is responsible for learning. The **environment** includes all aspects with which the agent should interact with, in order to get information. The agent and the environment are interacting continuously: the agent selects and implements **actions** and the environment, based on these actions, gives feedback to the agent, which corresponds to the mentioned **reward**. This mechanism is illustrated in Figure 3.9.

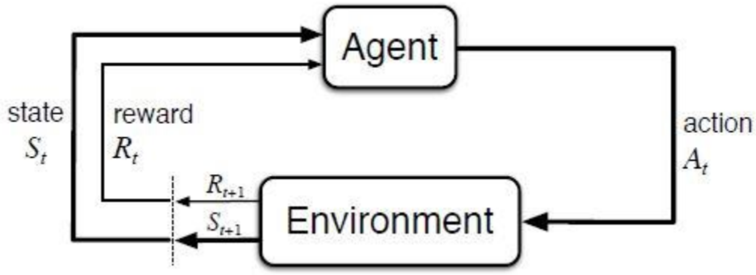

Figure 3.9. Agent-environment interactions in reinforcement learning (source [191]).

Regarding Figure 3.9, the agent and the environment interact at specific discrete time steps, t = 0, 1, 2, 3..., n. At each time step t, the agent receives a representative description of the environment's **state** $S_t \in$ S, where S is the set of all possible states of the environment. Then, given that he is in state S_t, the agent selects an action $A_t \in A(S_t)$, where $A(S_t)$ is the set of possible actions that are available in state S_t.

Consecutively, the environment sends back a signal (for instance, under the form of a numerical value) to the agent, which is usually influenced or determined by the agent's chosen action. This signal is called a reward in this context, and it is denoted as $R_{t+1} \in R$. Then, the agent is responsible for doing a mapping at each time step from states to actions. This mapping is called the agent's **policy** and it is denoted by π_t and basically $\pi_t(\alpha|s)$ represents the probability that $A_t = \alpha$, given that $S_t = s$. Finally, the system transits to a new state $S_{t+1}$and this procedure should continue iteratively until convergence is reached [191].

Q-Learning (QL) is one of the most well-known RL algorithms. It was originally proposed in [192] and it is fully detailed in [191]. It is a useful algorithm for solving MDP, and its implementation involves the evaluation of the payoff for a given state-action pair. This leads to the QL matrix that is composed by cells known as Q-values. Thus, Q-values are calculated for each pair of state *(s)* and action *(a)*, and therefore they can also be described as $q(s, a)$. As the Q-Learning focuses on the impacts of rewards (r) and on the choices of actions in each state, the Q-values are obtained by a function that provides the utility of taking a given action in a given state. This function corresponds to the Bellman equation, and it is given by (3.1.).

$$q(s,a) \leftarrow q(s,a) + \lambda[r(s,a) + \gamma max_a q(s',a) - q(s,a)] \quad (3.1.)$$

In this equation λ is the learning rate, which reflects the degree to which recently learned information will override the oldest one (when λ equal to 0 originates that the agent does not learn, while when equal to 1 it induces the agent to consider only the most recent information). The parameter γ is the discount factor that determines the importance of future reinforcements in the learning process (if γ equal to 0 the agent is myopic by only considering current rewards, while values closer to 1 turn distant rewards more important). The expression $max_a q(s', a)$ represents the best the agent thinks it can do in state s'. Finally, in this equation *r(s,a)* represents the reward that is associated to the pair state *s* and action *a*.

The classical structure of the QL algorithm used by an agent is presented in Table 3.4.

Table 3.4. Q-Learning algorithm

	Algorithm: Q-learning
1:	**initialization:** Q table
2:	**for** *every training episode* **do:**
3:	**initialization:** starting state s
4:	**for** *every decision period* **do:**
5:	select action a based on Q and ε-greedy policy
6:	observe reward r and next state s'
7:	$Q(s,a) \leftarrow Q(s,a) + \lambda\left[r + \gamma \max_a Q(s',a) - Q(s,a)\right]$
8:	$s \leftarrow s'$
9:	**end for**
10:	**end for**

In line 1, the QL matrix is initialized. Different states are represented along different rows and actions are in different columns, which defines the Q-table. For *every training episode* of the algorithm, the state of the environment is initialized and then for *every decision period*, an action is chosen based on the Q-table and following a ε-greedy policy. The ε-greedy policy refers to the exploration/exploitation tradeoff. Initially, the agent chooses actions almost randomly (which means that ε should be high) but as the simulation evolves and the convergence is approaching, the agent is induced to choose actions mostly based on the maximum Q-values of the Q-table, depending on the specific state (row) where he is located at any time (which means that ε should be low). After that, the agent observes the reward that he received and the next state to where he will move. Finally, it updates the corresponding element of the Q-table based on the QL update rule and also updates its next state. The QL has been proven to converge to the optimal solution, given Markov properties in the state-to-state transitions and admitting an infinite number of visits to each state-action pair [189].

Despite its simplicity and the fact that it is widely used in many MDP settings, in stochastic MDP the performance of the QL algorithm is affected by a large overestimation of action values [193]. This overestimation comes from the fact that positive bias is inherent to the QL algorithm from using the maximum action value as an approximation of the maximum expected action value. Van Hasselt [193] proved that this estimator is biased in highly stochastic environments because instead of the expectation over the next state, only the average over all possible results of the experiment is computed.

In order to solve the aforementioned problem, Van Hasselt proposed a **Double Q-Learning** algorithm [193]. The intuition behind this approach is that the selection of the best action should be de-correlated with the evaluation of this action. The classical structure of the Double QL algorithm used by an agent is presented in Table 3.5.

In the Double Q-Learning algorithm, there are two Q-tables, Q^A and Q^B, instead of one. Each of these is randomly selected to be updated during each iteration of the program. The main difference between this algorithm and the original QL is that the former's selection is based on one of the Q-tables, while the latter's evaluation is based on the other Q-table. So, it is possible to avoid the pitfall of overestimation bias that is associated with the classical QL.

Although the algorithms presented up to now display very good performance, there are still some limitations when it comes to generalization. Most of them use two-dimensional arrays for their Q-values, which is similar to how dynamic programming is done [189]. In higher dimensions, this issue can be considered a threat. Since the agent doesn't have the necessary knowledge about the unseen states or the less-seen ones, the performance of the simulation can be affected. The use of the Deep Q-Learning algorithm can help solve this issue.

Deep Q-Learning combines the perception function of deep learning with the decision-making ability of RL. It is an artificial intelligence approach closer to human thinking and it is often classified as an Artificial Intelligence procedure. Deep Reinforcement Learning gets the target observation information from the environment and provides the state information in the current environment as illustrated in Figure 3.10.

Table 3.5. Double Q-Learning algorithm

Algorithm: Double Q-learning

initialization: Q^A table and Q^B table
for *every training episode* **do:**
    initialization: starting state s
    for *every decision period* **do:**
        select action a based on Q^A, Q^B and ε-greedy policy
        observe reward r and next state s'
        generate $d \sim U(0,1)$
        if $d \leq 0.5$ **do:**
            $Q^A(s,a) \leftarrow Q^A(s,a) + \lambda\left[r + \gamma Q^B\left(s', \operatorname{argmax}_a Q^A(s',a)\right) - Q^A(s,a)\right]$
        else do:
            $Q^B(s,a) \leftarrow Q^B(s,a) + \lambda\left[r + \gamma Q^A\left(s', \operatorname{argmax}_a Q^B(s',a)\right) - Q^B(s,a)\right]$
        end if
        $s \leftarrow s'$
    end for
end for

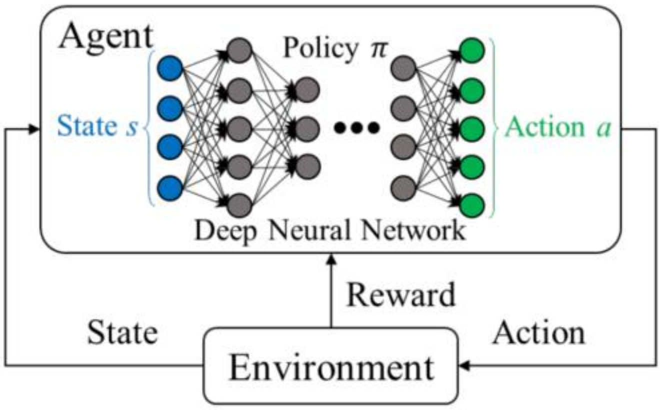

Figure 3.10. Schematic structure of Deep Reinforcement Learning agent (source [194]).

The two main aspects related to Deep Q-Learning are target network and experience replay. The first one is the selection of data for training the deep neural network. The second one is the method for storing the agent's experiences. One of the main concepts in deep neural network training is the selection of a random sample of experiences. This approach ensures that the correlation between training samples is low. It should be mentioned that the experiences are defined as a set of values that includes the state, action, reward, and the next state.

When it comes to training the target network, one should keep in mind that there might be significant differences between the predicted and the actual target value if a single network is used. A good analogy that is often given is that this process looks like someone who is trying to hit a moving target. Therefore, a separate target network can then be used to estimate the predicted values. The main network parameters can also be copied to this target network at predetermined intervals. This method can help improving the training process [194]. Overall, a visualization of how Deep Q-Learning relates to tabular Q-Learning can be seen in Figure 3.11.

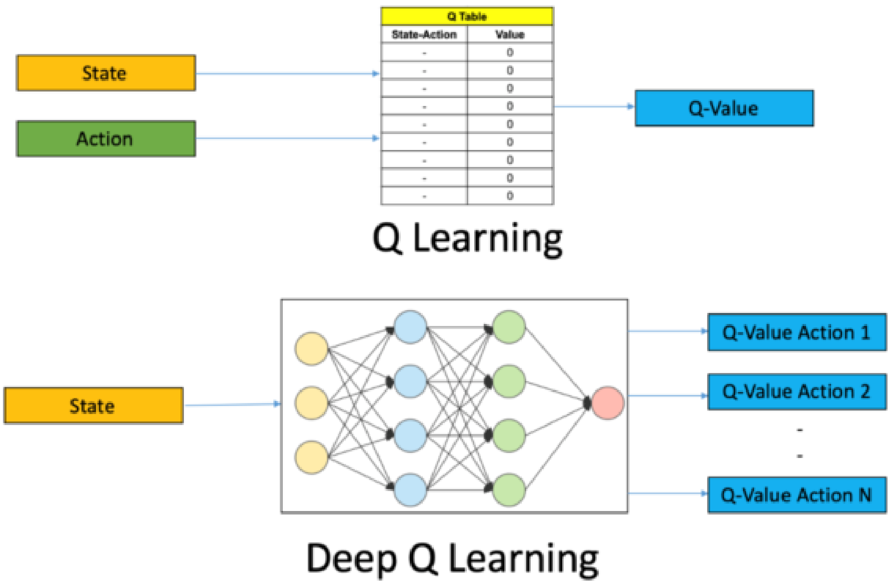

Figure 3.11. Relationship between Q-Learning and Deep Q-Learning (source [194]).

3.4. Agent Based Models in Power Systems

Power systems have experienced several changes, mainly related to organizational and operational restructuring. The transition from vertically integrated utilities to an electricity market environment and the appearance of new actors and rules, increased the complexity of power systems modeling. Smart grids and microgrids [195-199], Electrical Vehicles [200], consumption flexibility and demand response mechanisms [201, 202], bid based electricity market [203], energy efficiency measures [204], building energy management and energy modelling in general [205-209], among many others, contribute to the mentioned increasing complexity.

As a direct result, there is a need for new simulation and management control solutions and strategies that enable integrating these different actors. So, considering the operation of power systems with the participation of these new players, rather than just looking at the overall picture, this makes the problem solving in this domain an increasingly complex task. ABM can be considered as a suitable tool to address this complexity.

There are also many other applications for which ABM models are beneficial to power engineering, such as electrical grid diagnostics [210], assets condition monitoring [211], power system restoration [212], market simulation [213-219], network control [220, 221], automation [222] and transportation [223, 224].

Notwithstanding becoming a powerful tool to be used in power systems, ABM has been applied in different areas, including marketing [225, 226], diseases [227], biology [228], economics [229, 230], financial economics [231], urban planning [232], social sciences [233], transportation [234], geographical information systems [235], pandemics [236], etc. This development has been highlighted with several conferences and publications. The Multi-Agent-Based Simulation International Workshop series started in 1998 and aims to bring together researchers from artificial intelligence, computer science and social sciences interested in using multi-agent models and technology in social simulation [237]. The annual Computational Social Science Society of the Americas Conference focuses on Computational Social Science, a scientific discipline where computational methods and simulation models of social dynamics are employed to offer new insights into social phenomena beyond what is available with traditional social science methods [238]. Other conferences such as the annual INFORMS meeting [239] and the annual Military Operations Research Society Symposium [240] often have significant numbers of presentations involving ABM based models. CoMSES Net, the Network for Computational Modeling in Social and Ecological Sciences, is an open community of researchers, educators, and professionals with a common goal - improving the way agent based and computational models are developed, shared, used, and re-used for the study of social and ecological systems [241].

Considering the definitions of agents and the operation of power systems, we can list a number of requisites to use ABM in power systems:

- The rules of business and social interaction are at least as important as the rules of physics when it comes to the generation, sale, and delivery of electrical power;

- Agents operating within an agent framework can be used to model decentralized competitive decision-making;
- Agent frameworks allow groups of agents to interact in complex dynamic ways;
- Learning and adaptation of agent behavior can be modeled;
- Transient conditions of the system can be studied in addition to the equilibrium conditions;
- Alternative market rules can be tested.

The following sections provide some details regarding ABM tools applied to power systems, namely approaches applied to electricity markets, smart grids, energy storage systems and energy communities.

3.4.1. Applications of Agent Based Models to Power Systems

Considering the evolution of power markets, with the aforementioned restructuring and with new kinds of customer service requirements (ancillary service markets, advanced metering, etc.), it was fundamental to develop open-source code access software to model multiple market participants. In this sense, in June 2007 the IEEE officially recognized the newly created Task Force on Open Source Software (OSS) for Power Systems [242]. The mission of this task force is to promote the diffusion of the philosophy of OSS in the power systems community and the promotion of OSS for the benefit of the Power Engineering Society, from pedagogical to commercial purposes. Also, it was developed a special website [243], titled Open Source Software for Electricity Market Research, Teaching, and Training, that focuses more specifically to OSS electricity market applications. Some specified electricity markets modeled with ABM are presented in this section.

Bunn and Oliveira [244] use agent-based simulation in a coordination game to analyze the possibility of market power abuse in a competitive electricity market. Agents were modeled as having the capacity to learn. They use an RL algorithm to improve the performance of the participants: each agent evaluates the profit earned, and then derives new policies to bid or offer, given its strategic objectives of profit maximization and market exposure. They used the largest generation companies in England and Wales electricity market in 2000, splitting each generator's capacity into three categories, based on the degree of flexibility and running times of each technology (nuclear, large coal and combined-cycle gas turbines, and the rest). They concluded that the agent-based simulation technique enabled the modelling of complex adaptive behavior in an environment with possible multiple equilibria, with heterogeneous agents and price uncertainty. This shows that models capable of learning in complex electricity market environments can be utilized to model the behavior coordination in complex electricity markets and equilibrium selection processes.

In [245], different congestion management schemes in liberalized electricity markets were compared using an agent-based simulator. By modelling market participants as adaptive agents in oligopolistic structures, it considers the possibility of strategic behavior and the existence/exercise of market power. The simulator evaluates locational marginal pricing and zonal pricing (market splitting and flow-based market coupling), where congestion management schemes were assessed with regard to the distribution of producer and consumer surplus in the network while aiming at maximizing the overall social welfare.

In [217] it is described an agent-based conceptual model to simulate the Portuguese/Spanish Electricity Market (MIBEL) and to study the behavior of the involved agents, focusing on the representation of hydro power plants with pumping capability. The model simulates the Energy Market and the Ancillary Services Market as illustrated in Figure 3.12.

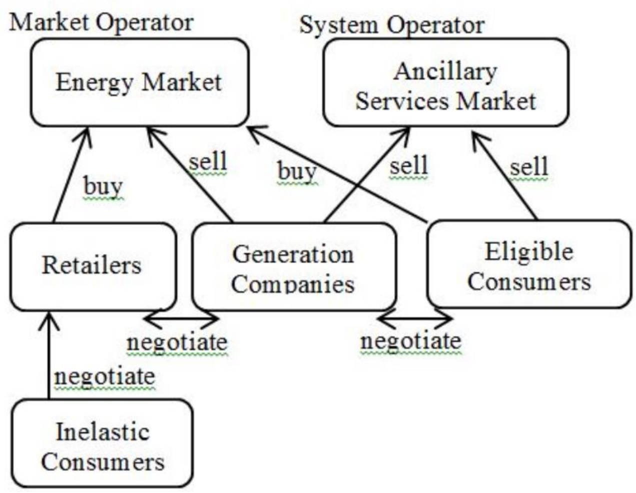

Figure 3.12. Structure of the proposed agent model to represent the MIBEL (source [217]).

In this structure, retailers are entities that buy energy in the Energy Market and negotiate it with the consumers. They have to bid in the energy market to supply the energy to the consumers who are not able to buy it directly in the market. The model includes commercial, industrial, and residential customers. They also have to negotiate with different retailers that act as aggregators of individual demands and operate as market agents. In the consumers group, there are also large consumers which can purchase energy directly from the market. These are referred to as Eligible Consumers. Generation companies, which own and operate power plants, submit selling bids to the Market Operator. They can also establish Bilateral Contracts with the Retailers or Eligible Consumers.

Regarding the Ancillary Services Market, the System Operator is responsible for ensuring that the power system operates safely and efficiently. It contracts reserves with different time durations and activation periods. It accepts offers for secondary and tertiary reserves from generation companies, and it selects the most cost-effective ones depending on the technical requirements.

The proposed ABM model used six types of agents and two artifacts:

- Inelastic Demand Agent – it corresponds to the individual clients (residential, commercial or industrial consumers) which are insensitive to the electricity price. Typically, they do not buy electricity in the market and have to negotiate with the Retailer Agents;
- Eligible Demand Agent – it corresponds to large consumers that can directly participate in markets (large factories or hydro pumping power stations). They can also establish bilateral contracts with Generation Companies;
- Retailer Agent – it corresponds to an aggregator entity that has a portfolio of contracts with individual clients, that is, with Inelastic Demand Agents. This agent can buy electricity in the market or establish bilateral contracts with Generation Companies;
- Physical Generator Artifact – it is related to individual power plants that have specific characteristics; it will be an artifact agent because it does not take any decision and it has a passive role in the market with no goal or autonomous activity. It will be used by Generation Company Agents;
- Generation Company Agent – it corresponds to the utilities that own a portfolio of generation assets, comprising different generation technologies, each one characterized by its generation operation and maintenance costs. These agents will have to decide whether they use their resources (hydro, gas, coal, wind) in the day-ahead market, in the ancillary services markets, or store some resources to be used in the future, when possible. It can also establish bilateral contracts with retailers;
- TSO Agent – it represents an entity that gathers the functions of an ISO with the ownership or the concession of a transmission network. It is also the ancillary services market operator thus being responsible for procuring and contracting reserves for frequency control;
- Organized Market Artifact – it is a process that models the energy market operator as a central entity that receives selling and buying bids for each trading hour of the next day and

organizes these bids to get generation/demand schedules. It is considered as an artifact because it presents neither internal goals nor any kind of autonomous activity;

- Regulatory Agent – this agent is in charge of evaluating the behavior of the agents according to the market regulation and eventually promoting regulatory changes or imposing penalties if market rules are violated.

Each of the mentioned agents assumes a role (i.e., sells, buys or regulates) according to the group it belongs to. Their decisions are essentially associated with the market type (energy or ancillary services), the player type (traders that operate in markets or individual inelastic demand) and about physical constraints, from grid and from generators. Their decisions will be supported by learning processes, such as QL and genetic algorithm based learning, and also by decision-support models [217].

Following the previous work, [246] describes an agent-based approach to model the day-ahead electricity market having a particular emphasis on hydro generation. The developed model considers four types of hydro agents (run of river, pure pumping, storage and storage with pumping), which bid their energy in the market and their strategy depends on the type of hydro. The bidding strategies are determined by the water value on the reservoir, by a learning parameter α in the scope of a QL approach, and by a decision supporting tool. It also includes thermal and renewable generation agents. The Market Operator agent is an artifact agent because it doesn't have a decision-making process. It performs the market clearing operation determining the market price and the cleared energy and communicating the market results to all market agents. Regarding demand agents, two types of agents were considered: inelastic agents that buy energy at the maximum value allowed by the MIBEL rules and elastic agents that are designed to model the behavior of consumers that can directly participate in the market, typically large industries, or hydro pumping stations. A Regulator agent is also used to monitor the generator bids and penalize the generation agents if the bid prices are very different from the marginal cost of thermal stations or from the water value for hydro stations.

The results reported by the authors confirm that the agents have learning capabilities (learning by experience) and are maximizing their profit using the reinforcement QL strategy.

With the increase in the number of EVs and Demand Response (DR) customers, ABMs can be a potential solution to model challenging problems in smart grids. In [247] a payment scheme has been designed to compensate EV customers for participating in the VPP. In this publication, the VPPs are considered as coalitions of wind generators and EVs, where wind generators seek to use EVs as a storage device to deal with the variations of generation. EVs provide an interesting potential to control electricity generation and demand in an intelligent way given their possible use for load-shifting. In this context, a combination of a stochastic model for mobility behavior and ABM simulation tool is presented in [248].

The effect of the participation of commercial buildings in DR programs has been studied in [249]. It was concluded that using DR programs in commercial buildings reduce electricity prices and volatility when there are more buildings. It was also concluded that DR actions by commercial buildings shave the load profile at the peak hours and reduce the volatility of electricity demand. In [250] a learning approach for strategic consumers in smart electricity markets was designed using a machine learning algorithm to smarten the customers. A business idea associated to the DR potential of households through aggregators is exploited in [251]. The authors of this publication detail that using this approach it will be possible to reduce the peak load.

An ABM architecture for coordinating locally-connected microgrids, thereby supporting more cost-effective integration into the main power grid, is detailed in [252]. The interconnected microgrids, with renewable energy sources and energy storage devices, employ agents so that each microgrid can choose to save or resell its stored energy in an open market in order to optimize its revenues.

A detailed review of the literature using ABM techniques for modeling smart grids from a system perspective is provided in [253]. For that purpose, it is provided a general classification regarding the application of ABM and simulation techniques to electricity systems.

A prototype ABM to examine the effects of the individual behaviour and social learning on patterns of electricity use is presented in [254]. This paper provides a holistic view on the electricity system considering technical aspects, human interaction, and framework policies. A flexible power system modelling tool using an agent-based approach to simulate smart grid paradigms, such as demand response, energy storage, retail markets, electric vehicles, and new automated distribution systems is present in [255].

An agent based approach to model zero energy communities is described in [209]. This paper details a conceptual ABM for an urban neighborhood to predict the behavior of households regarding the level of renewable energy usage in presence of multiple options. In this scope, an energy-efficient community where, on a source energy basis, the actual annual delivered energy is less than or equal to the on-site renewable exported energy, is called zero energy community [256].

In [257] it is modelled a community of residential prosumer agents that individually optimize the energy use to minimize energy costs and dissatisfaction. Each residential prosumer is modeled as an individual agent, with specific energy needs and preferences.

ABMs are well suited to study different investment decisions in electricity markets like generation, transmission and distribution level investments. In this scope, [258, 259] propose an ABM to identify strategic developments regarding investment amongst different players in the market based on the benefit that each player gets by setting up the assets in the system. The long-term impact of DR on generation adequacy in an energy market has been addressed in [260] with the help of an ABM. This work considers only the German electricity market and the estimated generation adequacy levels can drive new generation investments. However, with the expansion of interconnections and European electricity market coupling, the role of cross border exchange of electricity needs to be accounted for in the model.

3.4.2. Electricity market simulators using ABM

Electricity market simulators are used to model and simulate electricity markets. They are mostly agent-based, and they differ in the level of complexity and in the scenarios they are able to analyze. The following sub-sections presents some of the most known electricity market simulating models that use ABM.

3.4.2.1. Agent-Based Modeling of Electricity Systems, AMES

AMES is the acronym for Agent-Based Modeling of Electricity Systems, and it is an open-source agent based computational laboratory for the experimental study of wholesale power markets. It was originally developed in 2007 and it was specifically designed for the systematic exploration of strategic trading in restructured wholesale power markets operating AC transmission grids. The wholesale power market includes an ISO, load-serving entities, and generation companies, distributed across the nodes of the transmission grid. Each generation company agent uses stochastic RL to update the action choice probabilities currently assigned to the supply offers in its action domain. In addition, AMES facilitates augmenting the empirical input data with simulated input data to permit the study of a broader array of scenarios. Downloads, manuals, and tutorial information for all AMES version releases to date are accessible at the AMES homepage [261].

In [262], it is described the AMES framework, that models a wholesale power market which operated in accordance with Wholesale Power Market Platform features over a realistically reduced transmission grid subject to congestion effects. The traders within this market model a.re strategic profit-seeking agents whose learning behaviors are based on data from human-subject experiments.

3.4.2.2. Simulator for Electric Power Industry Agents, SEPIA

The Simulator for Electric Power Industry Agents (SEPIA) was developed in 2002 aiming at contributing to improve the efficiency of North American power network [263]. It was developed a bottom-up model and simulator which uses autonomous, adaptive agents to represent possible industrial components (e.g., generation units, transmission system, load) and the corporate entities that own these components.

According to the survey provided by Zhou et al. [264], SEPIA and its architecture display good results for electricity market systems. Its distinct features, which consist of its capability of adaptation, provided by both QL and genetic classifier learning modules, are highlighted as an advantage. Related with limitations, the survey mentioned the absence of an ISO agent. Also, the adaptation mechanism is restricted to generation companies and focuses on the bidding strategies although it could be extended to other decision-making levels.

The physical system structure is presented in Figure 3.13. and considers four assumptions:

a) Each defined zone represents a local region of the power system under analysis and each of them is modeled by a single bus;
b) Each *Generation Company*, with its loads, are limited to a specific local region;
c) Each zone has a *Generator of Last Resort*, which has unlimited power capacity. However, its generation cost will be much higher than that of the other generators;
d) It is assumed that the transmission capacity inside each zone is unlimited (within the same zone from a Generation Company to any Individual Consumer).

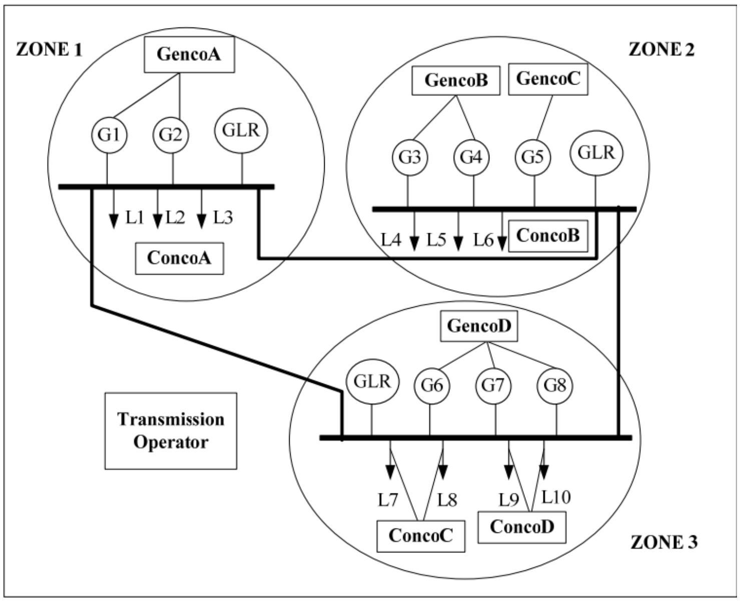

Figure 3.13. The Physical System Structures of SEPIA (source [265]).

All major markets participants in SEPIA are modeled as agents and interact with each other, such as Generation Companies (along with its generators), Generation of Last Resort, Consumer Loads, Consumer Companies (retailers including its consumers loads), and Transmission Operators. As previously mentioned, SEPIA does not include an ISO, which is an independent non-profit organization for coordinating, controlling and monitoring the regular operation of the power system.

Regarding the adaptation mechanism in SEPIA, both a QL module with Boltzmann selection and a genetic classifier learning module are designed to guide the Generation Company agents in making decisions [266]. These adaptation components are two complete and independent modules in SEPIA. The QL module in SEPIA tries to identify a promising action with the most rewarding result [264].

Figure 3.14. outlines the structure of the QL module in SEPIA, which uses the stochastic Boltzmann selection procedure in selecting possible actions for each state.

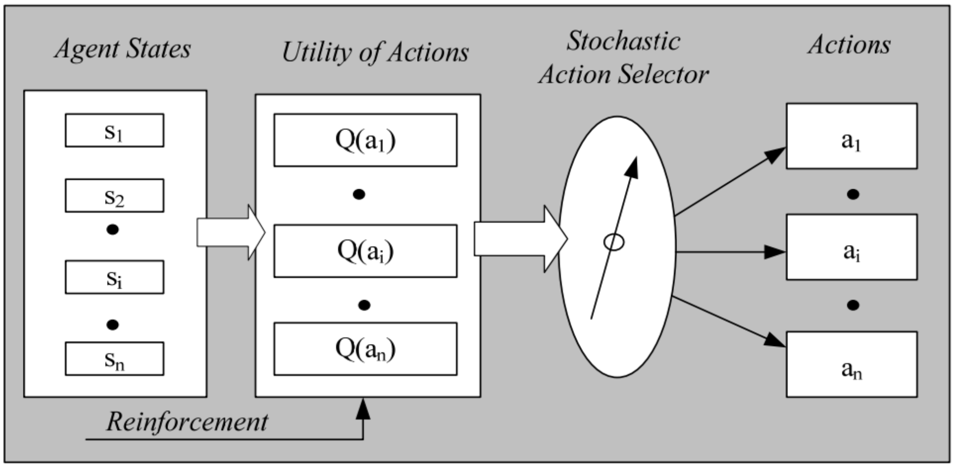

Figure 3.14. The Structure of the Q-Learning Module in SEPIA (source [264]).

The reward of *action a* as a function *Q(a)* is evaluated. Then, a stochastic selector based on the Boltzmann selection mechanism is used to choose a promising action. Usually, the higher the *Q(a)* value, the better is the chance that action *a* will be selected for a given state. However, because the learning algorithm also employs the annealing mechanism, as the process develops and the temperature decreases, it will tend to choose the action that has the highest Q value [264] thus progressively reducing the chances of selecting more diverse actions. Moreover, the QL module in SEPIA has a self-learning capability.

SEPIA also includes a Genetic Classifier-based Learning Module which includes three data sets (Rule Set, Match Set and Action Set) and four independent sub-modules (Genetic Algorithm, Matcher, Action Selector and Credit Assignment) as illustrated in Figure 3.15.

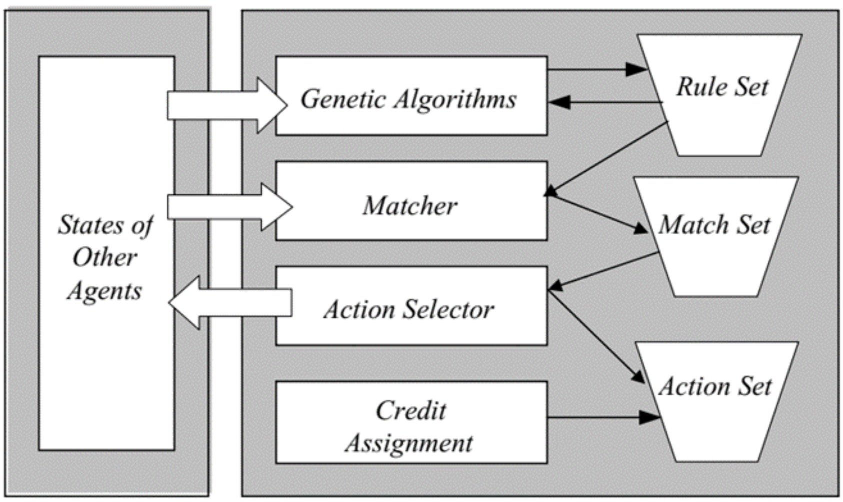

Figure 3.15. The Genetic Classifier Learning Module in SEPIA (source [264]).

The **set of rules** determines the knowledge base where each rule has a condition part that specifies an agent's current state, and an action part that specifies the consequent action the agent would take. Then, the rules with certain conditions satisfied are placed into a match set by the **matcher**. The **action selector** uses a stochastic selector based on the Boltzmann selection mechanism to choose a rule in the **match set** and then it implements the selected action. After the effects resulting from taking that action are cumulated and measured, a credit is assigned to the implemented rule in the **action set**. Finally, a Genetic Algorithm is used to optimize and update the rule set and the fitness of each rule is evaluated by its assigned credit.

According to the survey provided by Zhou et al. [264], SEPIA and its architecture display good results for electricity market simulation. Its distinct features correspond to its capability of adaptation provided by both the QL and the genetic classifier learning modules and are highlighted as relevant advantages. Related with limitations, the survey mentions the absence of an ISO agent. Also, the adaptation mechanism is restricted to generation companies and focuses on the bidding strategies although it could be extended to other decision-making levels.

3.4.2.3. Electricity Market Complex Adaptive Systems, EMCAS

The Electricity Market Complex Adaptive Systems (EMCAS) is a commercial tool developed by the Center for Energy, Environmental and Economic Systems Analysis at the Argonne National Lab Laboratory [267], which includes decentralized agent decision-making features along with learning and adaptation capabilities. This feature allows agents to learn from their previous experiences and change their behavior as future opportunities arise. That is, as the simulation progresses, agents can adapt their strategies based on the success or failure of previous efforts. This approach is especially suited to analyze electricity markets with many participants, each with their own objectives.

The modeling framework can be described in terms of three main components: agents, interaction layers, and planning periods. The agents represent the participants in the electricity market. The interaction layers correspond to the environment in which the agents reside and interact with each other. The planning periods correspond to the different time horizons for which the agents make decisions regarding their participation in the market [268].

In the simulation, different agents are used to model the full range of time scales and the entire value chain of restructured markets. EMCAS physical structure (Figure 3.16) is similar to SEPIA and it includes physical generators and generation companies, transmission companies, distribution companies, ISOs or Regional Transmission Operators when they exist, consumers, and regulators [269].

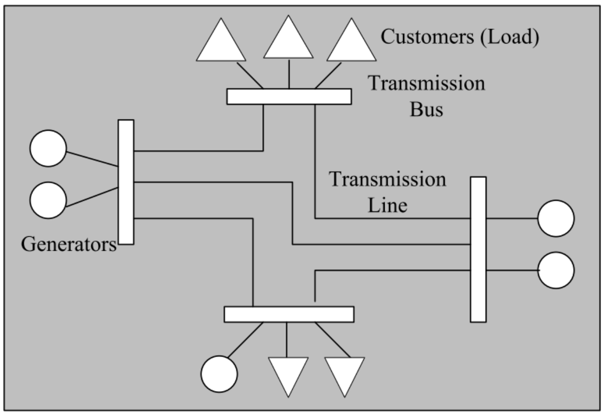

Figure 3.16. The Physical System Structures of EMCAS (source [264]).

The agents are specialized and perform diverse tasks using their own decision rules. A special feature of the agents is that they can learn and adapt based on past performance and changing conditions. Agents learn about the market and the actions of other agents using two forms of learning: observation-based learning and exploration-based learning.

The observation-based learning (Figure 3.17) goes through a structured process that includes the following steps:

- look back — to evaluate the past performance;
- look ahead — to project the future state of the electricity market;
- look sideways — to determine what others have done.

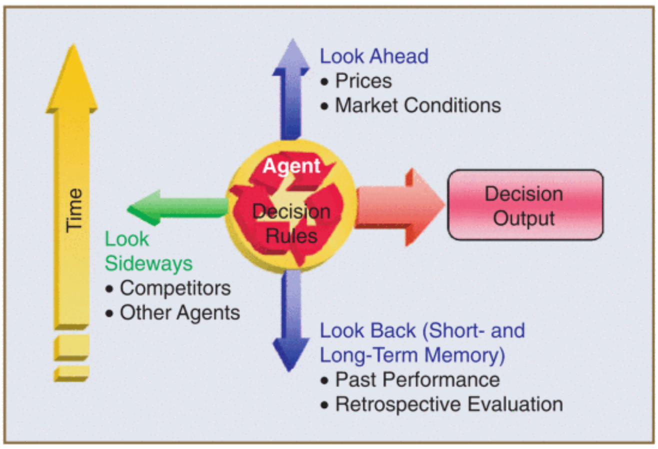

Figure 3.17. EMCAS' Agent observation-learning process (source [268]).

As a result of these evaluations, an agent can choose to 1) maintain the current strategy, 2) adjust the current strategy, or 3) switch to a new strategy.

EMCAS agents make informed decisions based on their past experiences and their expectations **- Look Back**. Whenever they make a decision, they will analyze the previous ones and come up with a better understanding of the factors that influenced their decisions. This method is also useful in analyzing the various types of trades offs (bid acceptation or rejection, unit utilizations and profitability, market versus bid price and weather versus load) that can be made in the market. It also takes into account various factors such as the availability of units, prices, and the weather when forecasting future results **- Look Ahead**. When it comes to analyzing the current conditions of the market, the agent often takes a **Look Sideways**. This strategy allows them to make informed decisions based on their own factors and the market's overall situation.

In the exploration-based learning scheme, the agent can identify various strategies that it can implement in the market. After the strategy has been selected, it is adjusted to reflect the changes in the market. If a strategy has failed, the agent may start to explore other options in an attempt to adapt its behavior to the changes brought about by the market. Even though a strategy may continue to perform well, the agent may still search for a better one. Through this process agents can identify their own potential influence in the market and improve their utility functions [268].

When compared with SEPIA, which has a self-learning mechanism for decision rules, the adaptation process in EMCAS is supported by pre-specified decision rules. Thus, agents in EMCAS have a lower adaptation capability than those in SEPIA. Moreover, the adaptation in EMCAS is restricted to Generation Company agents and to a smaller extent to Consumer agents. The main difference from SEPIA is the additional ISO/TSO agent. Bilateral contracts can be negotiated directly between generation companies and retailors or large consumers, or the bids can be submitted to the pool market managed by the ISO/TSO. All the transactions requiring the use of the transmission system are as well scheduled and dispatched by the ISO/TSO. The regulator is a special agent in EMCAS which has the responsibility for setting up market rules that should be obeyed by all participants in the electricity market.

The agents interact on several layers, including a physical layer, several business layers (namely related with the bilateral contract market, the pool market, and the transmission and retailers) and a regulatory layer as illustrated in Figure 3.18.

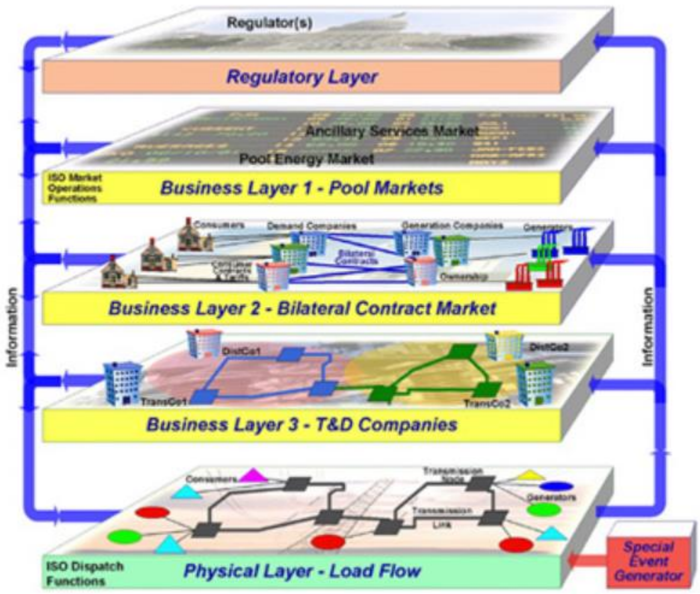

Figure 3.18. EMCAS multi-layer architecture (source [267]).

The bottom layer consists of physical elements (generators, transmission systems, distribution systems, and customer loads). In the physical layer, the ISO/TSO exercises its dispatch function to operate the system to match generation and load and to adjust to changes in load, generator or transmission outages, and other unplanned events. The ISO/TSO uses a transmission-constrained optimal power flow methodology to dispatch generators to meet the load. This part of the simulation relies on conventional power flow methods to ensure that the physical limitations of the system are observed.

In the pool market layer, Generation Companies' hourly offers are based on bidding strategies that are formulated for the entire day. The offer prices may vary as a function of the time of the day. Generation Companies use public information as well as private information to formulate their bidding strategies. A unit commitment algorithm is employed by Generation Companies to determine if units can be profitably operated at projected prices. Retailers also prepare bids into the pool energy market. They specify how much energy they are willing to purchase at a given price. In effect, their bids are formulated in terms of a demand curve. On the basis of bid prices, transmission constraints, and energy security considerations, the ISO/TSO accepts or rejects the bids it receives and establishes the schedule for the next day.

In the bilateral power market layer, bilateral contracts between Generation Companies and Retailers or large consumers are established. This process is similar to that of SEPIA, however in this last one only bilateral contract as a market option are allowed because SEPIA does not include an ISO or a pool market operator.

The third business layer, the transmission and distribution company layer, is designed to account for the ownership of the transmission and distribution systems and for the fees charged by these companies for the use of their assets.

The responsibility for preparing and monitoring bidding rules, bilateral contract rules, and settlement rules in the electricity market is assigned to the Regulator, which is included in the top layer. There is also an agent for special event generation, which allows EMCAS to become more realistic and its role is to generate contingent events such as fuel price increases, the change of customer loads, and generator or transmission outages.

Six distinct time scales or decision levels are considered in EMCAS, including hourly dispatch, and day-ahead, week-ahead, month-ahead, year-ahead, and multi-year planning (Figure 3.19):

- Hourly/Real-Time Dispatch: the dispatch of power plants is carried out according to the procedures established by the ISO/TSO. These procedures are carried out in line with the previous market arrangements made under bilateral contracts and in energy and ancillary service markets;
- Day-Ahead Planning: it begins with the agents determining the market allocations for their selling products. After the generation companies have prepared their unit commitment schedules, the demand side begins accepting offers for bilateral contracts;
- Week-ahead Planning: it allows the demand agents to make bilateral contracts with individual generation agents. These contracts are then sent to the ISO/TSO for approval. The day-ahead strategies can be modified in order to comply with the grid operation constraints;
- Month-ahead Planning: it involves monthly bilateral contracts involving demand and generation agents. These are sent to the ISO/TSO for approval. The week-ahead marketing strategy can be modified in this phase if necessary, in a similar way to what was mentioned in the Weak-ahead Planning level;
- Year-ahead Planning: in this level, month-ahead marketing strategies can be adjusted. It also allows the generation companies to plan their maintenance schedules;
- Multi-year-ahead-planning: in this level, year-ahead marketing strategies can be adjusted. System capacity expansion both at the generation and transmission levels or long-term planning can be done at this level.

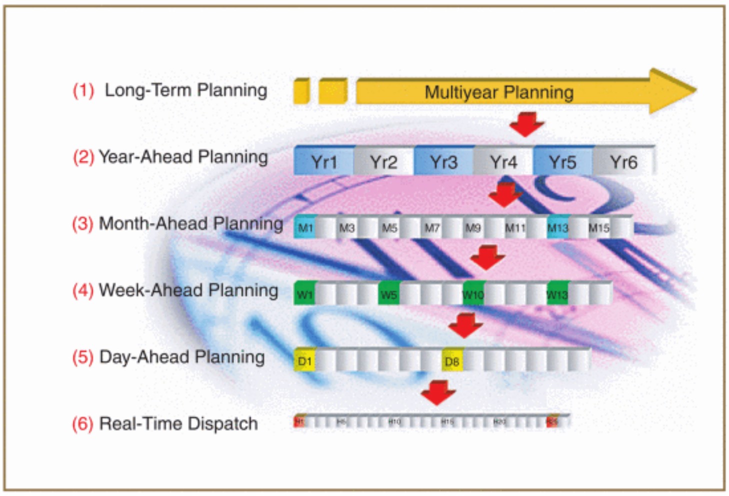

Figure 3.19. Planning periods (source [267]).

At each decision level, agents make their own decisions regarding their future activities. For instance, in the long-term planning stage, the generation companies commit to increase their capacity. Similarly, in the year-ahead planning phase, they establish their maintenance schedules. At day ahead, they bid into selected markets for each trading period of the next day. Each agent has their own set of decisions that they can make at different planning levels. It is clear that their decisions made at long time periods can have an impact on their shorter time horizons.

In spite of the existence of several references to ABM applied to power systems, the available models do not adequately consider a number of features that are common in several power systems such as the large presence of hydro stations and the possibility of pumping, as well as the large share of zero or near zero marginal cost technologies using renewable primary resources as wind and solar. In these cases, the short-term bidding decisions and strategies should coordinate with a longer-term vision or plan. In this sense, in [270] it is described the integration of EMCAS, with a hydro-thermal coordination model, VALORAGUA.

VALORAGUA has been in use for several decades as a hydro-thermal coordination model with the objective of optimizing the overall system operation over a period of up to 1 year. It establishes the optimal operation strategy for a given power system using the "value of water" concept, in each power station, for each time interval (i.e., month/week) and for each hydrological condition. The model optimizes the operation of hydro and pumped-storage power plants, computes thermal-based power generation emissions, and optimizes the maintenance schedule of power plants. The objective function minimizes the overall system operating cost based on the calculated expected value of the water in each time period (52 weeks). This model takes into account the system configuration, projected loads, thermal and renewable capacity, reservoir characteristics, hydro cascading, and historical water in-flows and it generates weekly schedules for each of the hydro power plants based on stochastic dynamic programming and non-linear programming-based algorithms.

VALORAGUA is often used to [271]:

- analyze energy import/export contracts;
- maximize power generation revenues;
- manage the long-term water stored in reservoirs with regulating capability;
- obtain a better use of the water in a multi-purpose scheme, considering its operation constraints [271].

A comprehensive description of the main characteristics and capabilities of VALORAGUA is provided in [272]. On the other hand, [270] provides a comprehensive overview about the integration between EMCAS and VALORAGUA.

3.4.2.4. Short-Term Electricity Market Simulator - Real Time, STEMS-RT

The Short-Term Electricity Market Simulator - Real Time (STEMS-RT) was developed by the Electric Power Research Institute. Each bidding process in STEMS-RT runs for several rounds. In each round, an agent submits bids according to the public information from the Market and the bidding results from previous rounds. Usually, the suppliers (Generation Companies) in STEMS-RT use two bidding strategies. In the first strategy, generation companies bid all the production capacity at the marginal cost (conservative approach). The other strategy tries to maximize the profit on a short-term basis (ambitious approach). The consumers use only one strategy, which is to bid the willing-to-pay price.

The STEMS-RT architecture consists of three layers: Application, Modeling, and Solvers as illustrated in Figure 3.20.

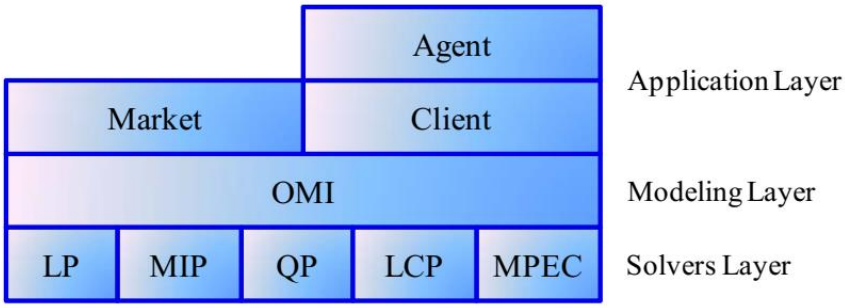

Figure 3.20. Three Layered STEMS-RT System Architecture (source [264]).

There are three types of applications in the Application Layer. The Market Application, which handles the decisions related to accepting or rejecting the bids submitted by computer or human agents. It allows the participants to submit their proposals and receive the results. The Client Application provides interfaces for human participants to submit their bids to the market and to receive the bidding acceptance results. The Agent Application helps the computer agent to make the best decisions based on the previous results and the market clearing issues.

The Optimization Modeling Interface supports the modeling layer. It is in his layer where models can be created in order to solve market clearing problems for market applications and problems on bidding strategies for agent applications. The mathematical models built in the modeling layer can be solved in the Solver Layer, which includes tools to solve LP problems, MIP problems, Quadratic Programing problems, Linear Complementarity problems, and Mathematical Programs with Equilibrium Constraints.

Agents in STEMS-RT utilize mathematical programming to solve bidding problems. New strategies can also be added, and their effects analyzed, though it does not have an ISO agent and demand companies and transmission operators as agents. Another disadvantage of this system is that it does not have an adaptation process that can be used by each agent.

3.4.2.5. National Electricity Market Simulator, NEMSIM

The National Electricity Market Simulator (NEMSIM) is an agent-based simulation model that represents the Australia National Electricity Market, as an evolving system of complex interactions between human behavior in markets, technical infrastructures and the natural environment. The structure of NEMSIM is displayed in Figure 3.21. [273].

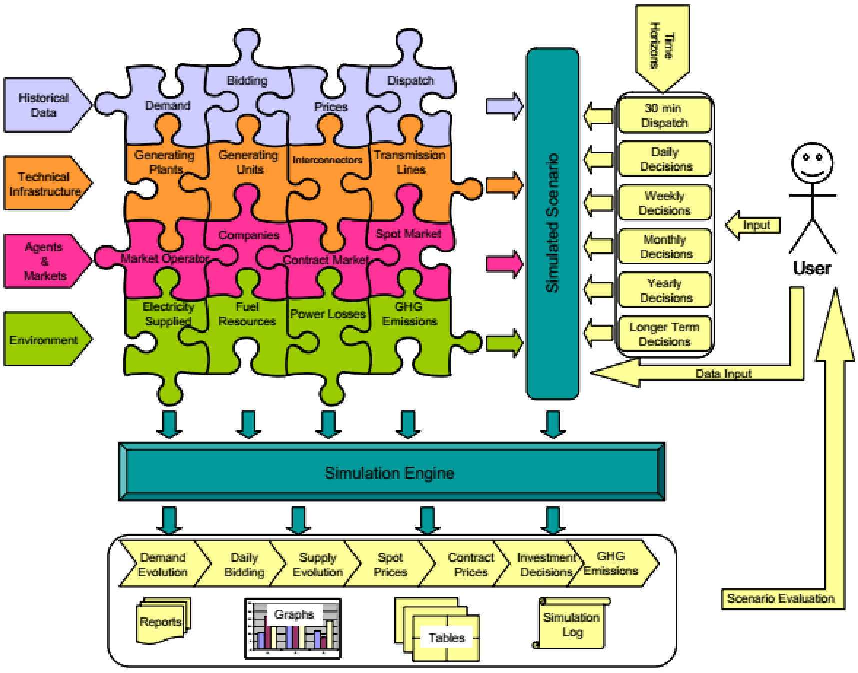

Figure 3.21. NEMSIM overview structure (source [273]).

Its physical configuration (technical infrastructures) consists of generating plants, inter-connectors, and transmission lines. Each physical element has its own technical or operational attributes. The agents defined in NEMSIM include Generation Companies, Network Service Providers, Retail Companies and a Market Operator, which buys and sells electricity in a simulation trading environment. The model is designed to examine scenarios using companies' bidding practices, bilateral inputs of generator financial contracts, transmission network limitations and new investment in generating plants and transmission lines. Regional demand for electricity is based on historical demand patterns and can be changed to accommodate growth forecasts and exceptional weather conditions. A Market Operator agent clears the market to ensure that demand is always met within every 30 minutes (the market-clearing trading interval). In the short term, NEMSIM can solve problems to help generation companies to improve their bidding strategies. Retailers can use NEMSIM to inform their decisions on medium-term contracts with power generators. They can reduce their exposure to short- term price volatility or wholesale price rises by signing contracts for fixed-price bulk power allocations. NEMSIM is also a useful modelling tool for power-generation companies to schedule investments in extra generation capacity or network upgrades to accommodate growing demand, or changing demand patterns [273].

Summarizing, NEMSIM considers all the important system participants in the Australian electricity market allowing each agent behavior to be modeled. Functions of the pool market in NEMSIM can be extended to the bilateral contract market. It is also possible to investigate and compare the operation of the system considering new scenarios such as the connection of new plants, the definition of maintenance schedules, the specification of new market rules, and the modelling of special events. Short-term trading, medium-term contract market, long-term investment, environmental issues such as the estimation of greenhouse gas emission, are also studied in NEMSIM. However, and because NEMSIM is designed particularly for the Australia electricity market, its extensions to other markets would require significant modifications.

3.4.2.6. Multi Agent Simulator of Competitive Electricity Markets, MASCEM

The Multi Agent Simulator of Competitive Electricity Markets (MASCEM) is multi-agent platform, developed in the Polytechnic Institute of Porto, Portugal [274] to study competitive electricity markets, that includes independent agents with their own ability to perceive the states and changes in the world and to act accordingly. These agents are provided with bidding strategies, which must be adequate and refined to let them gain the highest possible advantage from each market context. So, they can adapt their strategies based on the success or failure of previous experiences and, in each situation, they can adapt their behavior according to the present context and using the dynamically updated detained knowledge. Figure 3.22 illustrates MASCEM's most important features, such as the ability to simulate several types of negotiation platforms that exist in electricity markets, the consideration of algorithms to define bid prices and the inclusion of distributed generation. Also, important features such as power flow analysis and scenarios definition based on real data are also available.

The Market Operator agent is responsible for managing the pool negotiations. It uses various algorithms to determine the optimal conditions for the negotiation. It also handles other administration functions such as receiving selling and buying proposals from consumers and generators. It informs the pool members about the market price and establishes an economical dispatch.

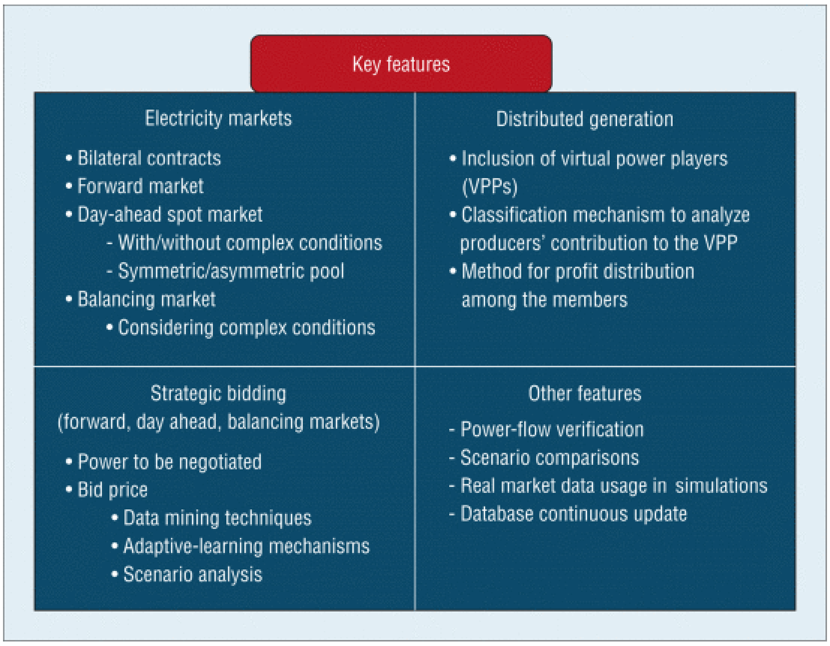

Figure 3.22. MASCEM key features (source [274]).

The seller agents usually include generation and distribution companies. They compete with each other in order to maximize their profits. On the other hand, buyer agents are usually composed of electricity consumers or distribution companies, in cases where the unbundling between retailing and distribution network activities was not implemented.

There are also agents that act as market independent entities. For instance, the System Operator checks the economic dispatch through a power flow analysis to evaluate eventual technical problems that can affect power system operation.

The MASCEM platform also allows considering VPP agents. They represent a set of producers, mainly based on distributed generation and renewable sources. They can provide the means to adequately support distributed generation increasing use and its participation in the context of competitive electricity markets. Virtual Power Player agents are implemented as a coalition of agents, each one acting as an independent multiagent system [275].

Chapter 4

4. Problem Description and Proposed Model

Energy Communities provide an emerging mode of negotiating and exchanging energy that defy the traditional hierarchy based on vertical agreements involving energy providers, retailers and consumers. Regarding the significant number of prosumers, the penetration of local energy generation, and the concept associated to Energy Communities, it is becoming important to develop decision tools to support energy transactions among Energy Community agents and between the communities themselves and the Wholesale Market. Local Electricity Markets (LEM) associated with Energy Communities and more specifically with RECs are fostering new optimization models to enable the development of strategies regarding the increase of community energy savings and profits.

In this scope, this chapter details Energy Communities business models and presents the structure of the model that was developed. It is presented an ABM as a decision tool to support energy transactions between the LEM and the Wholesale Market (WSM). The proposed simulation model will help community agents (consumers, prosumers and producers) to adequate their bids by running several scenarios. In this chapter, the developed ABM will be fully described as well as the interaction of the local community local market with the Wholesale Market.

4.1. Energy Community's business models

As detailed in Section 2.2, REC and CEC definitions describe energy communities as non-commercial legal entities, based on the open and voluntary participation of their members, which can be householders, public authorities and small and medium-sized enterprises, provided that their main activity is not energy-relate. Community members must be fully or partially involved in daily decision-making and operation control, and the potential revenues that will be attained must be used to provide local services/benefits. However, these definitions diverge in what concerns the following items [276]:

- the geographical scope, since REC requires participants to be in the vicinity of renewable projects, while CEC does not set physical boundaries or constraints;
- the activities performed, as CEC comprises generation even not from renewable sources, distribution, supply, consumption, aggregation, energy storage, EV charging, energy efficiency and other energy services, while REC promotes the engagement into generation, trading, storage and supply of energy from renewable sources;
- the generation technologies, since REC only allows the use of renewable technologies whereas CEC are technology-neutral, meaning that both renewable and fossil-based technologies are acceptable under this concept.

Before the energy market liberalization, the monopolistic utilities' value proposition was based on providing an undifferentiated commodity to a broad segment of customers. The unbundling of traditional vertically integrated utilities together with the increase of renewable-based decentralized generation imposed changes on the Business Models of classical utilities, allowing smaller energy retailers to develop and offer innovative electricity supply packages, making room for new Energy Business Models to emerge. Reis et al. [276] addresses Energy Business Models over different perspectives:

- The Customer-side business models, which are based on the direct purchase of energy technologies by end-users, to become prosumers. The 'all sold to the grid' or 'self-consumption with surplus sold to the grid' modes may be exploited, allowing the full injection of the generated power into the grid or self-consumption and surplus injection, respectively. Also Demand Side Management programs, eventually put in place by Distribution System Operators, DSO, or by retailers or eventually activated by these two types of agents in conjunction, could also be explored as a way to help managing and operating distribution networks;
- The Third-party-side business models, fully financed by third-party companies, generally utilities, which keep the assets control and ownership and bear all the related costs and risks. Renewable generation assets are installed either on customers' roofs and backyards or in the vicinity of consumption sites when space is constrained. This allows increasing the generation close to end consumers thus reducing the liquid demand seen by distribution networks which would contribute to improve their operation performance in terms of reducing losses and get a better voltage profile and also eventually reducing or postponing reinforcement and expansion network requirements;
- The Energy Community business models, where all the members should be considered in the overall arrangement design, implementation and operation. As advocated by the European Directives, Energy Community Business Models 'key activities' include local

generation, supply, storage, consumption, trading, aggregation, e-mobility and energy related services, as well as system administration.

Most energy communities have been primarily involved in local generation and self-consumption due to the longstanding tradition of these initiatives in Northern European countries [277]. However, and regarding the evolution of technology and energy exchange platforms, the sharing and selling activities in collective buildings were boosted, allowing to optimize the utilization of local energy resources, to maximize the community members' economic benefits and underpin the deployment of LEM. In addition, the 2019 Electricity Market Directive [7] opened room for Member-States to grant communities the right to own, establish, purchase or lease the distribution network in their area of operation [7]. As stated by Reis et al. [276], Energy Communities may, therefore, become local DSO, under the general or the "closed distribution system operator" regime, meaning that the community becomes responsible for "ensuring the long-term ability of the system to meet reasonable demands for the distribution of electricity, for operating, maintaining and developing under economic conditions a secure, reliable and efficient electricity distribution system in its area with due regard for the environment and energy efficiency" [7].

In view of these ideas, this work is directed to an electricity market design and simulation tool considering community energy sharing concepts where agents are responsible for the planning of the energy transactions between consumers and prosumers. Any member of the community can buy and sell its electricity within the community boundaries considering different regulatory and grid tariff designs. The simulation of these different operation cases will enable getting insights on the economic viability of this business model (as will be detailed in simulations to be described and discussed in Chapter 6). In fact, the developed model is flexible enough to accommodate different tariff designs including the possible exemption of the Costs of General Economic Interest, (CIEG in Portuguese) [278], that are included in the Access grid tariffs in force in Portugal or the non-payment of HV and MV grid tariffs [49, 279]. This will allow running several simulations in order to get information about the eventual need of some sort of support schemes in order to turn the energy communities viable. In order to complete this model and given that in some periods there may exist excess or deficit of local generation over the community demand, the developed model also addresses the interaction of the community with the centralized wholesale electricity market.

4.2. Overview of the proposed market design

As reviewed in Chapter 3, in Agent-Based Modelling the system is modelled as collections of rule-based agents interacting with one another dynamically and intelligently, simulating the behavior of human beings in order to build optimal bidding strategies. Agents can interact with each other directly or through the environment, resulting in a complex emergent global behavior of dynamic-equilibrium and adaptation. Agents can also emulate the behavior of different entities as, for instance, generation, demand, and retailing entities.

In this work, the market participants will be modeled as adaptive **agents** with different bidding preferences and strategies. The optimal bidding strategy will be developed by each agent, by learning from its past experiences obtained from the direct interaction with the environment. The market mechanism design used in this work is illustrated in Figure 4.1.

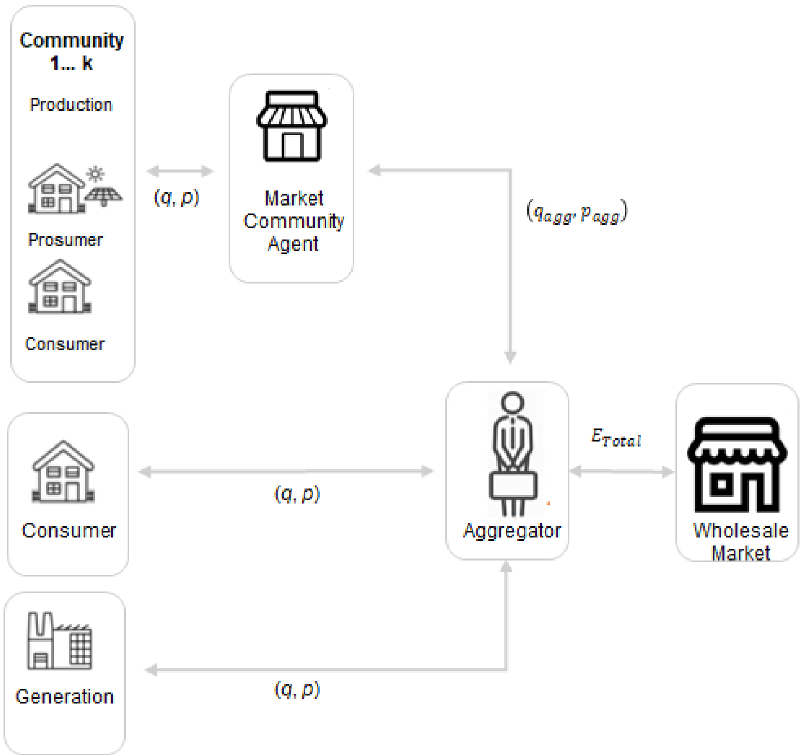

Figure 4.1. Energy Community market design

The proposed structure considers an Energy Community constituted by different types of agents, such as consumers, or prosumers agents. Each of these agents, submit their bids (quantities q and price *p*) to a **Market Community Agent** which is in charge of maximizing the Energy Community self-energy consumption and the profit in consequence of selling the energy surplus. This agent is considered as an **artifact**, since it will be utilized to carry out Energy Community Agents' activities in a competitive or cooperative manner. It will receive bids from the Energy Community Agents and perform a set of operations developed according to pre-defined rules along the simulation and aiming at obtaining a schedule for each trading period. In more complex structures, several Market Community Agents could be considered.

The developed framework considers that the Community energy deficit or surplus in each trading period will be traded between the Market Community Agent and an **Aggregator** through a bilateral contract. In the developed model real data of PV generation and demand profile will be considered and detailed in Chapter 6.

The Aggregator operates as a traditional retailer regarding the market clearing mechanism in the **WSM**. It will gather the information about the energy deficit or excess from the Market Community Agent together with the estimates from demand and generation from entities not included in the Community under analysis. After having the mentioned information for each trading period, the Aggregator communicates the buying or selling bids to the Wholesale Market as a way to balance supply and demand in the community.

Regarding the coordination mechanism to integrate the Local Energy Community Market, LEM, into the existing Wholesale Market, Figure 4.2. presents the diagram, adapted from [280], that details the sequence of activities developed by each entity. The initial trading is done locally followed by the trading in the WSM. The Aggregator receives the quantities to buy and sell in the WSM and sends back the cleared hourly prices to the Market Community Agent. The obtained values will be considered in the optimization model of the community in an hourly basis. In order to encourage the participation of local agents in the local trading at the LEM, the electricity price of LEM is determined by the energy sold by prosumer agents, the energy bought by all the community members, and the electricity produced by PV panels installed in the community.

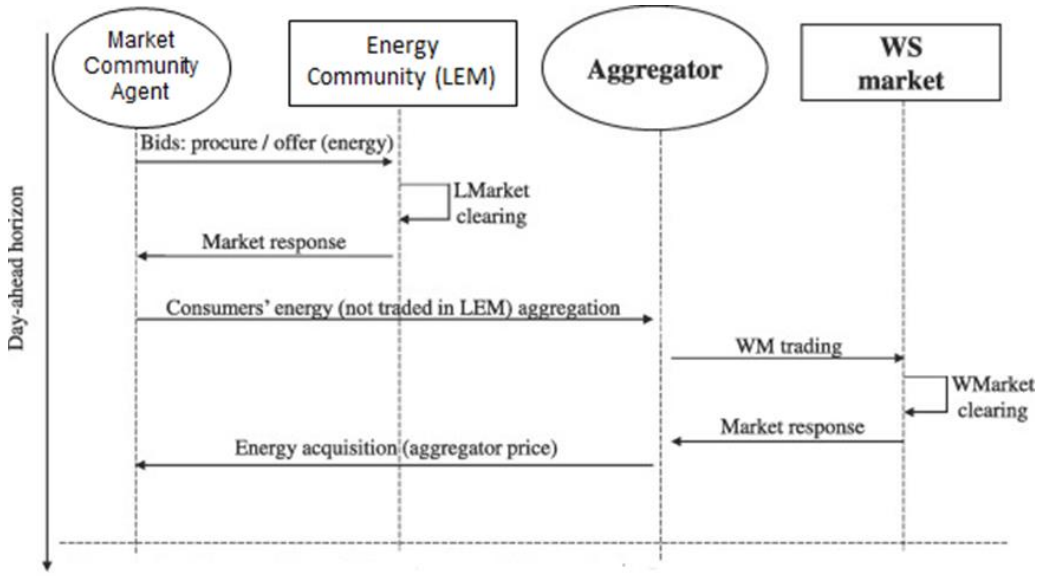

Figure 4.2. Sequential diagram of Energy Community market with wholesale market integration

Figure 4.2. illustrates the sequential interactions between the LEM, the Aggregator and the WSM in a day-ahead time horizon. The market agents will present buying and selling hourly bids that cover all 24 hours of the next day. The market gate closure in the Day-ahead market will be before noon.

The initial trading is done locally, which results in a Local Market Clearing that jointly with the energy traded outside the community, determines the quantities to buy and sell in the WSM. This is done via the Aggregator which assumes the role of a retailer and that behaves as a price-taker, i.e., assuming that its bidding decisions do not affect the clearing prices of the WSM. After the submission of demand and supply bids by the Aggregator to the day-ahead energy market, the Wholesale Market is cleared. The cleared hourly quantities and prices are sent back to the Market Community Agent through the Aggregator Agent. The obtained values will be considered in the optimization model of the community which will be detailed in the following sections.

In this sense, the problem formulation cannot be translated into a single mathematical global formulation. The next sections will address the model construction and the agent's definition used in the scope of the electricity market model considered in this framework.

4.3. Local Energy Market Agent-Based Model

4.3.1. General Aspects

The developed ABM incorporates the LEM concept since this is well suited to address the Energy Communities main purposes. These mechanisms can induce investments in renewable energy sources, can improve the integration of RES into the energy system, and can contribute to empower local communities by increasing the participation of local agents as well as the awareness of local consumers to the energy problems [281].

In this work, the **Market Community Agent** is in charge of guaranteeing the supply of the community demand, maximizing the profits resulting from the reduction of the generation cost, the increase of self-consumption, and of selling the energy surplus in the Wholesale Market. The backup energy will be provided by the **Aggregator Agent** through the WSM, if the energy traded in the LEM is insufficient to satisfy the local demand of the Community. The players in the LEM will put bids (C^{Bid}) with a minimum guaranteed price defined according to a bilateral contract that includes the price paid to the renewable PV generation (C^{PV}). In order to guarantee that the LEM favors local transactions rather than buying electricity from the grid, this price should be lower than the aggregator tariff ($C^{PV} < C^{agg}$).

The above indications mean that when there is energy deficit at the community, the community buys electricity from the grid at the WSM price (C^{agg}). When there is surplus of electricity in the community and after considering self-consumption, the LEM has a minimum ensured price that corresponds to the C^{PV} associated to the PV technology. However, in order to increase the revenues from selling this excess, the ABM will try to increase the selling price as close as possible to the WSM price. If the LEM price gets higher than the WSM, that would mean that the selling bid of this excess would not be accepted at the WSM and therefore this amount is sold at the minimum ensured price, that is, at the C^{PV} value.

The following assumptions are also considered in this model:

a) There is a geographically distinct and close community of residential prosumer and consumer agents. It will be possible for them to trade their electricity within the community boundaries, eventually exempting them from paying some tariff components related with LV, MV or HV access tariffs (admitting that all the participants are connected to the same private busbar and don't use the public electrical grid for self-consumption purposes), at least in some time periods namely when the generation in the community is enough to balance the local demand. However, the developed model is flexible enough to consider other regulatory and tariff options, as detailed in Chapter 5 and Chapter 6, in order to get insights about the economic feasibility of this business case;

b) It will be assumed that energy community agents are equipped with adequate infrastructure, namely communications and home energy management devices;
c) It is also assumed that the aggregator operates under the power limits established by the DSO which guarantees the operation of the grid, without violating network voltage limits and branch flow constraints.

In order to simulate the proposed LEM, two types of agents are considered, namely consumers and prosumers, in this case corresponding to consumers with PV generation or consumer installations equipped with storage units, as it will be detailed in Chapter 5. As detailed in Figure 4.2, the initial trading is done locally followed by an interaction with the WSM. The achieved results, namely the combination of the marginal prices of the LEM and of the WSM will be considered in the decision-making mechanism that will be implemented in the communities in order to plan the exchanges with the WSM.

4.3.2. Community Agents

The **Consumer Agents** are those who do not have their own generation units and thus depend on trading and on the grid for their electricity supply.

Prosumer Agents are always aiming at benefiting the community by making the best use of the energy resources available. In this model, prosumers with a PV system will be considered. The marginal cost function of the PV generation (c_{PV}^{m}) has a price paid to the renewable PV.

The **Market Community Agent** is responsible for the local electricity pool market clearing. It receives bids and offers from community agents (prosumers and consumers agents) on a one-hour time-slot and based on the local PV generation and expected demand.

To ensure the balance of the community system, constraint (4.1) must be held for every time slot.

$$(P_{PV,t}^{i} + P_{Grid,t}^{i}) - (P_{L,t}^{i} + P_{C,t}^{i}) = 0 \tag{4.1}$$

In the previous expression:

- in case the agent i is a prosumer, $P_{L,t}^{i}$ and $P_{PV,t}^{i}$ are respectively its demand and PV generation at time slot *t*;
- in case the agent i is a consumer, $P_{C,t}^{i}$ represents its demand at time slot *t*;
- $P_{Grid,t}^{i}$ is the power exchanged with the grid at time slot *t*. This power is considered positive if it flows from the main grid in the local community. It is negative otherwise.

The representation of the net load of the community agent *i* either being a prosumer or a consumer at time slot *t* is given by NP_t^i (Equation 4.2.)

$$NP_t^i = (P_{L,t}^i + P_{C,t}^i) - P_{PV,t}^i \tag{4.2}$$

If $\sum_{i=1}^{N} NP_t^i < 0$, the community has a surplus of PV generation that will be used to trade between the Market Community Agent and an Aggregator. If $\sum_{i=1}^{N} NP_t^i \geq 0$ the energy is insufficient to satisfy the local demand of the Community and this deficit will be provided by the Aggregator Agent through the WSM. So, the developed framework considers that the Community energy deficit or surplus in each trading period will be traded between the Market Community Agent and an Aggregator through a bilateral contract. Once this information is received, the pricing strategy is updated for the next round. In this sense, the community optimization model is changed every hour and established by local generation and demand profile. Its strategy is based on the comparison between the WSM and the LEM prices (one hour time slot price). The iterative procedure will be detailed in Section 4.6.

4.4. Aggregator Agent Based Model and Wholesale Energy Market

As illustrated in Figures 4.1 and 4.2, the Aggregator Agent of the Community interacts with the Market Community Agent and with traditional agents that participate in the WSM. It has the role of a traditional retailer but also as an intermediary between Market Community Agents. As presented in Figure 4.2, it is in charge of informing the agents about the bids that were accepted in the Wholesale Market and returning the cleared values to the local market.

The retailer/aggregator price (C^{agg}) obtained in the WSM day-ahead spot market, will be taken in consideration in the optimization decision process of the community. The Aggregator Agent, after having the market clearing price for each trading period of the next day, on a one-hour basis, interacts with the market community agent and the optimization model starts. The community optimization model is changed every hour considering the local generation and the local demand profile.

In this work, it will only be considered the day ahead market of the WSM that is the intraday discrete and continuous markets were not considered. It is divided into the day-ahead, intraday and continuous intraday market exchanges. Typically, the day-ahead energy market is a double-sided Uniform Price Auction, where demand agents submit bids to buy energy and supply agents submit bids to sell energy. An alternative auction design is a Pay-as-Bid framework, where generators sell the cleared quantity at the offered bid price (the same is applicable to the demand-side). Once the day-ahead energy market is cleared, the Market Operator adds the physical bilateral contracts to the cleared offers. Afterwards, the Market Operator and/or the System Operator performs congestion management to generate feasible daily schedules [282].

The discrete intraday markets are similar to the day-ahead energy markets and the main difference is the gate closure. They follow the day-ahead session being usually activated at the end of day n-1 and continuing along day n, the delivery day, and work as adjustment markets, i.e., the market agents can correct accepted bids from the day-ahead market.

The continuous intraday market has the purpose of facilitating energy trade between different bidding zones of Europe in a continuous manner and increase the overall efficiency of transactions in intraday markets throughout Europe.

In this work a day-ahead energy market model similar to the Iberian Electricity Market, MIBEL, was considered. It is a double-sided auction, where market agents submit energy hourly bids for the 24 hours of the next day. Market participants submit energy bids to the power exchange until 12.00 hour. The bid prices can range from -500 €/MWh to 3 000 €/MWh, with minimum price increments of 0.1 €/MWh. The energy bids of MIBEL and other markets are collected and submitted to the EUPHEMIA platform (European market solver [283]). The EUPHEMIA clears the offers (MWh) and prices (€/MWh) such that the social welfare is maximized and the power flow limits between the European bidding areas are not exceeded. The clearing prices and quantities are published at the 13.00 hour. Market-based or technical-based TSO mechanisms are also activated if network problems are detected inside each trading area.

4.5. Agents Environment in the implemented model

The environment is defined as the part of the system within which the agents operate. As mentioned in Section 3.2.1, the complexity of an ABM can be driven by its environment and the most complex ones are those that are partially observable, stochastic, sequential, dynamic, continuous and multi-agent.

In this work, the day-ahead spot market is simulated in a way that the environment definition is simplified. As mentioned in the previous sections, the prosumers (with PV systems) and consumer agents will bid on their energy and price in the LEM and receive only information on the clearing price and if their bids were cleared or not. The Market Community Agent purchases the energy to balance the Energy Community electricity deficit from the Aggregator Agent and sells the excess electricity considering specified price limits. The Aggregator receives all the bids (from Market Community Agent and all other agents that participate in the WSM) and gets from the WSM the market clearing price for each trading period of the next day. The decision process in this environment will be based on the WSM price and on the LEM price.

In terms of the classification of this environment, it can be considered as:

- Partially Observable, as the agents have access to a partial state of the environment at each point of time, namely the market clearing price for each trading period;
- Stochastic, because the next state in which the environment will reside is not completely determined by the current state. So, there is no certainty about the state that results after performing a specific action. Agents don´t know if their actions will lead or not to a clearing in the market;
- Sequential because current actions will affect future decisions. This means that the performance of an agent depends on a number of discrete episodes, which are associated with the several trading hours and days of the WSM day-ahead market and the trading periods of the LEM;
- Static because the environment remains unchanged except by the performance of the actions taken by the agents;
- Continuous, because there is an infinite number of actions and percepts on the environment which are represented by the hourly decisions of the agents through the environment;
- Multi-agent because there is more than one agent operating in the environment.

4.6. Utility Function

As mentioned in Chapter 3, in the ABM, market participants are modeled as adaptive agents with different bidding preferences and strategies. On the other hand, they are enabled to utilize their past experience to improve their behaviors. This implies that the tasks to be carried out must be specified by the user in some way. One way of doing this is to select tasks indirectly via some kind of performance measure.

A utility function is a numeric representation of how good some sort of possible residence state of a system under analysis is. It is the main driver for decision making problems and it allows each agent to rank its decisions and make choices. This function can therefore be used to determine if the agent should continue in its current course of action or should seek to change its behavior and to adapt. Each agent seeks to maximize its own utility function derived from the rewards he can obtain from its possible actions and can combine multiple objectives. So, the Agent-Based modelization allows each agent to have a set of personal objectives, such as profit, risk exposure, market share, etc. [14].

In the proposed framework, the LEM could return surplus energy to their agents. It is also possible to sell energy (C^{Bid}) at a higher price than the bilateral contract price associated to the PV generation (C^{PV}) but lower than the WSM price (C^{agg}) ($C^{PV} < C^{Bid} < C^{agg}$). This means that it is defined that $C^{PV} < C^{agg}$ to guarantee that LEM favors local transactions rather than buying energy from the grid. In order to encourage the participation of local agents in the local trading at the LEM, the electricity price of LEM is determined by the energy sold by prosumer agents, the energy bought by all the community members, and the electricity produced by the PV panels in the community.

After defining the Bid Price (C^{Bid}), the Market Community Agent calculates the Utility Function, that consists of the ratio between C^{Bid} and C^{PV}. The higher this ratio is, the higher will be the community profits by applying the optimization model. If the WSM price (C^{agg}) is lower than C^{PV}, the Market Community Agent will receive the guaranteed reward defined by the bilateral contract, that is C^{PV}. Otherwise, and if the C^{Bid} is lower than the C^{agg} and higher than C^{PV}, the reward will be equal to the difference between C^{Bid} and C^{PV}.

The ratio presented in Equation 4.3 represents the Utility function of the Market Community Agent.

$$U = \frac{\mathrm{C}^{Bid}\,(t)}{\mathrm{C}^{PV}(t)} \tag{4.3}$$

The higher this ratio is, the higher will be community profits by application of the optimization model. This formulation between two consecutive periods is related with the state's definition of the Markov Decision Process and with the Q-Learning procedure that will be detailed in the next section.

Regarding the previous explanation, the bidding strategy defined in this work follows the iterative procedure illustrated in Figure 4.3.

The iterative procedure considers the community electricity balance, taking into account the demand (if the agent is a consumer) and the demand and PV generation (if the agent is a prosumer). If the community demand is higher than the local production, the Market Community Agent buys electricity at the WSM price (C^{agg}). In other hand, and if the balance is negative (i.e., production higher than consumption), the selling process starts with the definition of the Bid Price ($C^{Bid,i}$) that the Market Community Agent communicates to the Aggregator. At this moment, the Utility Function is calculated using (4.3). As previously explained, the Bid Price ($C^{Bid,i}$) is the Bid Price offer that the Market Community Agent uses to sell the energy surplus in the WSM (through the Aggregator).

In order to get the reward that will be obtained during the surplus selling process, the following considerations will be taken into account:

- If $C^{agg} < C^{PV}$, the energy surplus will be sold at the guarantee bilateral contract price (C^{PV}). In the same way, and if the Bid Price ($C^{Bid,i}$) is lower than the bilateral contract price (C^{PV}), it will be sold at C^{PV} price.
- If the Bid Price ($C^{Bid,i}$) is higher than the bilateral contract price (C^{PV}) and lower than the WSM price (C^{agg}), the energy surplus will be sold at the defined Bid Price ($C^{Bid,i}$). In this case, the Market Community Agent will have a reward r_m that will be equal to the difference between the Bid Price ($C^{Bid,i}$) and the bilateral contract price (C^{PV}).

This is an iterative process and the Market Community Agent will try to increase the selling price as close as possible to the WSM price and in this sense have a higher reward. This process, namely the definition of the action and agent state's definition will be detailed in the next sections.

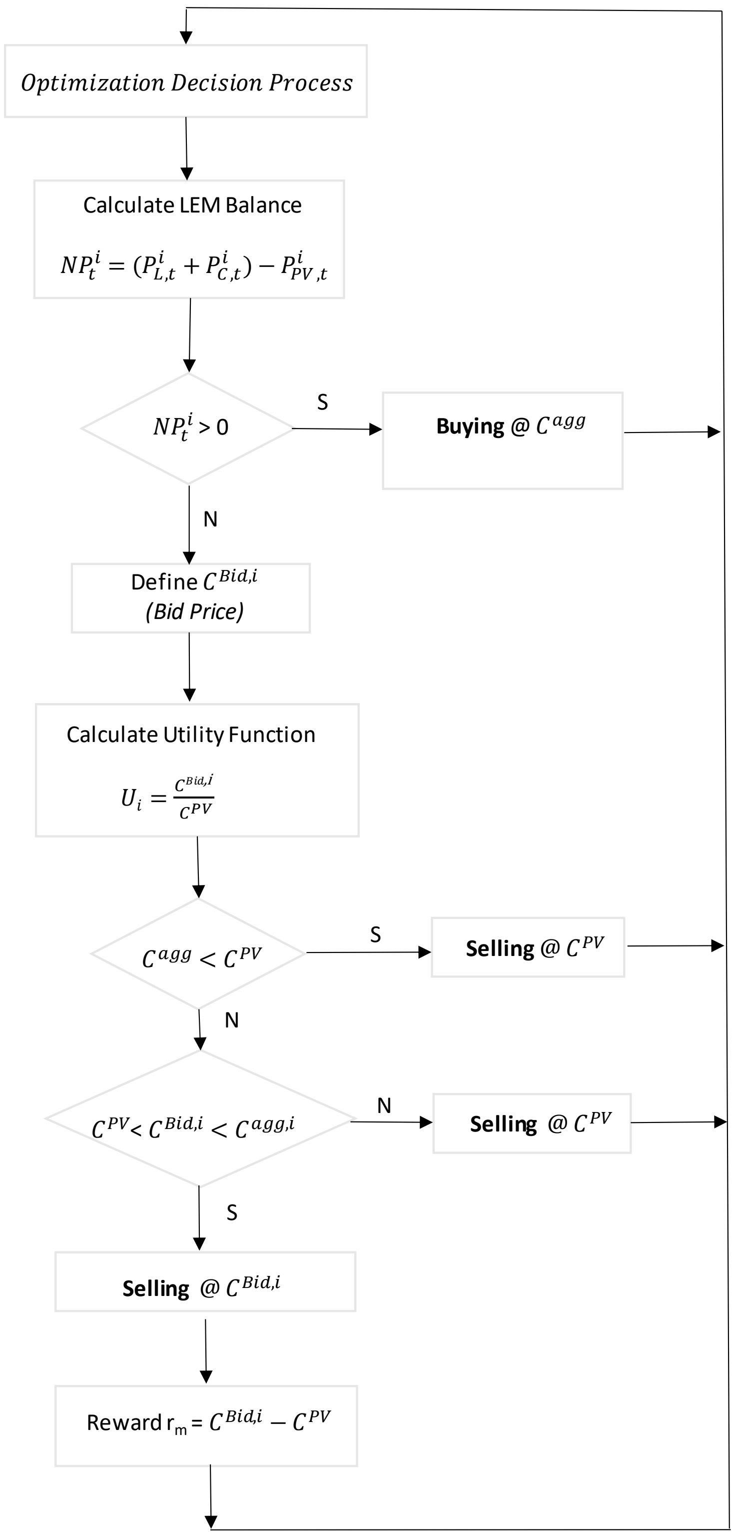

Figure 4.3. Iterative procedure included in the operation strategy

4.7. Q-Learning procedure to be used in the proposed model

Based on the indications above, the problem under analysis can be transformed in a decision making with multiple coupled states. The MDP provides a mathematical framework for modeling decision making in situations where outcomes are partially random and partially under the control of the decision maker.

The decision-making process of an MDP agent is based on choosing the optimal action according to a specific utility function. The decision maker could take any action from the set that is available for each state and subsequently the process will move from state *s* into a new state *s'*.

The characteristics of electricity markets contribute to create a complex dynamic and adaptive system. In this circumstance, learning and construction the model of the economic system is a very complicated task for market participants, and a model free learning can be an appropriate alternative to build a desired bidding strategy. Agent Based Models have been reported as a complement to traditional models when the problem is too complex. In this sense, this work uses an ABM associated to the reinforcement Q-Learning approach to simulate the LEM market and its interactions namely with the WSM. Reinforcement Learning is used when the probabilities or rewards in MDPs are unknown and allows an agent to improve its behaviour and its decisions from experience in sequential and uncertain environments.

Figure 4.4. illustrates the operation of the ABM.

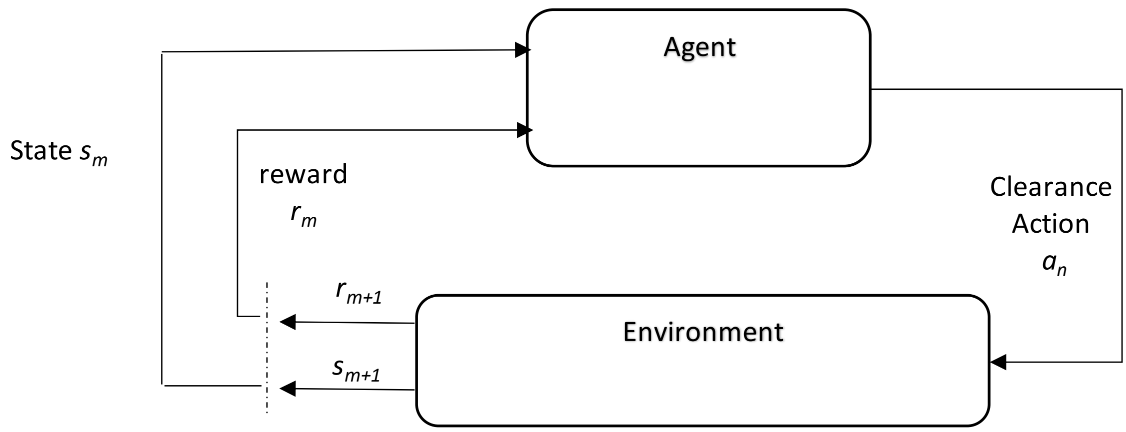

Figure 4.4. Market model as an MDP with agent-environment interaction

When using an Agent-Based Model to model a MDP, the agent first observes the current environment state and then takes an action. Then, the agent receives an immediate reward from the environment, and the environment moves to the next state based on the transition probability. This process is repeated until termination. As mentioned in Section 3.3, an MDP is composed of four essential elements (s, a, p, r), where *s* is the finite number of states, *a* represents the finite number of possible actions, *p* is the state transition probability that falls within $[0; 1]$, and *r* is the reward function.

The agent´s interaction with the environment consists of a sequence of different stages. We consider $S = s_1, s_2, \ldots, s_{\mathrm{n}}$ as the set of possible states of the environment and the actions that agents can take as $A = a_1, a_2, ..., a_{\mathrm{n}}$. In the n^{th} episode, the agent procedure using the QL methodology can be defined as illustrated in Table 3.4. Following the Bellman equation (Eq. 3.1), the Q-value for the pair $Q(s_m, a_n)$ is given by expression (4.4).

$$Q(s_m, a_n)^{new} = (1 - \lambda) \cdot Q(s_m, a_n) + \lambda \cdot [R(s_m, a_n) + \gamma \cdot maxQ(s_{m+1}, a_n)] \quad (4.4)$$

Expression (4.4) gives the reward that the agent receives from state *s*. Only Q-values corresponding to the current state and the last chosen action are updated. The learning rate λ ∈ $(0,1)$ and it reflects the degree to which estimated Q-values are updated by new data and can be different in each episode. If λ equals 0 then the agent does not learn, while if it equals to 1 it induces the agent to consider only the most recent information. γ is a discount factor ∈ $(0,1)$ that represents the weight given to future reinforcements. A value of γ equal to 0 makes the agent myopic by only considering current rewards, while values closer to 1 turn more important distant rewards [284]. The expression $maxQ(s_{m+1}, a_n)$ represents the best the agent thinks it can do in state s_{m+1}. In an initial phase, the agents will randomly explore state to state until they learn and reach the end of simulation period. Then, using these Q-values, the agents start their biddings taking into account the learned experience. Typically, the learning process converges when the Q-values do not change more than a pre-determinate convergence value regarding the values in the Q-matrix that was built in the previous iteration.

One of the main challenges in RL is the trade-off between exploration and exploitation, which is represented by the greedy policy ε. Agents use the past information from exploitation, but they also have to explore other actions. By following a greedy policy constantly (choosing always the action with the higher reward value), the agents may not explore some states that could be more profitable or that could lead to rewarding sequences of states in the future. On the other hand, if the agent explores too much the environment, without exploring its knowledge, it will not actually learn. Thus, it is necessary to achieve a good balance between exploration and exploitation, to ensure that the learning process evolves towards optimal solutions.

In this work, an ε-greedy variation is applied. Instead of always taking the best action, that is the one having the highest Q-value as in greedy policies, there is a small probability ε for the agent to select randomly another action. This is similar to the strategies that exist in meta-heuristics to avoid local optimal by increasing the diversity of the search procedure. As referred by [191], the ε-greedy policy is a good strategy that makes a balance between exploration and exploitation by attributing and ε selection probability to other actions. It is expressed as follows:

$$a = \begin{cases} \arg\max Q(s,a)_{a \in A} \ \textit{with probability}\ 1 - \varepsilon \\ \textit{any action selected uniformly and randondly in A with probabilty}\ \varepsilon \end{cases} \tag{4.5}$$

Initially, the agent chooses actions almost randomly but as the simulation evolves and the convergence is approaching, the agent is forced to choose actions mostly based on the maximum of Q-values, depending on the specific state where he is located at any time. After that, the agent observes the reward that he received and the next state to where he will move. Finally, it updates the corresponding value based on the QL update rule and also updates its next state.

Subsequently, the energy trading to be developed in this work will be modeled as a MDP. In Q-Learning algorithms, agents can learn the best action by interacting with the environment through a trial-and-error search and this approach doesn't require having an explicit knowledge about the environment. Instead, the knowledge regarding the optimal strategy improves while the historic interaction with the environment is built by a trial-and-error process.

The Q-Learning algorithm is one of the most effective ways to solve MDP problems because it is concerned with how agents should select actions in an environment [285], and therefore the cumulative reward could be maximized. The agent's interaction with the environment consists of a sequence of different states. Let us consider $S = s_1, s_2, \dots, s_m$ be the set of possible *states* of the environment and $A = a_1, a_2, \dots, a_n$ be the set of *actions* that the agent can take. In the n^{th} episode, the agent procedure using the Q-Learning methodology can be defined as illustrated in Figure 4.5. [191, 286].

As mentioned in Section 4.5, agents are autonomous entities and interact in an environment. In this work, the day-ahead market is simulated, which simplifies the definition of the environment, since we can now consider that the Agent's environment just corresponds to the day-ahead market.

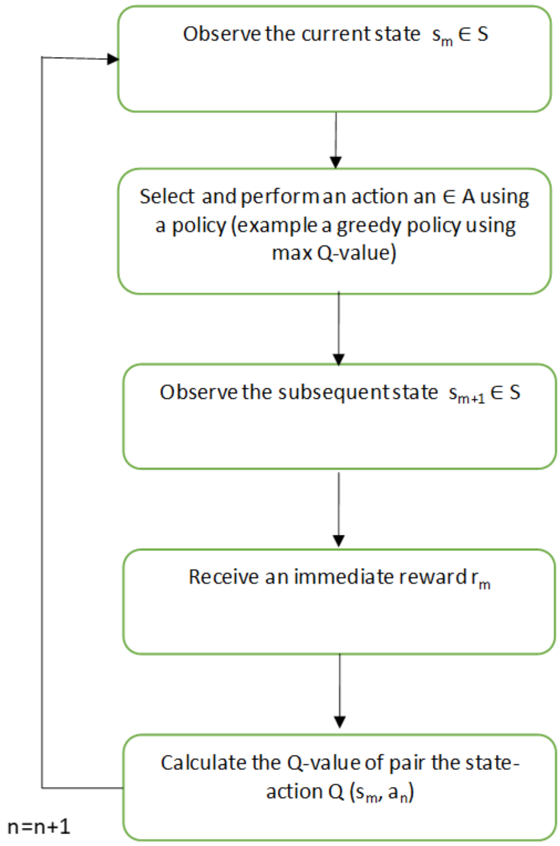

Figure 4.5. Steps of the algorithm to model the LEM and the WSM as an ABM with Q-Learning

When there is surplus of electricity in the community and after considering self-consumption, the LEM has a minimum ensured price that corresponds to a tariff associated to the PV technology. However, in order to increase the revenues from selling this excess, the ABM tries to increase the selling price as close as possible to the WSM price. If the LEM price exceeds the WSM, then the selling bid for this excess will not be accepted using the auction mechanism. Instead, it will be sold at the lowest price, which is the guaranteed tariff value.

The Q-Learning procedure evaluates the payoff that can be obtained for a given state-action pair *Q(s,a)*. In this sense, the state's definition should be in line with energy communities' perspective, i.e., to enhance the self-supply capacity and to minimize the dependency of the grid.

As shown in Figure 4.5, the trading system involves a set of states and a set of possible actions per state. It also contains a Q-value table which is used to record the *Q(s,a)* values for different actions $a \epsilon A$ when the agent is at state $s \epsilon S$. The core of the Q-Learning algorithm is the value iteration update, using the weighted average of the old value and the new information as indicated by expression (4.4). In this way, the agent can select the most adequate action when being in a given state using a Q-value according to the Q-value table.

In this problem, we considered the following 5 possible states (Table 4.1):

- State 1 - the agent has obtained a higher reward, compared to the previous episode, which it is not possible to increase;
- State 2 - the agent has obtained a higher reward, compared to the previous episode, which it is possible to increase;
- State 3 - the agent has not obtained any change on reward, compared to the previous episode;
- State 4 - the agent has obtained a lower reward, compared to the previous episode, which it is possible to increase;
- State 5 - the agent has obtained a lower reward, compared to the previous episode, which it is not possible to increase.

This is based on the state's definition used in [14] , which on the other hand corresponds to an adaptation from [286]. This implementation is in line with the derivative-following strategy presented in [287]. A derivative follower does incremental increases (or decreases) in price, continuing to move its price in the same direction until the observed profitability level falls. At this point, the direction of the movement is reversed.

Table 4.1. Definition of the Q-Learning States

State	Reward	Reward (related with previous episode)
S_1	Increased	Not possible to increase
S_2	Increased	Possible to increase
S_3	Equal	Indifferent
S_4	Decreased	Possible to increase
S_5	Decreased	Not possible to increase

The function represented in Figure 4.6. models the bidding strategy used in the learning approach, where each agent increases or decreases its bid price in an attempt to increase reward. It is also an adaptation of the derivative-following strategy discussed in [287]. It is considered a sigmoid function that reflects the risk profile of an agent. If an agent has a higher risk profile, the bid range will be larger (Figure 4.6.a). On other hand, a low risk profile leads to a narrow bid range (Figure 4.6.b).

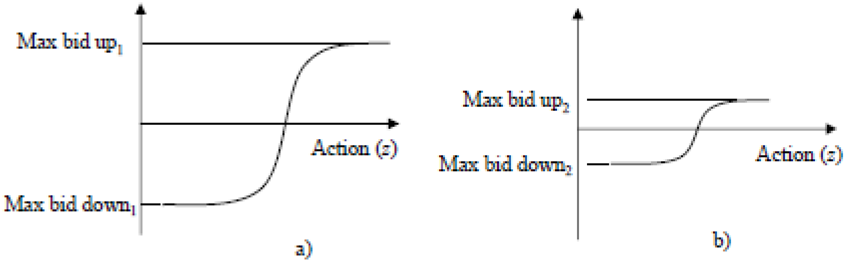

Figure 4.6. Bidding strategy taking into account the risk profile of each agent for large risk profile (a) and for lower risk profile (b)

In the developed model, seven alternatives actions will be available for each agent when deciding his bid price as indicated in Figure 4.7.

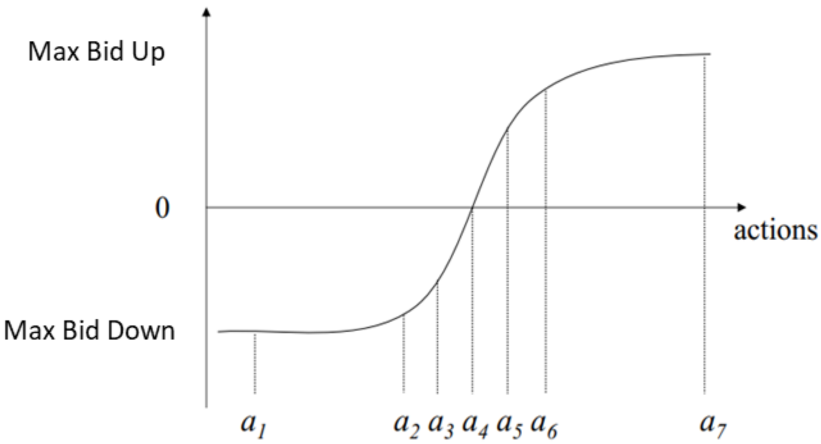

Figure 4.7. Actions (a_1 to a_7) used in the Q-Learning procedure

For example, action a_1 corresponds to a maximum bid down, a_4 means that neither a bid up nor a bid down is used and a_7 represents a maximum bid up. Actions a_2, a_3, a_5 and a_6 represent intermediate values. The reward function r_m corresponds to the profit that each agent obtains in the market if an action *a* is adopted or selected for a given state. As referred in [14] , where this kind of function was also used, the main goal of choosing this type of functions is that it is possible to do an easy parameterization in the values of the bid up/bid down actions by changing the Bid Price, and at same time have different gradients between the actions, where the actions near 0 bid up/down have higher gradient, and actions near maximum values have lower gradient.

Chapter 5

5. Enhanced Model considering Energy Storage Systems

5.1. Overview

The previous chapter presented a framework that considers market mechanisms to model the participation of community agents in the LEM and then its relationship with the WSM. The proposed market design was implemented considering the day-ahead market on a one-hour basis. It was proposed an Agent-Based Model as a decision tool to support energy transactions among Energy Community agents and between the communities themselves and the wholesale market. The proposed environment considers a LEM, established by Prosumers with PV systems and Consumer Agents. As described in Section 4.3, the initial trading is done locally in the LEM followed by an interaction with the WSM. The combination of the marginal prices of the LEM and of the WSM were considered in the ABM decision tool.

As supported by the European Directives, Energy Community Business Models can include not only local generation, trading and aggregation, but also storage systems. Following this definition, this Chapter is directed to an electricity market design, similar to the previous one, but now considering prosumers and energy communities with Energy Storage Systems (ESS), namely batteries. The operation strategy to be implemented aims at benefiting the community members by storing the excess of electricity for their internal consumption or to sell in the LEM. In periods in which local generation is expected to be smaller than the local demand, it is also envisaged the acquisition of electricity in the WSM in hours in which the market price is lower in order to supply the local demand. It is also possible to benefit community agents by making price arbitrage over time, that is, by moving the time intervals in which electricity would have to be bought to some other periods in which the price of the underlying asset is lower or to store electricity when local generation is in excess in order to sell it in periods in which the price is higher. However, the price arbitrage strategy will not be explored by our optimization tool and so it will not be considered in our simulation models.

The literature on Energy Communities, in general, and on Renewable Communities in particular, also suggests that the economic feasibility of their operation highly depends on the tariffs eventually applied to the electricity generated by some primary resources, on the electricity market prices and on the Access Tariffs that have to be paid by the community agents. In Portugal the legislation admits that Renewable Energy Communities are exempted from the payment of some tariffs [49, 279] or tariff components as it is the case of the Costs of General Economic Interest, (CIEG in Portuguese) [278]. In view of the relevance of this issue to create the conditions to the wide spread of RECs, this chapter also describes the approach that will be implemented to test the economic viability of the investments and operation of RECs, namely considering different tariff and charge exemption designs, as a way to get meaningful conclusions on what is the required level of exemption that would have to be implemented to achieve the breakeven of the investment.

5.2. Overview of the proposed market design

The main difference of the market design to be described in this Chapter regarding the one that was considered in Section 4.2 (Figure 4.2), is the utilization of ESS devices, namely batteries. Regarding the system structure, ESS can be placed anywhere in the community, not only near the prosumer installation but also on a centralized way in the community, as shown in Figure 5.1. Considering a decentralized structure, we can consider ESS devices placed behind the prosumer's installation (Figure 5.1.a). In this case, the battery storage system is located at the building level and in this way, the power flow between the batteries and the community doesn't directly use the public grid. In a centralized storage architecture, the location of the battery is not inside the community itself, and in this sense, it is termed as a centralized one. This kind of architecture may allow having higher volumes of stored energy since the battery will be located at a more central position in the grid, eventually connected to the upstream voltage level. Figure 5.1.b illustrates an architecture with a centralized storage system.

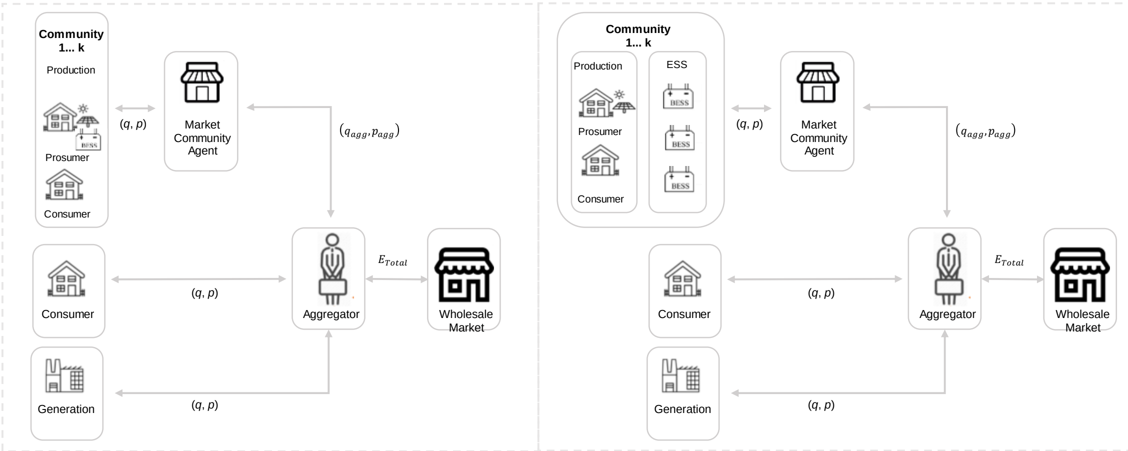

Figure 5.1. Energy Community market design using: (a) a decentralized ESS (behind prosumer's); (b) a community centralized ESS

The optimal bidding strategy when considering battery operation will be developed by each agent, by learning from its past experiences obtained from the direct interaction with the environment. In the decentralized structure of this model, the prosumer agents will now have not only PV units as it was considered in the model described in Chapter 4 but also an ESS. Regarding the structure of the centralized EES model it considers not only local producers, prosumers and consumers, but also an ESS located at a Low Voltage side of the MV/LV substation that feeds a set of buildings. In this case, the location of this battery is not inside the community itself, and in this sense, it is termed as a centralized one. The market design used in this work and the coordination mechanism to integrate the Energy Community Market, LEM, into the existing WSM, is illustrated in Figure 5.2.

The proposed structure considers an Energy Community constituted by consumers and prosumers, as agents. Each of these agents submit their bids to a Market Community Agent which oversees maximizing the Energy Community self-energy consumption and the profit in consequence of selling the energy surplus. This agent is considered an artifact since it will be utilized to carry out Energy Community Agents' activities in a competitive or cooperative manner. It will receive bids from the Energy Community Agents and perform a set of operations developed according to pre-defined rules in order to obtain a schedule for each trading period. The developed framework considers that the Community energy deficit or surplus in each trading period will be traded between the Market Community Agent and an Aggregator through a bilateral contract. On other hand, the Aggregator operates as a traditional retailer regarding the market clearing mechanism in the Wholesale Market. It will gather information about the energy deficit or excess from the Market Community Agent and communicates the buying or selling bids to the Wholesale Market as a way to balance supply and demand in the community.

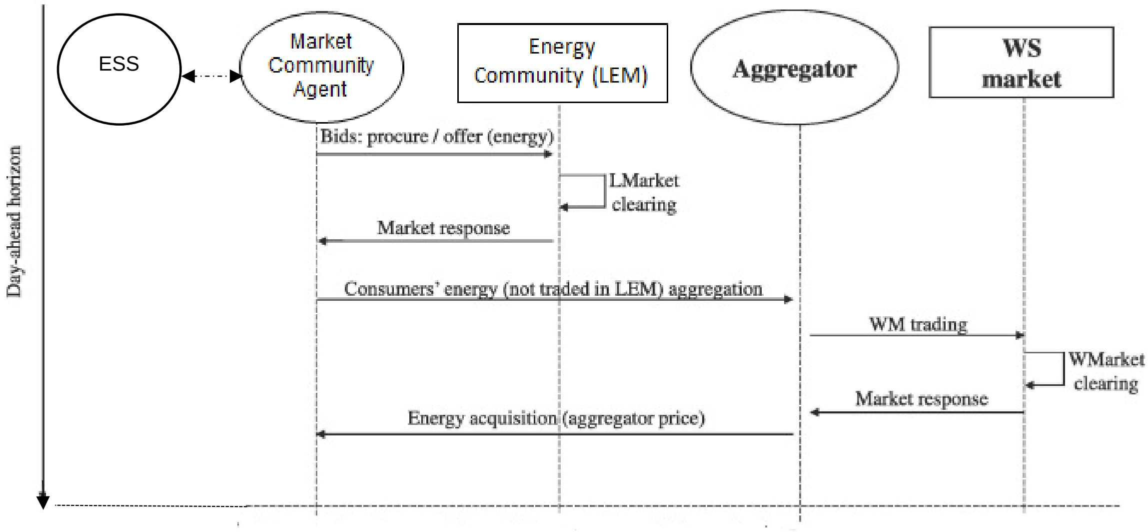

Figure 5.2. Sequential diagram of the integration of the Energy Community market with the wholesale market considering ESS

The initial trading is done locally followed by the trading in the WSM. The Aggregator receives the quantities to buy and sell in the WSM and sends back to the Market Community Agent the cleared hourly prices. The Market Community Agent receives the quantities and the bids from the community, considering the existing ESS, which performs its strategy based on energy deficit or surplus and taking into account the technical characteristics of the batteries.

The batteries will be in the charging mode if there is any surplus of PV generation regarding the local demand and in discharging mode if the community demand is higher than local generation. However, and if the stored energy is sufficient to feed the demand, and it also has some surplus, those additional quantities will be considered in the selling bids optimization strategy of the Market Community Agent. So, the social welfare of the community members will increase by reducing the cost of buying electricity from the grid, by increasing the self-consumption level of the community and also by eventually selling stored electricity. The iterative process will be further detailed in this section.

Before the local initial trading, it is solved an optimization problem to identify the most adequate operation strategy of the ESS, taking into consideration the local energy demand and production, and an estimate of the LEM prices. The bidding energy that the Market Community Agent trades will consider the ESS strategy, namely if the batteries will be charging, discharging or in the idle mode. Having in place the clearing of the LEM, jointly with the energy traded outside the community and the ESS optimization, the quantities to buy and sell in the WSM are determined. Subsequently the demand and supply bids are submitted to the WSM by the Aggregator and the Wholesale Market is cleared. The cleared hourly quantities and prices are sent back to the Market Community Agent through the Aggregator Agent.

5.3. Energy Storage Systems

5.3.1. General Aspects

Energy storage technologies are able to store energy under some form, such as mechanical, electrical, chemical, thermal, potential, etc. In some cases, electricity is the original form of energy that is converted in another form of energy and then, whenever necessary or more adequate, it is converted back to electricity. In other cases, as for example in hydro units with large reservoirs, energy is stored under the form of potential energy, and it is converted when necessary to electricity. In addition, if hydro units are equipped with pumping devices, the electricity is used in some periods to pump water to an upstream reservoir and then the potential energy of this water is converted back to electricity in some later periods profiting, for instance, from the price spread thus adopting a price arbitrage operation strategy.

Due to the increasing interest in renewable energy sources and distributed energy resources, the attention to ESS has also increased. ESS is also regarded as a complementary technology that supports the development of renewable energy resources and the balance of power systems. It allows for the increased flexibility of the electricity generation system by allowing it to meet the needs of the demand while ensuring the security of supply [288]. The introduction of ESS in power systems is also helping to manage the operation of wind and PV parks turning them more flexible and dispatchable and contributing to facilitate the control of the electricity that they can inject in the grids.

In addition, in small and isolated systems, as for instance in islands, the introduction of storage can enable the increase and more efficient use of renewable units because local utilities frequently adopt conservative dispatch policies in terms of always maintaining in operation a minimum number of thermal groups for security of supply reasons. Since these groups typically have technical minimum generation values, in periods in which these technical minimum values together with the expected renewable generation (from wind and/or PV units) exceeds the demand, wind or PV generation has to be curtailed. In these cases, introducing storage units will enable avoiding this generation curtailment and can eventually enable or economically justify further increasing the wind and PV installed capacity. For example, this is the case of the São Miguel Island in Azores where this problem is even more critic since geothermal units (which also use a renewable primary resource) have priority in the dispatch policy.

ESS can be classified according to the nature of the energy that is stored. In [289], the authors differentiate among devices using mechanical, electrical, electro-chemical and chemical storage.

Concerning the energy transformation process, one can identify:

- Mechanical storage: pumped hydro storage, compressed air energy storage, flywheel energy storage;
- Electrochemical storage: conventional batteries storage (Lead acid, Li-ion), high-temperature batteries (NaS, ZEBRA) and flow batteries (VRB, PSB, ZnBr);
- Electromagnetic storage: superconducting magnetic energy storage, capacitors and supercapacitors;

When it comes to the time frame use, the ESS technologies can perform [290]:

- Intertemporal shift of energy: capacity to transfer the energy over a variable length of time (from some minutes to some hours or even some days or months);
- Fast response: capacity to rapidly inject or absorb energy to/from the grid, within some tens of milliseconds thus enabling improving quality of service and the provision of services, namely frequency control services, requiring small time steps.

As a consequence of the surge of distributed generation, the increase of prosumers has brought new challenges to the established supply-demand dynamics in electricity generation and increased the need for on-site flexibility. In this sense, one can anticipate that ESS systems, for instance constituted by batteries, will play an important role on the development of RECs and of LEM. A thorough analysis and research on ESS, namely the maturity of the different energy storage systems, capacity, charging and discharging duration and response time is available in [289]. The main potential applications of ESS are listed in [289], and the majority of them fall into one of the following categories:

- Short-term power supply: during a power outtake or scheduled maintenance, storage can act as uninterruptible power supply for short timeframes;
- Integration of renewables into the grid: storage devices can help smoothing the delivery of power and minimize the power curtailment, which can increase the value of renewable resources or enable their growth in small isolated systems, in line with what was mentioned in the beginning of this section;

- Transmission and distribution upgrade or expansion investment deferral: the installation of storage devices, can help reducing the need for new infrastructure and extend the life of existing equipment by reducing peak loads;
- Time shifting: the use of storage devices can help shifting the consumption patterns of electricity from peak periods to cheaper off-peak times. This can contribute to lower the electricity bill. From a tariff perspective, this can help reducing the energy taken from the grid during more expensive periods. In addition, in some countries as in Portugal, the average power in peak periods is one of the tariff variables used by the Regulatory Agency to set regulated tariffs, namely the tariffs for the Use of Transmission and Distribution Networks that integrate the Access Tariff. Therefore, shifting consumption from peak periods will reduce the corresponding average power value and so it will reduce this component of the bill;
- Peak shaving: storage can reduce the maximum instantaneous power consumption from the grid. This reduction can be important because in some countries as in Portugal the contracted power is another of the tariff variables used by the Regulatory Agency to recover the regulated revenues of the Access Tariff components. This means that controlling or reducing the mentioned maximum instantaneous demand will contribute to reduce or at least not to increase the contracted power term of the electricity bill;
- Ancillary services: some types of storage devices have shown to efficiently provide fast response reserves and are already being used to improve power quality and to contribute to frequency control. This is the case of Germany or the UK where there are some markets specifically designed to enable the participation of some ESS technologies and to contract frequency control products;
- Electric mobility: besides stationary usage, batteries can also be used as a distributed storage system able to provide flexibility and frequency control services to network operators provided that a Vehicle to Grid, V2G, approach is adopted and implemented.

5.3.2. Energy Storage Systems' modelization and bidding strategies

ESS plays an important role in the supply and demand balance and therefore its operation will potentially impact on market prices namely if the capacity of storage systems becomes relevant. By performing energy arbitrage by shifting energy in time, ESS can take advantage of price differences. Integrated with PV, ESS are estimated to be able to reduce the energy costs. In the case of decentralized systems (ESS integrated at the consumer/prosumer level), [291] presents an aggregated management scheme of many small-scale batteries in a community with PV and batteries to carry out local energy sharing, where the self-consumption of the aggregated PV and storage units is optimized. There are also benefits when ESSs are centralized, namely because their higher energy capacity of storage.

Two market designs taking into account totally different rules for the availability, capacity and pricing of storage are presented in [57]. The results reported in this paper indicate that, in the case of a decentralized storage system, the overall savings lead to an electricity bill reduction of 31% when compared to a reference case (without storage neither P2P trading). The monetary savings in a centralized storage configuration are estimated at 24%, which is slightly lower than in the decentralized storage system. According to [57], the main factors that impact on the previous results are the system configuration and the different market designs.

The energy stored in the batteries can be modelled by a simplified linear expression taken from [291]. Assuming that the charging and discharging power rate remain constant during a time slot, the stored energy of a battery is described by:

$$W_{B,t}^{i} = W_{B,t-1}^{i}\left(1 - \sigma_{SD,t}^{i}\right) + \left(P_{BC,t}^{i}\eta_{BC,t}^{i} - \frac{P_{BD,t}^{i}}{\eta_{BD,t}^{i}}\right)\Delta t \tag{5.1}$$

In this expression:

$W_{B,t}^{i}$ is the stored energy at time slot *t;*

$W_{B,t-1}^{i}$ is the stored energy at time slot *t-1;*

$\sigma_{SD,t}^{i}$ is the self-discharge rate (number from 0,0 to 1,0);

$P_{BC,t}^{i}$ is the battery charging power;

$P_{BD,t}^{i}$ is the battery discharging power;

$\eta_{BC,t}^{i}$ is the battery charging efficiency (number from 0,0 to 1,0);

$\eta_{BD,t}^{i}$ is the battery discharging efficiency (number from 0,0 to 1,0).

Equation (5.1) presents the overall storage level for an ESS device over time. Its battery charging and discharging levels are limited by α and β respectively originating constraints (5.2) and (5.3).

$$0 \leq P_{BC,t}^{i} \leq \alpha \tag{5.2}$$

$$0 \leq P_{BD,t}^{i} \leq \beta \tag{5.3}$$

The State of Charge of the battery (SOC) is given by (5.4) in which $W_{B,N}^{i}$ is the nominal capacity of the battery (i.e., battery size).

$$\text{(SOC) } v_t^i = \frac{W_{B,t}^{i}}{W_{B,N}^{i}} * 100\% \tag{5.4}$$

To ensure the balance of the community system, constraint (5.5) must hold for every time slot. Any power deviation can always be balanced by exchanging power with the grid. During each time slot, the batteries can be charging or discharging or in the idle mode.

$$(P_{PV,t}^{i} + P_{BD,t}^{i} + P_{Grid,t}^{i}) - (P_{L,t}^{i} + P_{C,t}^{i} + P_{BC,t}^{i}) = 0 \tag{5.5}$$

In the previous expression:

- in case the agent i is a prosumer, $P_{L,t}^{i}$ and $P_{PV,t}^{i}$ are its demand and PV generation at time slot t;
- in case the agent i is a consumer, $P_{C,t}^{i}$ represents its demand at time slot t;
- $P_{Grid,t}^{i}$ is the power exchanged with the grid at time slot t;
- $P_{BC,t}^{i}$ is the battery charging power;
- $P_{BD,t}^{i}$ is the battery discharging power;

The representation of the net load of the community agent i either being a prosumer or a consumer at time slot t is given by NP_t^i (Equation 5.6.)

$$NP_t^i = (P_{L,t}^{i} + P_{C,t}^{i}) - P_{PV,t}^{i} \tag{5.6}$$

Batteries are in the charging mode when $\sum_{i=1}^{N} NP_t^i < 0$, and the surplus PV power is used to charge the battery system, unless the SOC reaches the maximum. The charging power of a centralized system is calculated by (Equation 5.7):

$$P_{BC,t}^{i} = \begin{cases} \frac{-\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BC,max}^{i}} * P_{BC,max}^{i} & \frac{-\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BC,max}^{i}} < 1 \text{ and } SOC_t^i < SOC_{max}^i \\ P_{BC,max}^{i} & \frac{-\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BC,max}^{i}} \geq 1 \,\&\; and\; SOC_t^i < SOC_{max}^i \\ 0 & SOC_t^i = SOC_{max}^i \end{cases} \tag{5.7}$$

A battery is discharging when $\sum_{i=1}^{N} NP_t^i \geq 0$. In this case, the residual demand of the consumer (prosumer or the community) is met by discharging the battery system, unless the SOC reaches the minimum. The discharging power is calculated by (Equation 5.8):

$$P_{BD,t}^{i} = \begin{cases} \frac{\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BD,max}^i} * P_{BD,max}^i & \frac{\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BD,max}^i} < 1 \text{ and } SOC_t^i > SOC_{min}^i \\ P_{BD,max}^i & \frac{\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BD,max}^i} \geq 1 \; and \; SOC_t^i > SOC_{min}^i \\ 0 & SOC_t^i = SOC_{min}^i \end{cases} \tag{5.8}$$

The operation strategy of the ESS aims at reducing the energy costs of the community and to increase the community self-consumption. The strategic participation of an ESS in the electricity market is based on different bidding structures. A comparative analysis on bidding structures of ESS systems is presented in [292] and consider four options:

a) A simple quantity bidding, where the ESS participates in the market by deciding availability offers (i.e., charging and discharging capacity) in the form of quantity bids;
b) A simple price bidding, that reflects the ESS willingness to charge and discharge at each time step on a price-based approach;
c) A quantity-price pair bidding structure that represents a combination of the previous two approaches. The strategic agent is able to withhold charging/discharging capacity and express its willingness to charge/discharge in the form of price bids;
d) A complex bidding where the strategic agent discloses all its technical constraints to the Market Operator and this one is responsible for fulfilling these constraints when clearing the market. This implies that the Market Operator has knowledge on the ESS's characteristics, technical constraints and of the value of the stored energy.

The decision problem of the ESS owner presented in [292] is formulated as a bilevel programming model, where the upper-level problem represents the profit maximization of the ESS and the lower-level problem simulates possible market clearing outcomes. The presented bilevel models are reformulated as an equivalent mixed-integer linear programming problems by means of the Karush-Kuhn-Tucker optimality conditions, the strong duality theorem and the Big-M method. In [293] it is proposed a different approach, less complex and time intensive and based on intelligent agents. With the emergence of ESS, some operation strategies of the ESS regarding the maximization of their overall profit by controlling the placement proportion of the ESS in different markets has been proposed. The model presented in [294] details a Performance-Based Regulation optimal bidding model. It addressed not only the optimal strategy for the ESS in different markets but also considered the battery life time. In [295] it is proposed the integration of an energy storage system and solar power plant. This publication details an optimal strategy for a Concentrating Solar Power plant, which considered the energy, the reserve and the regulation markets.

However, with the increased penetration of storage systems and new market designs and agents (e.g., RECs concepts), different approaches and bidding strategies within prosumers and retailers (aggregators) are necessary. One of the major concerns is that traditional bidding strategies only solve the allocation problem of a single ESS and neglect biddings from other actors and prosumers [296]. During the process of bidding, the bidder does not know the rivals' bidding price and bidding quantity, which is hard to address by traditional optimization algorithms. Furthermore, since bidding is a highly random and uncertain process, the bidders cannot know the specific revenue model during bidding. Considering incomplete information of stochastic demand from the market and unknown bids from rivals, some individual based approaches have been widely applied to develop bidding strategies in electricity markets, where the individual agents learn to maximize their own profit based on their past experiences [297-299] .

Therefore, the model developed in this work is based on the methodology proposed in [296] which presents a Markovian based bidding model that is used to build the optimized bidding strategy of ESS in day-ahead energy and regulation markets, considering the charging/discharging losses, the SOC and the deficit or surplus in the community.

Similar to the proposed strategy used in Chapter 4, each ESS will have an associated Agent that will submit the day-ahead bids to the Market Community Agent, including bidding energies and bidding prices. The electricity will be allocated according to market requirements. However, and during the bidding process, the ESS agents cannot know the bidding data of their rivals (in case of decentralized ESS, for instance), but the MCP and offers from the Market Community Agent are public. The ESS agents are supposed to be price-takers, since they will not affect the energy price in the LEM. They submit their bids to the Market Community Agent, considering that their energy will be firstly self-consumed in the community or sold into the WSM if there exists any remaining surplus.

The objective function of the proposed bidding model is to maximize the total profit of the ESS considering its operational constraints, costs, and the allowed bid structures (Equation 5.9).

$$max_{Profit} = \sum_{t \in T} \left(Profit_t^e - Cost_t^{total} \right) \tag{5.9}$$

In this expression $Profit_t^e$ is the hourly revenue from the LEM and $Cost_t^{total}$ is the hourly cost, which includes operation and maintenance cost, and loss costs (related with batteries charging/discharging efficiency). The hour index is t.

As referred in Section 5.2, the energy deficit or surplus in each trading period will be traded by the Market Community Agent via the Aggregator in the WSM. In this framework, the ESS owners (both centralized and decentralized) submit their bids to the Market Community Agent. Since ESS are price-takers, the revenue of an ESS in the LEM, $Profit_t^e$, can be calculated by Equation (5.10.) [296].

$$Profit_t^e = p_t^e \cdot P_{e,t} \cdot h_e \tag{5.10}$$

In this expression, p_t^e is the LEM electricity price, $P_{e,t}$ is the power of the ESS and h_e is the trading period of the energy market, set at 1 hour in this work. The subscript *t* is the index of the hours in each day since the bidding strategy is day-ahead with hourly bids in the wholesale electricity market.

The power of the ESS, $P_{e,t}$, depends on the charging or discharging requirements of the ESS, $b_{e,t}$, which can be positive or negative (equation 5.11.). In this expression $b_{e,t}$ is assumed positive when the battery is discharging and is taken as negative when it is charging.

$$P_{e,t} = \begin{cases} b_{e,t} \cdot \frac{1}{\eta_{BD}}, \ if\ b_{e,t} > 0 \\ b_{e,t} \cdot \eta_{BC}, \ if\ b_{e,t} < 0 \end{cases} \tag{5.11}$$

The total cost is calculated using (5.12):

$$Cost_t^{total} = C_{O\&M,t} + C_{loss,t} \tag{5.12}$$

Where $C_{O\&M,t}$, $C_{loss,t}$ are the operation and maintenance cost, and the charging and discharging costs, respectively.

The operation and maintenance cost of an ESS is usually a variable term proportional to the size of the ESS, which can be calculated as:

$$C_{O\&M,t} = C_a \times E_{max} \tag{5.13}$$

where C_a is the annual maintenance cost of ESS [300].

The charging and discharging efficiencies can be different [301] and the corresponding losses can be represented as:

$$C_{BCloss} = p_{e,t} \cdot P_{BC}(1 - \eta_{BC}) \cdot \Delta T \tag{5.14}$$

$$C_{BDloss} = p_{e,t} \cdot P_{BD}\left(\frac{1}{\eta_{BD}} - 1\right) \cdot \Delta T \tag{5.15}$$

An analysis of the effect of the SOC and battery wear cost can be found in [302] which will be considered in the batteries' economic assessment (detailed in Section 5.5).

The energy balance model of the ESS is based on the physical constraints and the market requirement. The SOC of the ESS in each time slot *t* can be calculated as:

$$soc_t = soc_{t-1} + \Delta_{SOCt} \tag{5.16}$$

Where Δ_{SOCt} indicates the amount of energy change from time slot $t-1$ to t, which is usually expressed in %. According to the energy selling and buying, the value of Δ_{SOCt} can be negative and positive. Therefore, the charging/discharging rate of the ESS (Δ_{SOCt}) is expressed as:

$$\Delta_{SOCt} = (\Delta E_t^e)/E_{max} \tag{5.17}$$

In this expression, ΔE_t^e represents the amount of energy change in the battery. The SOC_t is used to calculate the next state of the reinforcement learning algorithm (to be detailed in Section 5.4), which is the actual state of the ESS.

The ESS must keep its SOC within its energy capacity limits. According to [303], the ESS performs better if the SOC lies in the range 20% - 80% of its capacity. To get the best performance of the ESS the capacity limits are set as:

$$\rho_{min} \cdot E_m \leq SOC_t \cdot E_{max} \leq \rho_{max} \cdot E_m \; \forall t \in T \tag{5.18}$$

Where ρ_{min} and ρ_{max} are the minimum and maximum operation limits. E_m is the rated energy capacity of the battery storage.

The initial and final SOC are usually set to be same during the optimization period, as described below. t_o and t_{24} represent the initial and the final periods of the day.

$$SOC_{t_0} = SOC_{t_{24}} \tag{5.19}$$

Regarding the previous explanation, the ESS operation strategy defined in this work follows the iterative procedure illustrated in Figure 5.3. It considers that the battery discharging is in operation mode (until the pre-defined SOC minimum limits) if the demand is higher than the community production (until the minimum SOC level is reached, (5.3)). On other hand, and if the PV production is higher than the demand, the surplus will charge the batteries (until the predefined maximum level of SOC; Equation 5.2.). If there is still an energy surplus, this energy will be traded between LEM and the WSM followed by the optimization model using the reinforcement learning approach, which will be detailed in the next section. If the energy stored is insufficient to feed the demand, then the market community agent has to buy the required energy at the WSM.

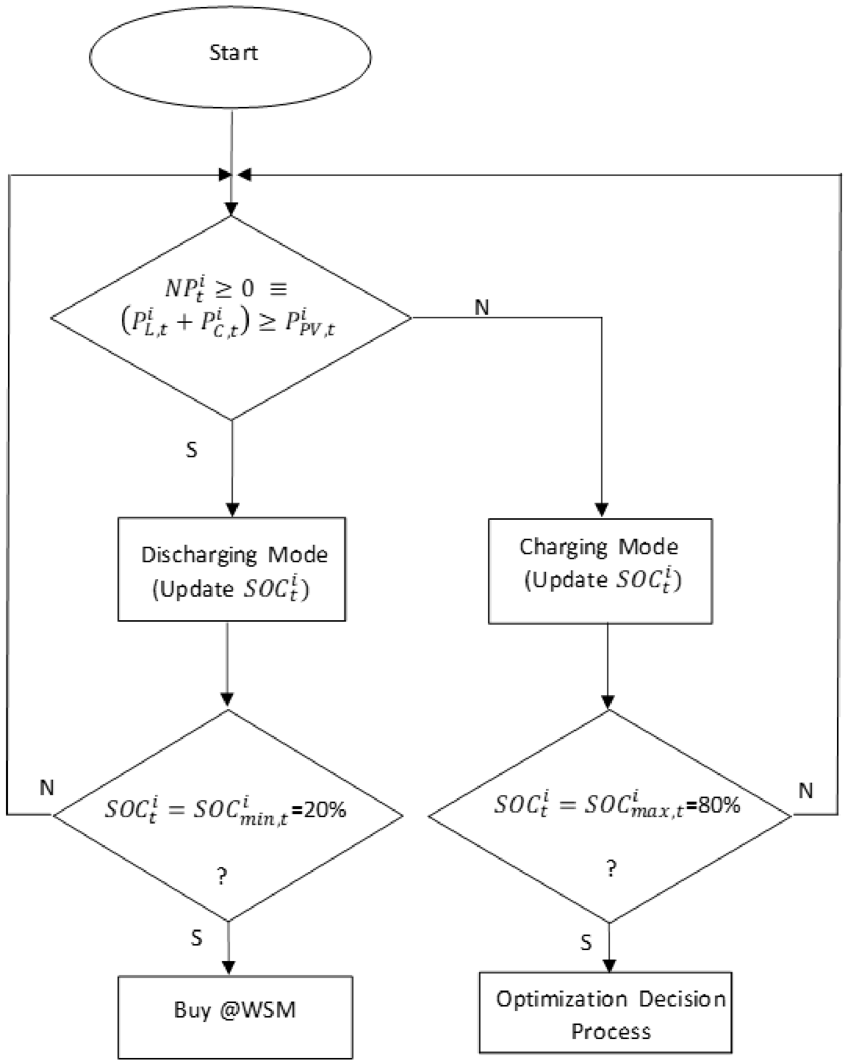

Figure 5.3. Iterative procedure included in the operation strategy of the ESS

5.4. Modelling the ESS, the LEM and the WSM as an ABM with Q-Learning

The optimization of the operation strategy of the ESS in the scope of the operation of the Energy Community can be transformed into an optimization decision making problem with multiple coupled states. The developed model is similar to the model detailed in Section 4.7 to simulate the Consumer and Prosumer (in that case without considering the ESS) Agents.

Considering the stochastic environment of power markets, the optimal bidding problem of an ESS in a stochastic environment is reformulated based in equation (5.20). This is formulated as a MDP, which is defined as a five-element tuple and includes the state space $\mathcal{S}$, the action space $\mathcal{A}$, the transition probability function $\mathcal{P}$, the reward function $\mathcal{R}$ and the discount factor γ.

$$\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma\} \tag{5.20}$$

At each time slot the ESS owner has its observation of the bidding market, namely state s_t. Considering that the bidding quantity and bidding price of rivals are uncertain, the state of the ESS owner is set as:

$$s_t = (v_t^{-1}, a_{t-1}^T, SOC_t, t)^T \tag{5.21}$$

Where $s_t \epsilon\ \mathcal{S}$ presents the observable information and v_t^{-1} is the clearing price of the previous day at time slot t and $a_{t-1}^T$is the last decided bidding action, including bidding quantities and bidding prices.

Having the quantities to buy or to sell between the LEM and the WSM, the reinforcement learning starts regarding the strategy to be performed. The state's definition is in line with the energy communities' perspective, i.e., to enhance the self-supply capacity and to minimize the dependency of the grid. This is similar to the strategy presented in Chapter 4 and based on the state's definition adopted in [14] where the following 5 states were considered:

- State 1 - the agent has obtained a higher reward, compared to the previous episode, which it is not possible to increase;
- State 2 - the agent has obtained a higher reward, compared to the previous episode, which it is possible to increase;
- State 3 - the agent has not obtained any change on reward, compared to the previous episode;

- State 4 - the agent has obtained a lower reward, compared to the previous episode, which it is possible to increase;
- State 5 - the agent has obtained a lower reward, compared to the previous episode, which it is not possible to increase.

This strategy is in line with the derivative-following strategy presented in the last chapter and based in [287]. However, this strategy has in consideration the ESS characteristics (Equations 5.1-5.4). Each action taken by the Market Community Agent will increase or decrease its bid price in an attempt to increase the profit. However, the quantities to be submitted in the bidding process are limited by the state of the batteries (charging, discharging or idle mode) and SOC. As previously mentioned, the SOC of a ESS should be kept between 20% to 80% to obtain the best efficiency operation [304].

Remembering that when using an Agent Based Model to model a MDP, the agent firstly observes the current environment state and then takes an action, then the agent receives an immediate reward from the environment, and moves to the next state based on the transition probability. So, according to this modelling approach, the objective of the reinforcement learning is to obtain the best 24-hour reward, now considering the storage system and its technical characteristics as part of the environment. The Q-function can be defined by (5.22) in a similar way to the one defined in Section 4.7. (Expression 4.4).

$$Q(s_m, a_n)^{new} = (1-\lambda) \cdot Q(s_m, a_n) + \lambda \cdot [R(s_m, a_n) + \gamma \cdot maxQ(s_{m+1}, a_n)] \tag{5.22}$$

In this expression λ is the learning rate and γ is the discount factor. It gives the utility function that the agent receives from state s. It is also used a greedy police ε to keep the exploration of the behavior, so that all exploratory actions have probability to be chosen during the training period.

So, considering that the energy produced will be firstly self-consumed, the remaining surplus (if there exists) will be sold in the WSM following the derivative strategy already described in Chapter 4. Remember that these quantities depend on the battery's state, charging, discharging or idle and on the SOC. A derivative follower does incremental increases (or decreases) in price, continuing to move its price in the same direction until the observed profitability level falls. At this point, the direction of the movement is reversed. As illustrated in Figure 5.4, action a1 corresponds to a maximum bid down (in which the bid price is decreased as much as possible), a4 means that neither a bid up nor a bid down is adopted and a7 represents a maximum bid up action (in which the bid price is increased as much as possible).

In order to get the reward that will be obtained during the surplus selling process, the same assumptions referred to in Section 4.6. will be considered, namely that the Market Community Agent will try to increase the selling price as close as possible to the WSM price and in this sense have a higher reward. However, it will be considered the state of the batteries (charging, discharging or idle mode) and the SOC.

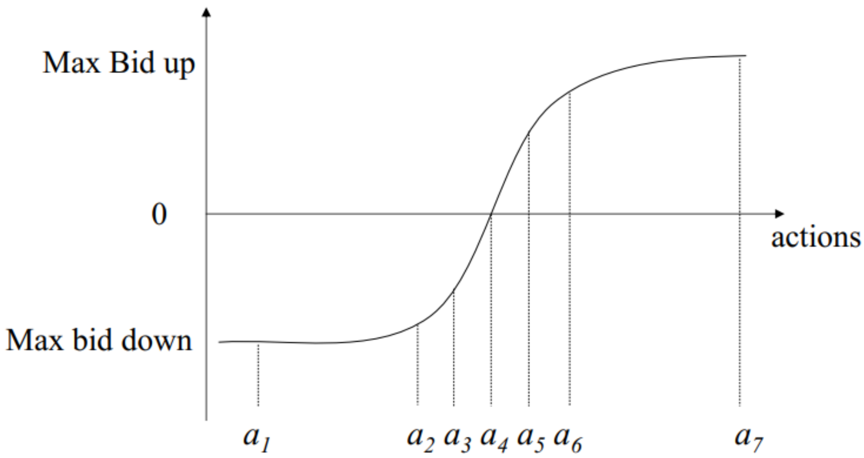

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Figure 5.4. Actions (a1 to a7) used in the Q-Learning procedure

5.5. Economic viability of Energy Communities business models

5.5.1. Overview

Besides the implemented legal framework and the incentives for the deployment of Energy Communities, it should be assessed the impact of different levels of charges and exemptions as a way of getting insights on the economic feasibility of the Energy Communities. The economic viability of the investments (namely in Storage Systems) and operation of RECs, specifically considering different tariff and charge exemption designs, should therefore be studied in order to get conclusions on the breakeven of the investments.

In Portugal, the DL 162/2019 Art. 18 (n. 4) [49], stated that the charges associated with the Costs of General Economic Interest, CIEG (*Custos de Interesse Económico Geral*, in Portuguese), that are internalized in the regulated revenues associated to Tariff for the Global Use of the System, can be totally or partially deducted from grid Access Tariffs to be paid by community members. In the 19th June 2020, a government dispatch [279] also stated that self-consumption and REC projects, starting operation till the end of the calendar year of 2021, benefit from an exemption of the CIEG charges included in the network Access Tariffs for seven years. This provision is intended to induce the wider deployment of self-consumption and of Energy Communities. Although this dispatch was associated to projects that started operation till the end of 2021, it is expected that similar decisions are published in the coming years. Nevertheless, the impact of this kind of exemptions should be evaluated namely to conclude if they are needed to ensure the economic feasibility of this kind of business model because in fact exempting some consumers from paying some costs does not eliminate these costs but it will rather contribute to increase the amounts to be paid by agents not profiting from these exemptions.

Recently, the mentioned DL 162/2019 was revoked by the publication of the new electricity law corresponding to the DL 15/2022 of January 14 [54]. This new Decree includes definitions and provisions for Renewable Energy Communities similar to the ones included in the DL 162/2019 and, in particular, the number 4 of article 212 states the CIEG can be totally or partially deduced from the Access Tariffs to be paid by the members of the communities and by self-consumption agents depending on a decision of the government till the 15th of September each year.

The legal framework also considers the definition of proximity among the members, devices and equipment that integrate a community. As detailed in Section 2.2.1., the definition of proximity provided in the DL 162/2019 and now included on the DL 15/2022 does not clearly set spatial limits for the location of prosumers and can consider that they are connected to the LV side of a MV/LV substation, to different voltage levels or considering other legal and technical issues.

Some of the simulations that will be detailed in Chapter 6, will consider the impact of having or not exemptions on the Access Tariffs, namely for the CIEG component of the tariffs. These scenarios will take into account the utilization of the public grid for self-consumption purpose, when the storage system will be located outside the electrical network of the buildings where the consumers are installed. A variety of studies will be developed to achieve a broad selection of results which consider different grid charges and tariffs. Once again, the main objective is to get insights related with the payment of grid tariffs and in particular with the CIEG component applied to self-consumption that uses the public grid.

In a different but complementary and also relevant way, admitting that the payment by the community members of all the Access Tariffs as define in the Tariff Code including the mentioned CIEG originates their economic unfeasibility, these simulations can also be used to identify the minimum level of charge reductions or exemptions to ensure the break even. From a regulatory point of view, enlarging the charge reductions or exemptions so that more and more network users benefit from them, originates an important regulatory problem. In fact, the Access Tariffs are designed to provide the amount of regulated revenues defined in the Tariff Code and required to finance several regulated activities as network distribution and transmission and the system control and management as well as a number of public policies that are designed to benefit all the society on the long term. As the number of consumers or network users benefiting from charge reductions or exemptions increases, the consumers that at the end will pay the complete regulated Access Tariffs reflecting the mentioned regulated revenues gets more and more reduced which means that each of them would pay more for the access to the system. This is a major concern as the number of RECs increase and clearly shows that these charge reductions or exemptions should be cautiously set and should only be accepted as a transitory provision to help inducing the development this new business case.

5.5.2. Economic Evaluation Methodology

The economic value of the investments and operation of RECs should offer a financially valued proposition to let communities to be viable under this new paradigm. One of the initial factors for consumers and prosumers to form and participate in an Energy Community is the willingness to lower the investment risk in renewable energy generation and storage equipment. For this reason, the investments in PVs and storage systems are relevant for the economic evaluation of RECs.

The decision on whether a project should be carried out or abandoned is commonly made relying on an “investment criterion”. The most commonly applied approaches found in the literature for storage and PV systems are based on the Net Present Value (NPV) and on the Internal Rate of Return (IRR). Less often, the Benefit-Cost Ratio and the Payback Period are also calculated [288].

Regarding the energy communities’ frameworks and strategies, it is also expected that the excess energy can be sold and therefore the community members should experience a profit from it, unless the payments from network operators charging energy communities to connect and use the grid as well as taxes charged by governments are not going to break an economic business case. The financial gains associated with different system configurations and interactions among LEM and the WSM should also be evaluated.

On this sense, the economic viability of the investments and operation of RECs depend on several factors listed below:

a) The tariffs and prices used to remunerate some primary resources, as for instance the energy from PV systems;

b) Electricity Prices;

c) Access Tariffs;

d) Investment Costs of ESS and PV systems.

5.5.2.1. Storage and PV systems economic analysis

The values of the investment and replacement costs, IRR, NPV and payback period are considered to access the economic viability of the PV and storage systems. These elements depend on the cost associated with the installation and on the Operation and Maintenance (O&M) of the systems, their lifetime and the interest rate.

Economic profitability of an investment project is commonly measured by its NPV, which is the difference between a project's present value and its cost. The present value of a forecasted cash flow is a measure of today's value of future cash streams. The sum of all discounted cash flows – both revenues and costs – corresponds to the Net Present Value. Economic theory dictates that an investment should only be undertaken if the **NPV** is positive, which is the case if future revenues exceed all costs under consideration considering the time value of the money [288].

Related to the calculation of the NPV is the determination of the **IRR**. This concept corresponds to the projects discount rate for which the present value of all cash flows equals zero. The resulting rate is typically compared to the required return on capital or to alternative projects having a similar risk level to determine if an investment is sufficiently profitable and should be pursued. However, IRR can be ambiguous if cash flows have a reversal of sign during lifetime [305, 306]. Furthermore, IRR oftentimes provides a too optimistic view as it inherently assumes that interim cash flows are reinvested at the IRR [288].

Related to the concept of NPV, the **benefit-cost ratio** is the ratio of the present values of benefits and cost, with numbers greater than one representing projects with a positive NPV. This figure is commonly used in project evaluations in the public sector [288].

The **Payback period** is another popular evaluation criterion. It measures "[…] the number of years necessary to recover the project cost of an investment under consideration" [307]. Therefore, projects should only be accepted if their payback period falls below some defined threshold.

Specific to the evaluation of energy related projects is the concept of **Levelized Cost of Electricity** (LCOE) or **Levelized Cost of Storage** (LCOS), which is an estimate of the value at which a unit of energy that is produced or stored should be sold. It is calculated by determining all expenses during the lifetime, discounting them to the base year and setting them in relation to the associated quantity of energy. LCOS / LCOE can also be interpreted as the revenue requirement to break-even [308].

Considering a battery as a storage system, the lifetime of the battery is restricted by two limits: the battery technology's degradation over time as well as its usage-based wear down. Once one of these limits is reached, the storage system is considered at the end of its usable life. The average price required over the lifetime of a storage device to break even the full costs of its operation is known as the LCOS. Alternatively, the LCOS can be viewed as the electricity price that makes the net present value of all storage cash flows over its lifetime equal to zero. Therefore, it gives an insight into the cost of storing and providing a unit of energy. This levelized cost can be determined using equation (5.23).

$$LCOS = \frac{C_{Storage}^{Invest}}{L_{Storage}^{Cycle} \times E_{Storage}^{Capacity} \times (1 - \delta_{Storage})} \tag{5.23}$$

In this expression $C_{Storage}^{Invest}$ is the investment cost of storage system, $E_{Storage}^{Capacity}$ is the energy that the storage can provide, $L_{Storage}^{Cycle}$ is the expected cycle lifetime and $\delta_{Storage}$ is the depth of discharge.

As a normalized figure independent of storage dimensions, this levelized cost then allows for a comparison of system configurations and between technologies. It also could be interpreted as a depreciation charge or as an average revenue hurdle.

The lifetime cost of electricity storage technologies (Pumped Hydro; Compressed air; Flywheel; Lithium-ion; Sodium-Sulphur; Lead-acid; Vanadium redox-flow; Hydrogen; Supercapacitor) in 12 power system applications (Energy Arbitrage; Primary Response; Secondary Response; Tertiary Response; Peaker Replacement; Black Start; Seasonal Storage; Transmission and Distribution Investment Deferral; Congestion Management; Bill Management; Power Quality; Power Reliability), from 2015 to 2050, was studied in [309]. Figure 5.5. shows an overview of the probability each technology has to exhibit the lowest LCOS, and the mean value of LCOS of the most cost-efficient technology for all 12 investigated electricity storage applications. The left-hand axis of each graph displays the probability that a technology will exhibit the lowest LCOS in a specific application. The right-hand axis displays the expected evolution of the LCOS of the technology that will most probably display the lowest LCOS for each application. Note there are different scales on the graphs in this figure.

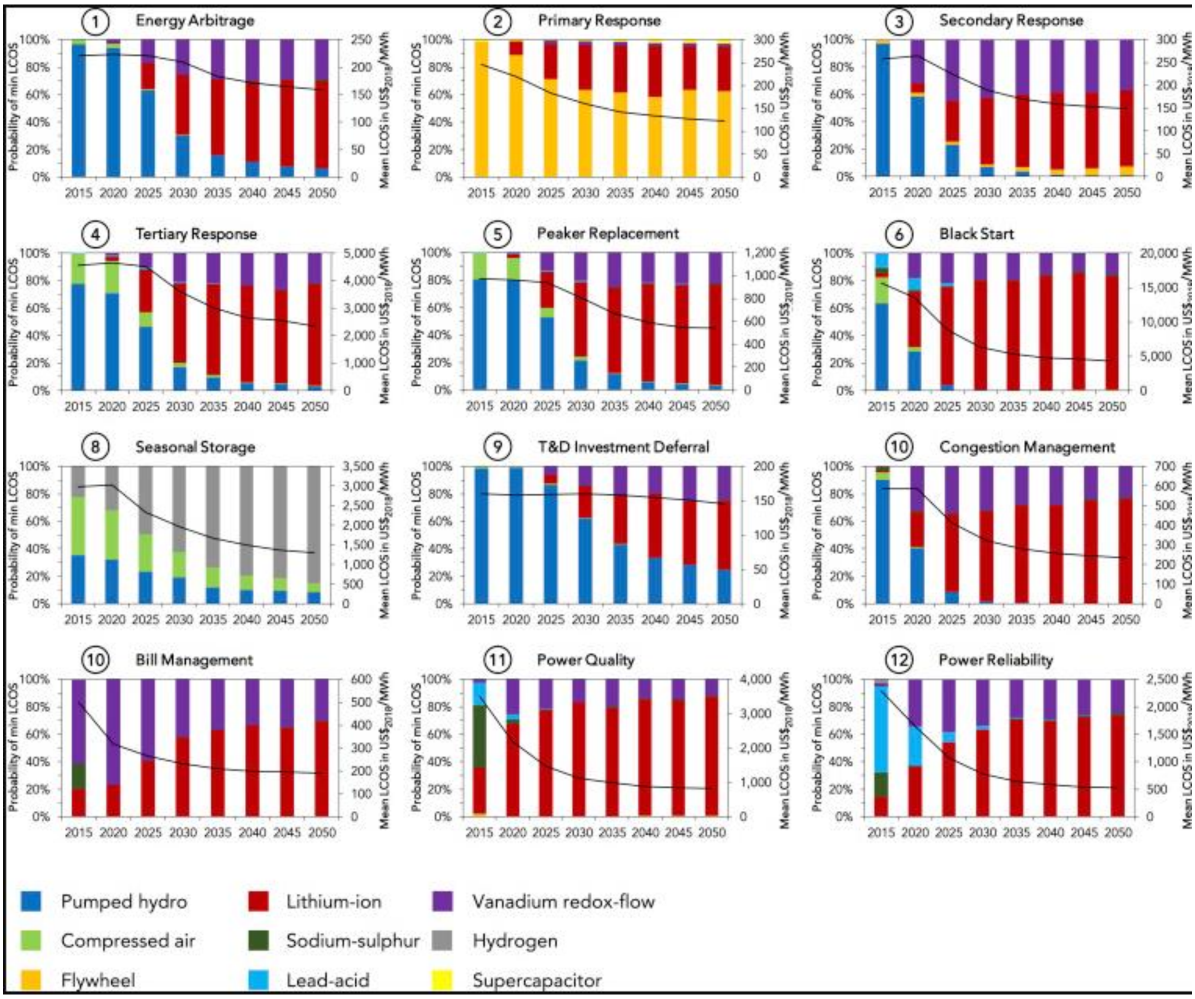


Figure 5.5. Lowest LCOS probabilities for 9 Electricity Storage Technologies in 12 applications from 2015 to 2050 (source [309]).

In 2015, pumped hydro and compressed air dominated most applications except for bill management, power quality and reliability, and primary response, where size and response time requirements made these technologies unsuitable for these applications. For these exceptions, battery systems such as lead acid, sodium sulphur, lithium ion, and vanadium redox flow compete for the least-cost, while primary response is dominated by flywheels. Projected cost reductions for battery technologies limit the competitiveness of pumped hydro and compressed air. Battery technologies exhibit the highest probability of getting the lowest LCOS for most applications beyond 2025. By 2030, lithium ion appears to be the most cost efficient in most applications, with <4 h discharge and <300 annual cycles such as power quality and black start. For applications with greater duration and cycle requirements, vanadium redox flow stays competitive, albeit never being the most likely to offer the minimum LCOS value. These applications are power reliability (>4 h) or secondary response and bill management (>300 cycles). For seasonal storage with more than 700 h discharge, hydrogen storage is likely to become the most cost-efficient technology. Primary response with 5.000 full equivalent charge-discharge cycles sees the dominance of flywheels contested by lithium ion. This report [309] concludes that the values of the LCOS will get reduced by one-third to one-half from 2030 and 2050, respectively, across the modeled applications, with lithium ion batteries likely to become the most cost efficient storage technology for nearly all stationary applications from 2030 onwards.

Regarding solar PV systems, the rapid technological evolution of these systems has made future-cost assumptions cheaper than average spot market electricity all over Europe. For instance, in 2030, utility-scale PV LCOE will range from 14 €/MWh to 24 €/MWh, making PV clearly one of the cheapest forms of electricity generation [310]. Solar PV modules have maintained a learning rate of 23% since 1976, i.e., their cost reduces by 23% every time the capacity doubles [311]. The main drivers for PV systems cost reductions include technological improvements, such as efficiency increase and high-level mechanisms, including economies of scale, automation, and standardization in manufacturing.

The LCOE for solar PV systems is calculated by dividing the sum of costs of the PV system over its lifetime by the electricity produced over its lifetime, as presented in equation (5.24).

$$LCOE = \frac{\sum_{t=1}^{N} \frac{I_t + M_t}{(1+r)^t}}{\sum_{t=1}^{N} \frac{E_t}{(1+r)^t}} \tag{5.24}$$

In this expression I_t and M_t are the O&M expenditure in year t. E_t stands for the electricity generated in year t, r is the discount rate, and N the lifetime of the PV system.

Since most of the investment expenditures are allocated in the initial year, lifetime extension can significantly reduce the LCOE for solar systems. Solar cells with low degradation rates, such as silicon solar cells (~0.5 %/year) [312], have an impact on the lifetime extension and consequently on the reduction of the LCOE.

The investment cost of a PV system (C_{pv}) includes the price of the photovoltaic modules (C_{Mod}), the inverter (C_{Inv}) and installation (C_{Ins}) as given in equation (5.25).

$$C_{PV} = C_{Mod} + C_{Inv} + C_{Ins} \tag{5.25}$$

On a PV-storage system, the battery cost ($C_{Battery}$) represents a considerable portion of the investment. The total cost of a PV-storage system, equation (5.26), depends on the sizing of the photovoltaic itself and the associated storage device.

$$C_{Total} = C_{PV} + C_{Battery} \tag{5.26}$$

A PV-storage project is considered to have a lifetime equal to the lifetime of the PV modules, which is around 20 years. The warranty of the battery and the inverter is approximately 10 to 15 years, consequently they will have to be replaced after that time [313]. Therefore, the costs presented in Equation (5.27) must be taken into consideration when doing an economic analysis.

$$C_{replace} = C_{Inv} + C_{Battery} \tag{5.27}$$

The IRR, defined by Equation (5.28), assesses the profitability of the PV-storage system. It represents the discount rate of the project considering the NPV (difference between the present value of cash inflows and the present value of cash outflows) equals to zero. IRR (%) considers the cash flows (CF) of each year of the project (t) and the lifetime (n) in years [314].

$$0 = \sum_{t=0}^{n} \frac{CF_t}{(1+IRR)^t} \tag{5.28}$$

The NPV, defined by Equation (5.29), reflects the difference between benefits and costs of a project, considering the yield expectation of the investor and therefore its time value of money. It is obtained by discounting all cash flows with the cost of capital r_{Equity}.

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{\left(1+r_{Equity}\right)^{t\times\Delta t}} \tag{5.29}$$

5.5.2.2. Electricity Prices and Access Tariffs

As previously mentioned, the impact of having or not exemptions on network tariffs, namely for the CIEG component of the Access Tariffs will be considered in order to access the economic feasibility of Energy Communities. In addition, it should also be mentioned that the DL 15/2022 of January 14th [54] states in number 3 of article 213, that storage systems are also exempted of paying the charges associated with the CIEG that are typically included in the Global Use of the System Tariff.

In order to better understand the different components that constitute the final price paid by consumers, a structure of the price of electricity supply in Portugal is presented in Figure 5.6. The electricity price paid by the final consumers can be grouped in three clusters: payment for use of networks (distribution and transmission), payment for purchased energy and taxes.

Access Tariffs reflect the cost of infrastructures and all services used by the consumers in a collective manner. It is composed by the Global System Usage Tariff, the Transmission System Use Tariff, the Distribution System Use Tariff and the Logistics Operator for Switching Electricity and Gas Supplier (OLMC) Tariff. These tariffs are typically paid by retailers on behalf of their consumers and the corresponding values are incorporated in the final energy bill to be paid by the end consumers. On the other hand, each supplier defines freely the corresponding value of the Energy and Retailing Tariffs, being in competition with other suppliers. The government is responsible for the definition and setting the taxes. All the regulated price components, namely the components of the Access Tariff, are annually published by ERSE [315].

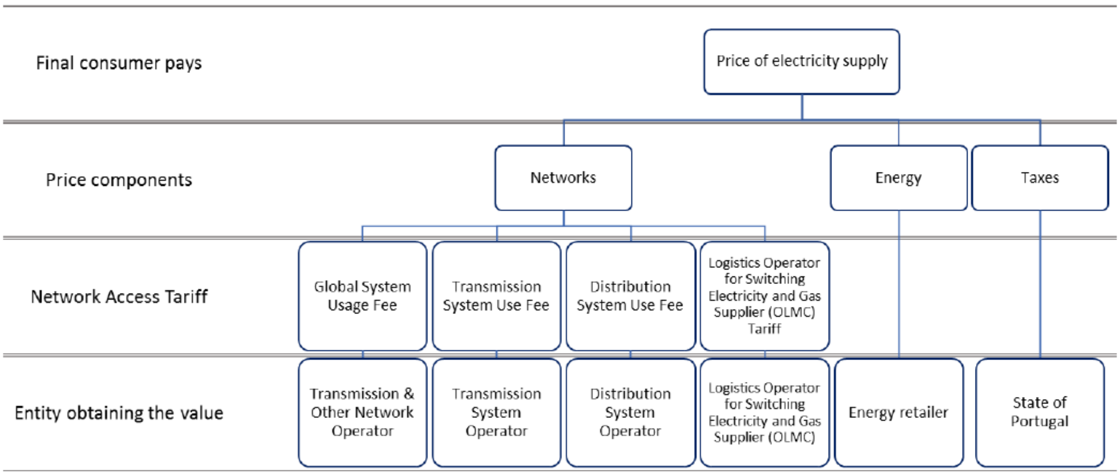


Figure 5.6. Structure of the price of liberalized electricity market supply in Portugal, adapted from [315]

The electricity tariffs and prices set by ERSE for 2022 were approved by the ERSE Directive nº 3/2022 on January 7th, and published in the *Diário da República* [316]. This Directive also approves the network Access Tariffs for electric mobility, the tariffs applicable to self-consumption, and the network access tariffs for autonomous storage facilities.

However, the Directive no. 8/2022, of 11 April [317] approved an extraordinary revision of the Energy Tariff applicable by the Last Resource Retailer, with effects on the transitory End-User Tariffs and End-User Social Tariff, in mainland Portugal and in the Autonomous Regions of the Azores and Madeira, on the End-User Tariffs to be applied in the context of supplementary supply and on the Energy and Supply Tariff for electric mobility.

The Access Tariffs that must be paid by the community agents regarding the utilization of public networks for energy transactions are presented in Annex B1. The charges associated with CIEG, without exemption, with 50% exemption and with 100% exemption, are provided respectively in

Annexes B2.1, B2.2 and B2.3. These correspond to values of the tariffs in force in 2020 and will be considered in the Simulations to be described in Chapter 6. We decided to use the tariffs applied to the year 2020, because the economic and market context (pandemic and Russian-Ukrainian war) in 2021 and 2022 had impact on the stability of these tariffs (e.g., negative values on the CIEG component).

Chapter 6

6. Simulations, Results and Discussion

6.1. Overview of the simulations to be described

As mentioned in previous chapters, the energy community proposed in this work considers a LEM constituted by prosumers with PV generation that can integrate, or not, storage systems. To understand how ESS systems can add value to a LEM, we propose two different architectures regarding their integration. In the first one, storage, constituted by batteries, is located at the building level. This architecture is termed as decentralized in the sense that each building has its own battery equipment. In the second one, termed as centralized, the batteries will be located at the LV side of the MV/LV substation that supplies a set of buildings that constitute the community. Specifically, the value of battery storage and the associated architectures in combination with LEM are examined. To understand the value of local markets and battery flexibility, we compared the outcomes of the two proposed designs against a reference case that does not incorporate storage systems.

As a reference case, designated as Ref-Case, we considered a Portuguese collective building with electricity demand distributed by the common services and by 15 flats. All the apartments are organized as an energy community considering a collective self-consumption scheme. It has a renewable generation unit constituted by PV systems without storage systems and the operation of the LEM is simulated not using the Q-Learning approach. The same as in the previous scenario but considering the optimization approach with the Q-Learning strategy will be named as scenario SC_PV. The architecture for these scenarios (without storage) is illustrated in (Figure 6.1).

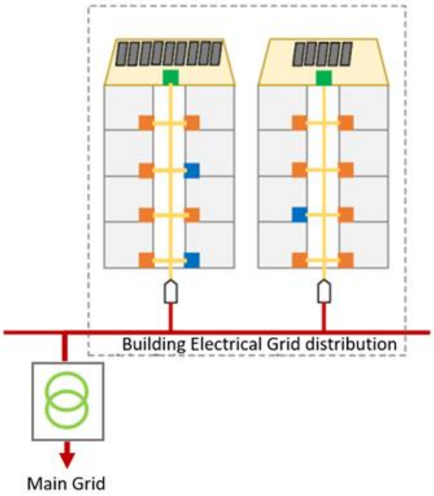


Figure 6.1. Illustration of the collective self-consumption design (scenario SC_PV) (adapted from DGEG [318])

As scenario for SC_ST45, it was considered a community that has a battery storage system located at the building level. The power flow between the batteries and the community doesn't use the public grid because they are located inside the building. This will be named as Decentralized Storage System as mentioned above and it is illustrated in (Figure 6.2) namely because there is a storage unit for each building that could be considered. It should be recognized that this does not correspond to a fully decentralized approach in which each consumer/prosumer would have its own small storage unit. Such a level of decentralization was not considered in this study because the current investment cost in storage systems is still large enough to prevent this type of dissemination. In other words, currently it is more feasible to adopt some level of decentralization involving sets of consumers rather than a fully decentralized design.

It was also studied a centralized storage architecture in which the storage system is located at a Low Voltage side of the MV/LV substation that feeds a set of buildings. This scenario is termed as SC_ST300. The location of this battery is not inside the community itself, and it is termed as a centralized one given that a set of buildings share the same storage unit (Figure 6.3). In order to get insights related with the payment of grid tariffs and in particular with the CIEG component applied to self-consumption that uses the public grid, its economic impact will be assessed in scenario SC_ST300. This evaluation will be done by considering different exemption conditions.

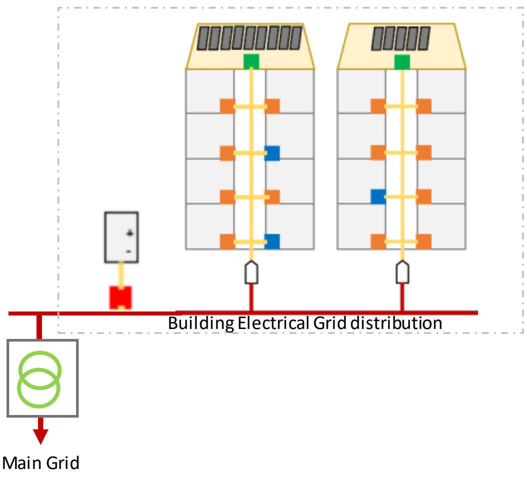


Figure 6.2. Illustration of the collective self-consumption installation with a decentralized storage system (scenario SC_ST45) (adapted from DGEG [318])

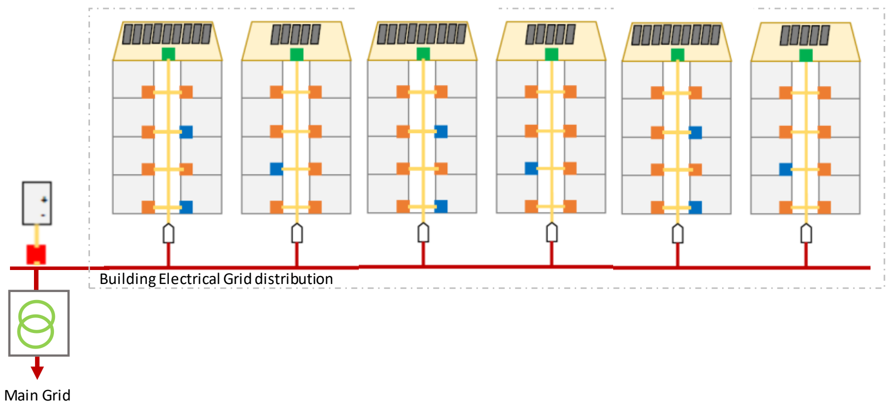


Figure 6.3. Illustration of the collective self-consumption installation with a centralized storage system (scenario SC_ST300) located at the LV side of the MV/LV substation (adapted from DGEG [318])

To assess the impact of the different parameters used in the developed Q-Learning methodology, i.e., the learning rate, the discount factor and greedy police parameters, several simulations will also be developed considering the scenario SC_PV.

To validate the previous results from an economic point of view, a long-term economic assessment will be presented considering the equipment live-cycle, CAPEX and OPEX expenditures. A sensitivity analysis will also be performed in order to assess the behavior of the Net Present Value considering the change of some parameters.

Table 6.1 summarizes the different scenarios that will be analyzed.

Table 6.1. REC configurations and scenarios to be analyzed

Scenario name	Description
Ref-Case	With PV, without storage and without Q-Learning strategy
SC_PV	With PV, without storage and with Q-Learning strategy
SC_ST45	With PV, with storage (decentralized) and with Q-Learning strategy
SC_ST300_A	With PV, with storage (centralized) and with Q-Learning strategy (without CIEG exemptions)
SC_ST300_B	With PV, with storage (centralized) and with Q-Learning strategy (with 50% CIEG exemptions)
SC_ST300_C	With PV, with storage (centralized) and with Q-Learning strategy (with 100% CIEG exemptions)

6.2. Global characterization and Reference Case description

The simulations to be described use real data from a Portuguese collective building with electricity demand distributed by the common services and by 15 flats. All the apartments and common services are organized as an energy community considering a collective self-consumption scheme. The installation includes a renewable generation unit constituted by PV systems with overall 45 kWp and 70,2 MWh of annual generation. The sample power profiles for the demand and the PV systems were built using open datasets available at [319] and with sampling periods of 15 minutes, starting on 1st January 2019 until the 1st January 2020. Table 6.2 presents the annual energy demand of the consumers and their contracted power.

As illustrated in (Figure 6.1) the PV systems are integrated at the building level and in this sense the electrical public grid is not used for self-consumption purposes, i.e., for physical exchanges of energy between the PV systems and the community consumers. The public grid is only used to inject eventual electricity surplus in some periods and to get electricity from the grid in other periods.

Table 6.2. Annual Energy demand

	Annual Demand kWh	Contracted Power kVA
Common Services	40205	13,8
consumer 1	3175	3,45
consumer 2	2250	3,45
consumer 3	2621	3,45
consumer 4	5809	3,45
consumer 5	3735	3,45
consumer 6	4872	3,45
consumer 7	3865	3,45
consumer 8	3393	3,45
consumer 9	5552	3,45
consumer 10	16376	6,9
consumer 11	9983	3,45
consumer 12	4249	3,45
consumer 13	15106	6,9
consumer 14	15351	6,9
consumer 15	8755	3,45

The annual hourly energy demand profile for all the apartments and common services are presented in Figure 6.4. These load profiles show that between 23.00 and 6.00 the demand is lower, which is related to hours with less activity. After 07.00 the demand starts to increase, having a relatively constant profile in the common services until 22.00. On the other hand, the demand of the apartments increases after 18.00 achieving the peak power by 21.00.

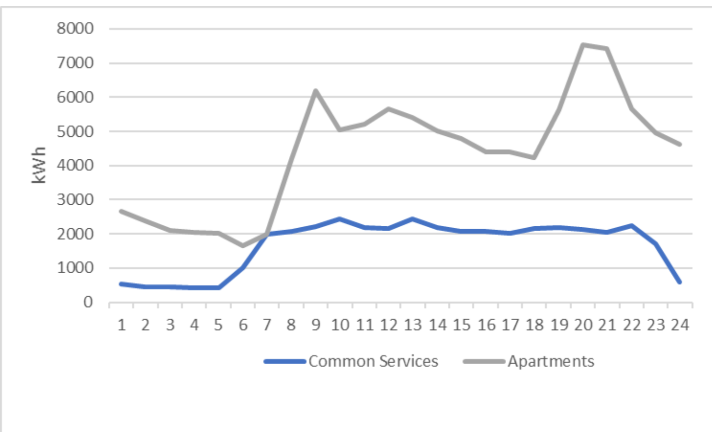


Figure 6.4.Global hourly energy consumption profile.

Regarding the photovoltaic generation, Figure 6.5. shows the corresponding hourly average generation.

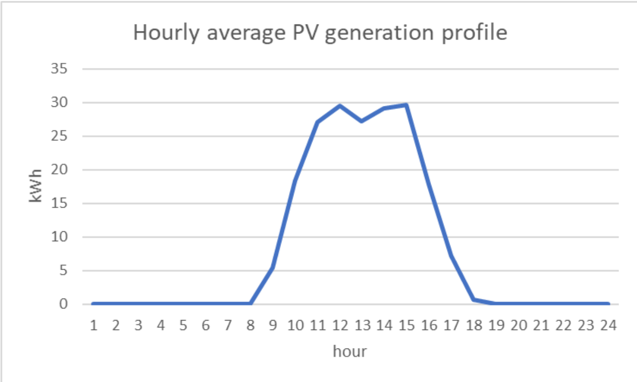


Figure 6.5. Average hourly PV generation

Considering the 15 min values of the demand of the 15 flats plus the common services and the generation of the PV systems, it was possible to estimate the demand supplied by the public grid, the demand supplied by the self-consumption and the electricity injected back to the grid. Table 6.3. presents the corresponding aggregated results.

Considering the community energy demand and production, Figure 6.6. presents the annual electrical energy balance. For a global energy demand of 145,4 MWh, 68% (98,6 MWh) are provided by the electrical supplier which means that the remaining 32% (46,8 MWh) are provided by self-consumption (left bar on Figure 6.6.). However, it is also possible to observe that the community produced more energy than the 46,8 MWh, corresponding to 70,2 MWh (right bar on Figure 6.6). This means that, 33% (23,4 MWh) of the community production was injected back into the grid and the remaining 67% (46,8 MWh) that was produced in the community was self-consumed.

Table 6.3.Annual Energy Community balance

	MWh
Global Energy demand	145,4
Demand supplied by the public grid	98,6
Demand supplied by self-consumption	46,8
Electricity injected back in the public grid	23,4

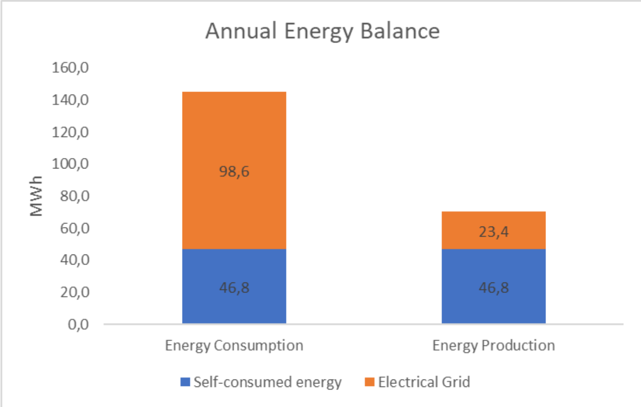


Figure 6.6. Community annual electricity demand and production

Figure 6.7 presents the monthly electrical energy balance. In this graph all the values are read in the left-hand side (LHS) vertical axis, except the energy injected back to the public network that is read in the right-hand side (RHS) vertical axis. It is possible to observe that the summer months (July, August, and September) are the periods when more electricity is injected back into the public grid. This is coincident with the months in which more energy is produced in the community, and this is obviously related with the higher PV output.

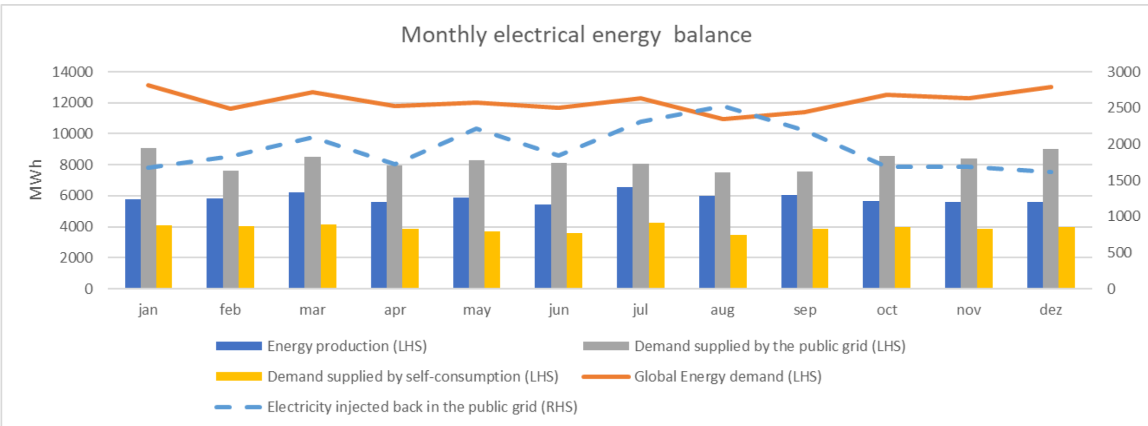


Figure 6.7. Monthly electrical energy balance

As mentioned before, this is the Reference Scenario, which doesn't consider storage systems (neither decentralized or centralized) and consists only of a PV system used for self-consumption purposes. In the case of any surplus, it will be injected back into the main public grid and will be remunerated by a bilateral contract established by the community and a traditional retailer which means that the Q-Learning approach is not used to optimize this remuneration.

The remuneration established for this bilateral contract (C^{PV}) was set at 50 €/MWh. The value established for C^{PV} had a relevant impact on the renewable energy promotion and on its penetration on the electric systems, namely electricity produced by PV systems. Since 2022, the Portuguese legislation [54] allows establishing bilateral contracts between producers (integrated in renewable energy communities) and retailers. The value defined for C^{PV} is somehow related but distant from the initial Feed In Tariffs supported by the Portuguese Legislation namely by the DL n.215-B/2012 [320] and the DL n.35/2013 [321]. In fact, the mentioned value adopted for C^{PV} in this work is much lower than the original Feed In Tariffs applied to PV generation units and this reduction is suggested by the values currently offered by retailers that accept buying the excess of electricity from self-consumption units.

In what concerns to the cost of electricity acquisition, all the demand supplied by the public grid will be paid at the WSM prices. In this work, and for all the scenarios considered, we used real electricity market prices for 2019 publicly available at the webpage of the Iberian Market Operator, OMIE, in [322].

Table 6.4. presents the energy annual costs for this Reference Case scenario. It presents the amounts associated with the Access Tariffs, the energy acquisition costs, and the remuneration obtained from selling the energy surplus generated by the PV generation regarding the demand.

Table 6.4. Energy annual costs (Ref-Case)

Costs	Ref-Case
Access Tariffs	5.171,07 €
Electricity acquisition	6.899,66 €
Selling energy	-1.167,18 €
Total	10.903,55 €

Analyzing the previous table, it is possible to observe that the total energy annual cost is reduced by almost 11% given the remuneration obtained by selling the electricity surplus (-1.167,18 €). Recall that this remuneration is obtained by selling the energy surplus at the C^{PV} price and without considering the Q-Learning process. The impact of using Q-Learning will be assessed and analyzed in the next sections.

6.3. Scenario SC_PV description and simulation results

6.3.1. Optimization model analysis and results

As it was explained in Chapters 4 and 5, the utility function used in the developed model corresponds to the ratio between the C^{Bid} and C^{PV}. The higher this ratio is, the higher will be the community profits by applying the optimization model. After defining the Bid Price (C^{Bid}), the Market Community Agent calculates the Utility Function. If the WSM price (C^{agg}) is lower than C^{PV}, the Market Community Agent will receive the guaranteed reward defined by the bilateral contract, that is C^{PV}. Otherwise, and if the C^{Bid} is lower than the C^{agg} and higher than C^{PV}, the reward will be equal to the difference between C^{Bid} and C^{PV}. This reward will be a consequence of the defined bidding strategy of the developed Q-Learning methodology. In case of energy deficit, and because we assume that consumers have no elasticity regarding the price, the bids in the LEM will correspond to the required energy paid at the WSM market price.

The LEM and the WSM markets are cleared individually, and their coordination is done as follows:

a) the local energy deficit is bought at the WSM price C^{agg};
b) the local generated electricity is firstly self-consumed and then the remaining energy will be traded in the WSM considering the price obtained after the optimization strategy process, i.e., due to the application of the Q-Learning methodology. If the LEM prices C^{Bid} are lower than the WSM prices C^{agg}, the community has a potential profit that is associated to the difference between both prices. Otherwise, if the WSM prices are lower than the LEM prices, the surplus energy will be sold at C^{PV} as previously referred.

The developed ABM model was applied to real data of consumption, PV generation and WSM prices. As mentioned in Sections 4.7 and 4.8, the definition of the Q-Learning procedure is based on a pair state-action $Q(s_m, a_n)$.

The learning rate λ reflects the degree to which estimated Q-values are updated by new data. If λ=0 the agent doesn't learn. If λ=1 then the agent is induced to consider only the most recent information. The discount factor γ represents the weight given to future reinforcements. If $\gamma = 0$ the agent considers only current rewards, otherwise if $\gamma = 1$ distant rewards become more important. The greedy policy parameter ε is related with the probability for the agent to select an action rather than the best one, that is, the one associated with the largest Q-value.

In this Case Study, we used the following 3 actions:

- a_1 represents Action 1 corresponding to a bid down of -1 €/MWh regarding the bid price of the previous iteration;
- a_2 represents Action 2 corresponding to no bid up nor bid down regarding the bid price of the last iteration (0 €/MWh);
- a_3 represents Action 3 corresponding to a bid up of +1 €/MWh regarding the bid price of the last iteration.

As mentioned in Section 4.8, the state's definition considers five states that are related with the reward associated with the previous episode and with the obtained profit. These states are detailed in Table 6.5.

Table 6.5. Definition of the Q-Learning States

State	Reward	Reward (related with previous episode)
s_1	Increased	Not possible to increase
s_2	Increased	Possible to increase
s_3	Equal	Indifferent
s_4	Decreased	Possible to increase
s_5	Decreased	Not possible to increase

The structure of the Q-matrix $Q(s_m, a_n)$, as well as the values of the parameters λ, γ and ε used to obtain this matrix are presented in Table 6.6.

Table 6.6. Q-matrix for the Scenario SC_PV

State/Action	a1	a2	a3	Parameter	
S1	Q1,1	Q1,2	Q1,3	λ	0,8
S2	Q2,1	Q2,2	Q2,3	γ	0,8
S3	Q3,1	Q3,2	Q3,3	ε	0,1
S4	Q4,1	Q4,2	Q4,3		
S5	Q5,1	Q5,2	Q5,3		

The learning rate λ was set at 0,8, as well as the discount factor γ. The greedy policy parameter ε was set at 0,1, which means that the agent has 90% probability of choosing the action with higher Q-value (greedy selection).

After describing the simulation conditions and having enumerated the values that were adopted for several parameters, we will now present and analyze the results that were obtained for Scenario SC_PV. Figure 6.8 presents the results for one year (52 weeks) simulation.

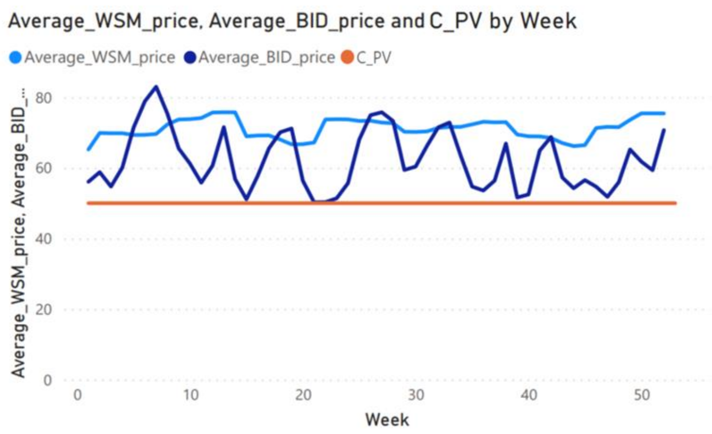


Figure 6.8. Bidding results for the SC_PV scenario.

In Figure 6.8., the light blue line corresponds to the WSM price C^{agg}, the orange line represents the C^{PV} specific value, and the dark blue line represents the LEM price C^{Bid} taking in consideration the bid strategy of the Market Community Agent. It is possible to verify that the community agent was exploring the environment by doing bid up and bid downs always above 50,00 €/MWh. This situation is explained by the learning experience that our agent has during the bidding process. The agent adapted his behavior considering the pre-defined strategy and learns with past experiences.

Figure 6.9 presents the WSM and LEM average prices observed in the month of January, as a consequence of the bidding strategy adopted by the Market Community Agent. In addition, Figure 6.10. includes a more detailed overview of the impact of the defined strategy. On January 27th the bid strategy of the agent reaches an average value little higher than the WSM price, where the WSM price was 69,46 €/MWh and the bid price was set as 69,71 €/MWh. In this case, the selling price will be equal to C^{PV} (50 €/MWh). In these cases, there will be no additional profit and the reward will be equal to 0 €/MWh. If the bid price was a little lower than the WSM price, the reward was equal to difference between those Bid Price and the bilateral contract price C^{PV}. This was a consequence of the fact that the agent explores the environment by doing bid up/downs between C^{PV} and the WSM price.

Figure 6.9. January average prices results for SC_PV

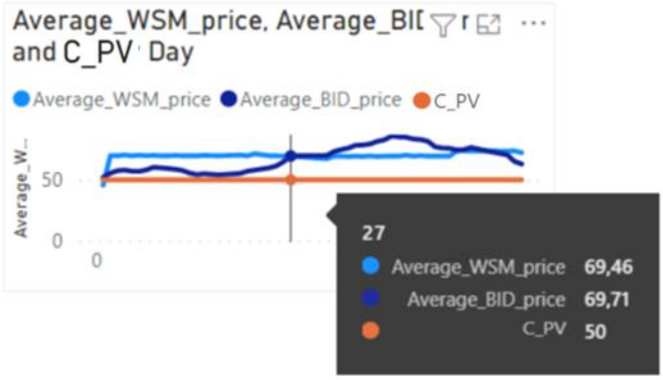


Figure 6.10. January average prices results for SC_PV highlighting the results for day 27.

Analyzing now in more detail the behavior of the Market Community Agent, regarding the actions and the states that were considered, Table 6.7. shows the Q-matrix on January 4th between hour 11 and 15. Given there is energy surplus at this period (after being self-consumed), the remaining energy will be traded considering the defined coordination between the WSM and LEM. The agent has 90% of probability (ε=0,1) of choosing the action which corresponds to the maximum value of the Q-matrix. At hour 12, the action that was chosen was a_3, that corresponds to a bid up of +1 €/MWh regarding the bid price of the last iteration. So, at this hour the bid was 58,00 €/MWh (the previous bid was 57,00 €/MWh at hour 11). Considering that there is an increase on the reward regarding the previous one (difference between C^{Bid} and C^{PV} changes from 7 to 8 €/MWh, and it is possible to get more profit (increase until WSM price), state s_2 was therefore obtained.

Table 6.7. Q-matrix for SC_PV (considering no storage) – January 4

hour	BID_price	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
10		68,44						
11	57,00	69,30	7,00	15,46	27,79	0,56	2	3
12	58,00	68,72	8,00	-25,86	-11,63	17,87	3	2
13	59,00	70,65	9,00	-25,86	-11,63	22,21	3	2
14	58,00	72,05	8,00	-43,50	21,76	-39,69	1	4
15	58,00	71,43	8,00	15,46	27,79	17,95	2	3
16		67,50						
17		67,78						

At day 4 hour 13, the agent chooses the action with higher Q-value (greedy selection), which was action a_3. This represents a bid up of 1 €/MWh which means a change of bid price from 58,00 €/MWh to 59,00 €/MWh. The agent state keeps in s_2, which means that the agent has obtained more profit, compared with the previous episode and it is possible to get more profit because the WSM price was 68,72 €/MWh and the LEM was 59,00 €/MWh. So, the LEM price still has margin to increase in order to get closer to the WSM price.

At hour 14, the chosen action is not the one having the maximum Q-value (there is 10% probability of the agent not choosing the action with maximum Q-value) and in this sense the agent didn't chose action a_2 and chose action a_1. This represented a bid of 58,00 €/MWh (change of -1 €/MWh regarding the previous bid). Since the reward decreases (regarding the previous episode) and it is possible to get more profit (the difference between the BID price and WSM price is not equal to zero) the agent assumes that the state is now s_4.

The Q-matrix is again updated and at day 4 hour 15 the agent choses the maximum value of Q-matrix (with 90% of probability) which originates the selection of action a_2. This means not to bid up nor bid down regarding the bid price of the last iteration (change of 0 €/MWh regarding the previous bid). Since the reward remains the same regarding the previous episode, the agent is in state s_3.

Analyzing with more detail the behavior of the Market Community Agent at day 27, Table 6.8. presents the corresponding Q-matrix results. At hour 12 the WSM price was higher than the LEM price. However, and since there was a bid up of 1 €/MWh (as consequence the agent takes the action a_3 at hour 13) the bid price became higher than the WSM price at hour 13. In this case, the revenue will be equal to the C^{PV} which was defined at 50,00 €/MWh. The potential reward corresponds to the difference between the C^{PV} (50,00 €/MWh) and the WSM price (69,82 €/MWh) and this explains why the corresponding reward value in Table 6.8 is negative meaning that it was lost the opportunity of having a reward of 19,82 €/MWh.

Table 6.8. Q-matrix for SC_PV (considering no storage) – January 27

hour	BID_price	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
10	68,00	71,23	18,00	30,16	61,20	20,77	3	2
11	68,00	72,37	18,00	35,39	31,06	63,81	2	3
12	69,00	70,18	19,00	30,16	67,48	20,77	3	2
13	70,00	69,82	-19,82	-43,50	29,77	62,21	3	4
14	71,00	68,72	-18,72	30,16	67,48	28,11	3	2
~~15~~	~~71,00~~	~~67,34~~	~~-17,34~~	~~30,16~~	~~42,01~~	~~28,11~~	~~2~~	~~2~~
16	71,00	66,59	-16,59	30,16	22,69	28,11	2	2

Now let us analyze the economical results for Scenario SC_PV considering a period of 12 months. Figure 6.11. presents the results obtained monthly as well as the accumulated results along the year. In this Figure, blue bars correspond to the monthly calculated rewards (values in the left vertical axis) whereas the dark blue line represents the cumulative reward (values in the right-hand side vertical axis).

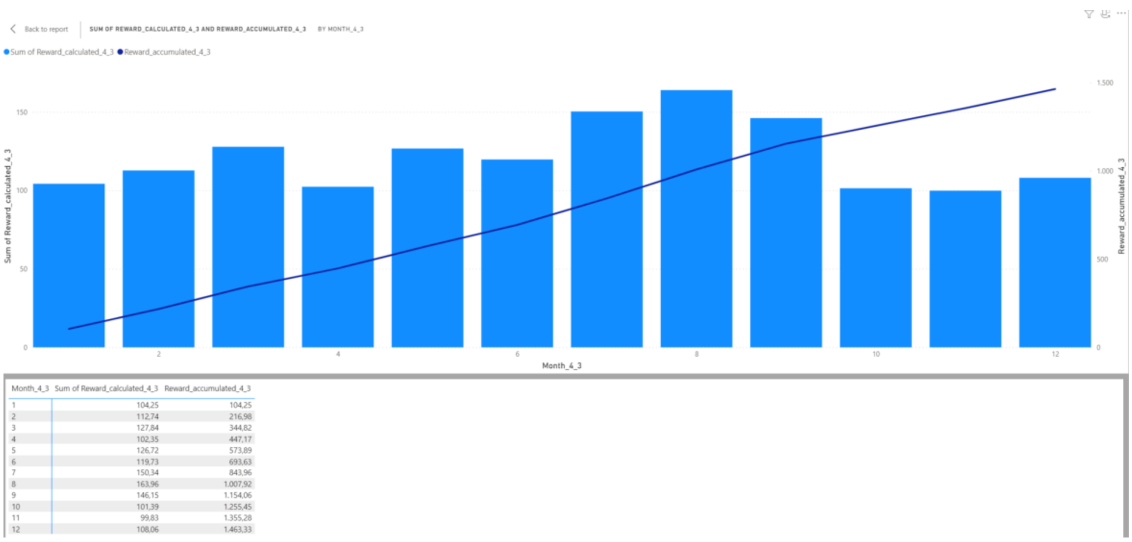


Figure 6.11. Scenario SC_PV - calculated reward by month and accumulated reward (€) for λ=0,8, γ=0,8 and ε=0,1

As can be observed, the accumulated reward at the end of the year is approximately 1463,33 €. As defined in our bidding strategy, when the bid price is higher than the WSM price, the bid price is not cleared and it is assumed a value equal to the C^{PV}, i.e., 50,00 €/MWh. When the bid price is lower than the WSM price, the assumed price is the bid price. It is also possible to observe that the months in which the rewards are larger correspond to July, August, and September. These are the months in which PV generation is larger (sunny months in Portugal). Month 8, August, has the highest calculated reward (163,96 €) and this value is 61% higher than the value obtained for November, which had the lowest calculated reward at 99,83 €. The exception is related to March. As it was possible to observe in the dataset, the consumption was lower in this month. Therefore, the energy surplus is larger and so this allows having more transactions in the LEM thus contributing to an increase in the reward.

6.3.2. Impact of the learning rate, discount factor and greedy policy

Let us now analyze the impact of the learning rate λ, the discount factor γ and the greedy policy ε parameters in the Q-matrix and on the results obtained in scenario SC_PV. This means that new simulations were run considering changes on each of these parameters, one at a time, so that they correspond to variations of SC_PV termed as SC_PV_A, SC_PV_B and SC_PV_C regarding the base case that is associated to scenario SC_PV that was previously described.

We will start by changing the greedy police parameter from 0,1 to 0,0 (Table 6.9.). This means that the agent will always choose the action with the higher Q-value which corresponds to a greedy selection strategy.

Table 6.9. Scenario SC_PV_A – changing the greedy police parameterε

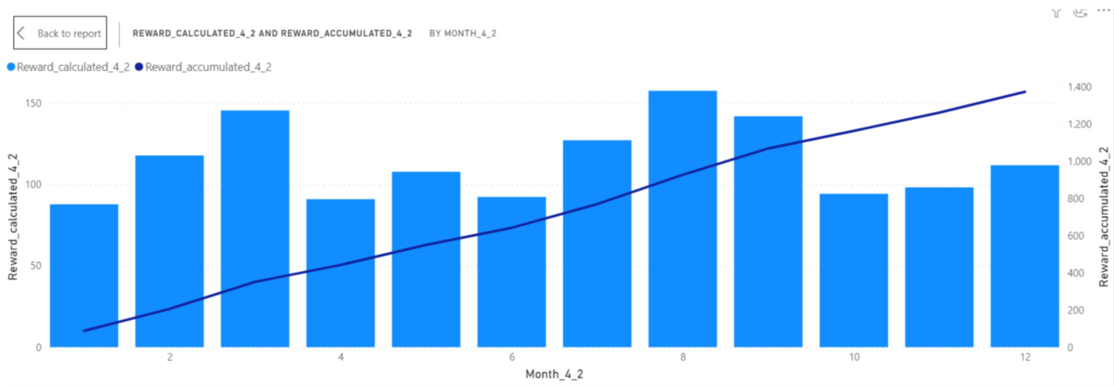
Parameter	
λ	0,8
γ	0,8
ε	0,1 –> 0,0

As we can observe in Table 6.10, for the same day that was analyzed previously (January 27 between hours 11 and 13), the agent always choses the action with higher Q value. In this case, at hour 13, it was chosen action a_2 which keeps the bid equal to the previous one at 55,00 €/MWh. This situation occurs because the agent always chooses the action with the highest Q-value (with 0% of probability of choosing a worse one). This behavior doesn't let the agent choose another action than the one associated with the highest Q-value which eventually means that the agent loses the opportunity of increasing its reward. For instance, if the agent increased its bid after taking action a_3 (which has not the highest matrix Q-value) the reward was higher because the bid instead of 55,00 €/MWh would be 56,00 €/MWh.

Table 6.10. Scenario SC_PV_A - Q-matrix – January 27; – λ=0,8, γ =0,8 and ε=0,0

hour	BID_price	WSM price	Reward	Q(s.1)	Q(s.2)	Q(s.3)	Action	State
10	55,00	71,23	5	8,12	22,01	14,80	2	3
11	55,00	72,37	5	8,12	22,49	14,80	2	3
12	55,00	70,18	5	8,12	22,89	14,80	2	3
13	55,00	69,82	5	8,12	23,23	14,80	2	3
14	55,00	68,72	5	8,12	23,51	14,80	2	3
15	55,00	67,34	5	8,12	23,75	14,80	2	3
16	55,00	66,59	5	8,12	23,95	14,80	2	3
17		67,85						

Figure 6.12. presents the values of the rewards for 12 months simulation, after changing the greedy police parameter from 0,1 to 0,0.



Month_4_2	Reward_calculated_4_2	Reward_accumulated_4_2
1	87,80	87,80
2	117,79	205,59
3	145,47	351,06
4	90,93	442,00
5	107,77	549,77
6	92,32	642,09
7	127,18	769,27
8	157,56	926,82
9	141,90	1.068,73
10	94,26	1.162,98
11	98,21	1.261,19
12	111,79	1.372,98

Figure 6.12. Scenario SC_PV_A - calculated reward by month and accumulated reward (€) for λ=0,8, γ =0,8 and ε=0,0

The values of the rewards per month and the corresponding accumulated value are depicted in Figure 6.12. The accumulated reward at the end of the year decreases from 1.463,33 € to 1.372,98 €

when compared with the result obtained using the greedy policy parameter equal to 0,1 (Figure 6.11). As observed for day 27, this “greedy” convergence doesn’t allow the exploration process to be more effective by experimenting all the actions even if they are worse at a given step of the learning process.

Now, we will analyze the behavior of the results of scenario SC_PV by changing the value of the γ parameter, that represents the weight given to future reinforcements, as indicated in Table 6.11. that is reducing its value from 0,8 to 0,1.

Table 6.11. Scenario SC_PV_B – changing the discount factor parameter γ

Parameter	
λ	0,8
γ	0,8 -> 0,1
ε	0,1

The same day that was previously analyzed (January 27) is now also considered. It is possible to observe that the bid price was lower than the WSM price only at hour 11 (Table. 6.12.) and consequently a positive reward was achieved. This is justified by the fact that in the other hours of this day, the agent uses bid prices higher than the WSM price. So, these bids were not cleared, and the agent sold the electricity at the bilateral contract price C^{PV} (and the reward obtained, i.e., the difference between C^{PV} and C^{Bid} was negative). At hour 11, the agent selected action a_1 (decrease the bid value by 1 €/MWh, from 72,00 to 71,00 €/MWh). Given that the reward increased, and it is not possible to get a larger profit, the state was s_1.

Table 6.12. Scenario SC_PV_B - Q-matrix – January 27; – λ=0,8, ϒ=0,1 and ε=0,1

hour	BID_price	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
10	72,00	71,23	-21	-6,64	-26,72	-25,84	3	5
11	71,00	72,37	21	-27,91	-18,80	-22,82	1	1
12	71,00	70,18	-20	13,97	-26,72	-25,84	2	5
13	70,00	69,82	-20	0,10	-11,67	-10,23	1	2
14	69,00	68,72	-19	-14,95	-11,67	-10,23	1	2
15	70,00	67,34	-17	-14,95	-11,67	-16,74	3	2
16	70,00	66,59	-17	-14,95	-16,54	-16,74	2	2
17		67,85						

Figure 6.13. presents the results for the 12 months simulation, after changing the value of the γ parameter from 0,8 to 0,1.

Month	Reward_calculated	Reward_accumulated
1	89,10	89,10
2	112,08	201,18
3	131,91	333,09
4	100,56	433,65
5	125,50	559,15
6	112,84	671,98
7	129,76	801,74
8	147,79	949,53
9	127,70	1.077,23
10	85,68	1.162,91
11	86,45	1.249,36
12	95,76	1.345,11

Figure 6.13. Scenario SC_PV_B - calculated reward by month and accumulated reward (€) for λ=0,8, γ =0,1 and ε=0,1.

By decreasing the value of the γ parameter, and in this way the weight given to future reinforcements decreases, the agent finds new strategies in each hour and doesn't have in consideration the impact of its decisions in future rewards. Due to this consideration, we choose to use a higher value for γ in our model. The accumulated reward at the end of the year is now 1.345,11 €.

Let us now analyse the behaviour of the developed model by changing the learning rate parameter λ. This parameter reflects the degree to which estimated Q-values are updated by new data. Table 6.13. presents the new parameters that will now be used. In this new simulation we only changed the value of the learning rate, while the values of the other two parameters remained unchanged regarding the original values that were used.

Table 6.13. Scenario SC_PV_C – changing the learning rate parameter λ

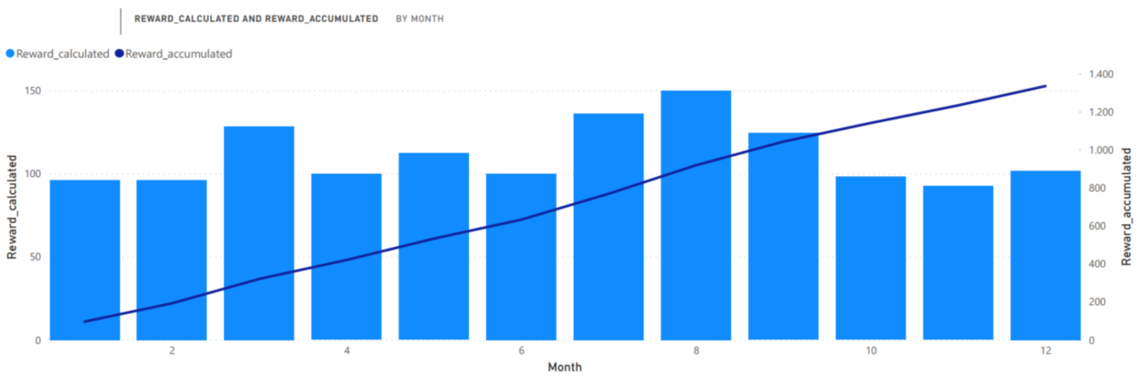
Parameter	
λ	0,8 -> 0,1
γ	0,8
ε	0,1

As observed in Table 6.14., at hour 13, the bid price was higher than the WSM and so the reward was negative. At hour 14, and after the agent performs action a3, the bid price increases by 1 €/MWh, from 70,00 €/MWh to 71,00 €/MWh. Since this bid continues to be higher than the WSM, the reward remains negative. At hours 15 and 16 the bid price maintains the value of 71,00 €/MWh followed by performing action a2 and the bid price continues higher than the WSM price. These results reveal that the agent doesn't "want to learn" using fresh information, namely the obtained negative rewards, and doesn't change its actions in order to decrease the bid price until achieving a lower value when compared with the WSM price. This situation happens because of the low value of the learning rate that was used in this simulation.

Table 6.14. Scenario SC_PV_C - Q-matrix – January 27; – λ=0,1, γ =0,8 and ε=0,1

hour	BID_price	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
10	68,00	71,23	18,00	30,16	61,20	20,77	3	2
11	68,00	72,37	18,00	35,39	31,06	63,81	2	3
12	69,00	70,18	19,00	30,16	67,48	20,77	3	2
13	70,00	69,82	-19,82	-43,50	29,77	62,21	3	4
14	71,00	68,72	-18,72	30,16	67,48	28,11	3	2
15	71,00	67,34	-17,34	30,16	42,81	28,11	2	2
16	71,00	66,59	-16,59	30,16	22,69	28,11	2	2
17		67,85						

The analysis of the rewards obtained for the entire year indicates that they are lower than the ones obtained on the simulation with λ equal to 0,8. In this case the annual reward is 1335,98 € (Figure 6.14). When using λ equal to 0,1, the agent does not completely explore its bid ups and bid downs taking in consideration its experience. Since the market dynamics are continuously changing, it is most desirable that agents can rapidly adapt to new situations so in this sense a value of 0,8 will be adopted for the learning rate.



Month	Reward_calculated	Reward_accumulated
1	96,20	96,20
2	96,28	192,48
3	128,50	320,98
4	99,74	420,72
5	112,35	533,06
6	99,97	633,04
7	136,29	769,32
8	150,10	919,42
9	124,28	1.043,70
10	98,01	1.141,71
11	92,57	1.234,28
12	101,70	1.335,98

Figure 6.14. Scenario SC_PV_C - calculated reward by month and accumulated reward (€) for λ=0,1, γ =0,8 and ε=0,1.

Table 6.15. presents an overview of the different parameters that were analyzed and the respective model annual reward of the selling bids. The adoption of the values used for λ, ϒ and ε will be justified below.

Table 6.15. Parameters data - summary table

Parameter	SC_PV	SC_PV_A	SC_PV_B	SC_PV_C
Λ	0,8	0,8	0,8	0,1
γ	0,8	0,8	0,1	0,8
ε	0,1	0,0	0,1	0,1
Annual reward (€)	1463,33	1372,98	1345,11	1335,98

By changing the greedy policy parameter (ε) to 0,0, the agent will always choose the action with higher Q-value (greedy selection) and has 0% probability of choosing a worse action. However, this greedy strategy doesn't allow the exploration process to be more effective by experimenting with all actions even if they are worse at a given step of the learning process. So, in our work we will adopt a value to the parameter ε equal to 0,1.

The γ parameter represents the weight given to future reinforcements and when it decreases the agent finds new strategies in each hour and doesn't have in consideration the impact of its decisions in future rewards. Due to this consideration, the value assumed to γ will be 0,8 to give importance to possible future rewards.

Analyzing now the impact of the learning rate parameter λ that reflects the degree in which estimated Q-values are updated by new data, a low value means that the agent doesn't want to learn using "fresh" information". In this case, the Q-values are updated with very small increments of new information and for that reason the new information is not valued, meaning that the agent has a very slow learning rate. Considering that electricity market dynamics are continuously changing, it is most desirable to have agents that can adapt their behavior with a very high capability of learning. For this reason, we chose to use in our work a value of the learning rate λ of 0,8.

There are different approaches to model the evolution of the learning rate, like for instance dynamic ones that evolve during the simulation process. However, the simulations done along this work do not use such a dynamic approach but in fact the value of the learning rate remains constant along the simulations. As a reference, the simulations developed in [14] present also good results using a similar environment with values of the parameters that will be considered in the simulations reported in this work (i.e., ε=0,1, γ =0,8 and λ=0,8).

6.3.3. Economic assessment of the scenario SC_PV

As previously indicated, we considered a Portuguese collective building with electricity demand distributed by the common services and by 15 flats. All the apartments are organized as an energy community considering a collective self-consumption scheme. It has a renewable generation unit constituted by PV systems without storage systems and the operation of the LEM is simulated not using the Q-Learning approach. The public grid is only used to inject eventual electricity excesses in some periods and to get electricity from the grid in other periods. Regarding the applicable tariffs, the access and energy tariffs (see Annex B1) [323] are applied to the energy imported from the grid.

For comparison purposes, we considered a Normal Exploration situation that has the same demand profile but without self-consumption, that is without the PV units. This means that all the electricity is taken from the grid, and so the annual energy costs (including the applicable Access Tariffs and electricity acquisition), as indicated in Table 6.16, will be larger than 18.000 €. When compared with Scenario SC_PV, the cost associated with access tariffs and electricity acquisition will be reduced to a value of approximately 12.000 €. Therefore, it is possible to observe a significant reduction in the global annual cost resulting in a total saving of 34,23%.

Table 6.16. Comparison of access tariffs and electricity acquisition cost– Scenario SC_PV with Normal Exploration

Costs	Scenario SC_PV	Normal Exploration	Savings	
Access Tariffs	5.171,07 €	8.135,26 €	2.964,20 €	36,44%
Electricity acquisition	6.899,66 €	10.218,71 €	3.319,05 €	32,48%
Total	12.070,73 €	18.353,97 €	6.283,25 €	34,23%

Figure 6.15 and 6.16 present the related costs and their distribution in both cases, scenario SC_PV versus normal exploration. It is possible to observe a reduction of more than 30% on the Energy Costs and on the Access Tariff using the self-consumption scheme associated with SC_PV, when compared with the Normal Exploration mode.

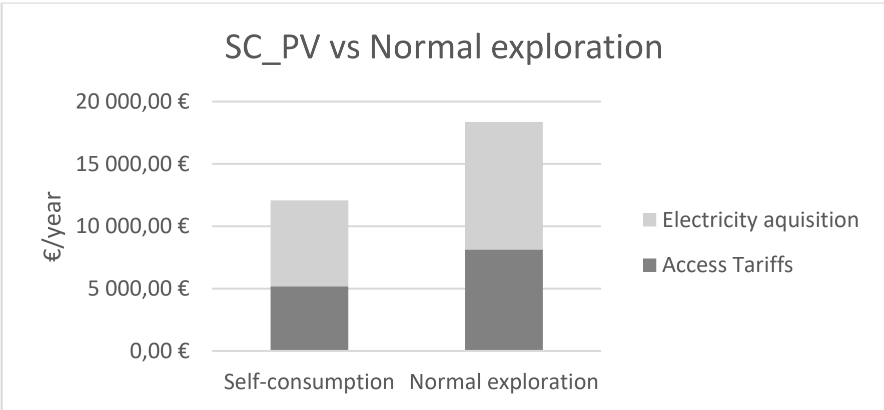


Figure 6.15. Comparison of costs between scenario SC_PV and normal exploration

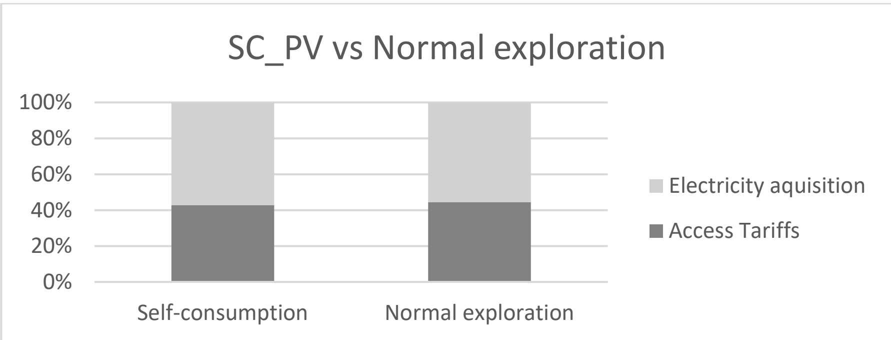


Figure 6.16. Breakdown of costs for scenario SC_PV versus normal exploration

Regarding now the total costs, considering the profits of selling the electricity surplus, and in order to assess the impact of the applied learning strategy, Table 6.17 presents the results that were obtained with and without the application of the optimization model, that is for the scenarios SC_PV and Ref-Case. For this, the right column considers the Ref-Case scenario in which the surplus energy generated by the PV regarding the demand is paid at the bilateral contract price, C^{PV}, set at 50,00 €/MWh and the energy supplied by the public network is paid at the market price so that no optimization strategy is used. On the central column, the energy is sold using the bids prices followed by the applied learning strategy. As it is possible to observe, the increase of the revenues by selling the electricity surplus has an important impact on the reduction of the total energy annual costs. When applying the optimization strategy, the revenue by selling the electricity surplus is 25% higher than in the Ref-Case.

Table 6.17. Energy annual costs (optimization and non-optimization models) (Scenario SC_PV and Ref-Case)

Costs	SC_PV	Ref-Case
Access Tariffs	5.171,07 €	5.171,07 €
Electricity acquisition	6.899,66 €	6.899,66 €
Selling energy	-1.460,66 €	-1.167,18 €
Total	10.610,06 €	10.903,55 €

To access the economic value associated with the scenario SC_PV, the NPV methodology will now be used. As mentioned in Section 5.5.2, the NPV is the sum of the present value of a series of present and future cash flows, considering a discount rate. Because NPV accounts for the time value of money, it provides a way to evaluate and compare products with cash flows spread over many years, as in loans, investments, payouts from insurance contracts and so on.

The NPV methodology, which will be calculated for all scenarios, will reflect the total costs, namely the operational and investment costs, and will consider the expected economic benefits of selling the surplus of energy with the grid.

To establish a baseline for further comparison, the reference case will be considered (Ref-Case). Recall that in this scenario the community to be assessed considers a collective self-consumption scheme with PV generation, where the surplus of energy generated by the PV regarding the demand is paid at a C^{PV} and the energy supplied by the public grid is paid at the market price. So, in the Ref-Case the Q-Learning strategy is not considered.

The dimensioned photovoltaic unit consists of PV systems with a total of 45 kWp peak power. This capacity is aligned with the peak power of the installation and in a way that self-consumption is privileged while reducing the excesses the energy injected into the grid. This self-consumption scheme is supported by D.L 15/2022 (Article 88 – 2 e) [54].

The estimation of the installation costs is based on the fact that economies of scale can originate benefits. Solar PV is already the cheapest form of electricity generation in many countries and market segments. Market prices of PV modules are evolving so fast that it is difficult to find reliable up to date public data on real PV capital (CAPEX) and operational expenditures (OPEX) on which to base the economic calculations. The report presented in [310] projects the PV LCOE until 2050. In this work, the assumptions for PV investment costs were made based on the previous report considering the year 2020. Table 6.18 presents the PV installations reference costs for CAPEX and OPEX.

Table 6.18. PV installations reference costs and economic parameters used for economic performance calculation

	Reference Cost
CAPEX	0,384 €/Wp
OPEX	8,1 €/kWp/year

Considering the investment in PV, for a 45 kWp system, the following data will also be considered:

- Lifetime of the panels: 20 years;
- Lifetime of the inverters: 10 years [324];
- 20% of the investment with equity interest rate, and the remaining by a financial loan; for 20 years with an interest rate of 2,5% [324];

In this sense, the expenses needed to do the investment on the PV system, considering 20% with equity for CAPEX and OPEX, are 17.280 € and 364,5 €/year, respectively. All the tariffs and electricity acquisition costs that were considered were the same throughout the years under analysis. The NPV of this scenario, Ref-Case that considers the PV system but does not use the optimization strategy, is –210.085,00 €.

Let us now consider the SC_PV scenario in which the energy in excess is injected in the public network using selling bids optimized according to the Q-Learning strategy. In this case, the revenue obtained from selling the energy excess is 1460,66 € per year as indicated in Table 6.17. Considering the same investment costs in the PV systems, the NPV is now –205.510,00 €.

It should be clarified that this negative value directly results from the investment cost, the acquisition of electricity from the grid and the associated access tariffs. Although the PV installation, operation and maintenance costs are considered in both cases, the NPV becomes less negative indicating that there is a decrease of the total cost to be paid by the consumers over the simulated period.

Comparing with the reference case, Ref-Case, the NPV decreases by 4575 € (Table 6.19.) which reveals that the optimization strategy that was used impacts on the final NPV namely because in several periods it allows selling the excess of local generation regarding the local demand at a price higher than the value adopted for C^{PV}. This result also means that, although investment, operation and maintenance costs of the PV systems are internalized in the calculation, the NPV evolves in the positive direction, meaning that it gets less negative and so the consumers obtain important savings.

Table 6.19. Net present values for the Ref-case and for the SC_PV scenario

	Ref-Case without optimization strategy	Scenario SC_PV with optimization strategy
NPV	-210.085,00 €	-205.510,00 €

6.4. Decentralized storage – scenario SC_ST45 description and results

6.4.1. Scenario description and energy balance

In this simulation, the installation to be analyzed differs from the previous one because we now consider an energy storage system (Figure 6.17.) located at the building level. As explained in Section 6.1 if a set of similar buildings was studied, then each of them would have its own storage unit and this sense this architecture is termed as decentralized. As explained before, this does not correspond to a fully decentralized installation in which each consumer/prosumer would have its own storage unit. This kind of fully decentralized architecture was not considered and tested since the investment cost of the storage equipment is still too large to justify such an approach. On the other hand, installing a storage system at each building level will turn the definition of its operation strategy less complex. As much as possible, the energy produced in the community is self-consumed and stored without any tariff payment. This is supported by the number 2 of article 212 of DL 15/22 [54], since the energy is self-consumed and stored using the building busbar and not using the electrical public grid.

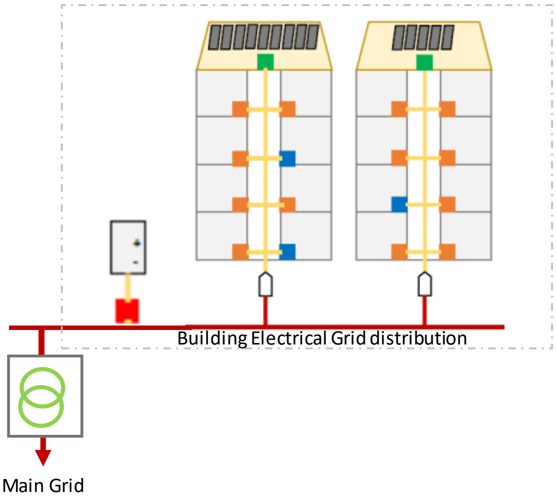


Figure 6.17. Illustration of the collective self-consumption installation with decentralized storage system (scenario SC_ST45) (adapted from DGEG [318])

As mentioned in Chapter 5.3.2., in this simulation the bidding strategy of the Market Community Agent considers the storage system. The objective of the community is to minimize the electricity consumption cost by prioritizing self-sufficiency and to sell any surplus to the WSM through the Market Community Agent. However, the quantities and the bids to be considered by the Market Community Agent will now take into account the existence of the ESS and depend on its technical characteristics, namely on the SOC of the batteries and if they are charging, discharging or in idle mode. They will be in the charging mode if there is surplus of PV generation regarding the local demand and in the discharging mode if the community demand is higher than the local PV generation. However, and if the stored energy is sufficient to feed the demand, and it also has some surplus, the energy in excess will be sold to the market following the optimization strategy defined in this work. Using this strategy, the social welfare of the community members will increase because the cost of buying electricity from the grid is reduced and it is increased the self-consumption level of the community.

In this simulation, three 15 kWh modules of *sonnenBatterie* [325] (leading to a total of 45 kWh), each one with an efficiency up to 98%, were considered. The charge and discharge rates depend on the performance of the inverters with a nominal power of 3,3 kW and a maximal efficiency of 96%. The SOC of individual batteries was restricted to a range between 20 and 80% of the nominal capacity [326]. We assume no degradation processes and do not consider lifetime expansion by smart charging control devices.

The demand and PV renewable generation profiles were built using the same dataset already used in Section 6.2. [319]. The annual energy community balance, considering now the ESS system, is presented in Table 6.20. This table includes the global energy demand (equal to the value in the previous simulation since the dataset used was the same), the demand supplied by the grid and by self- consumption, as well as the electricity injected back in the public grid.

Table 6.20. Annual Energy Community balance (with decentralized ESS)

	MWh
Global Energy demand	145,4
Demand supplied by the public grid	78,6
Demand supplied by self-consumption	66,8
Electricity injected back in the public grid	13,9

Comparing this balance with the one from the SC_PV scenario in which there is no storage unit (Table 6.3), the demand supplied by the public grid decreases 21% (from 98,6 to 78,6 MWh). This is due to the additional energy provided by the storage system. The demand supplied by self-consumption increases 30% (from 46,8 to 66,8 MWh) which is in line with the strategy defined in our simulation model. This means that the energy produced by the PV system and the additional one provided by the storage system follows the Energy community philosophy which aims at incentivizing self-consumption. In what concerns the electricity injected back to the public grid, it is now more reduced than the one that was injected in the grid without storage, and it decreases by almost 41% (from 23,4 to 13,9 MWh). This reduction is explained by the fact that the adopted strategy prioritizes the self-consumption, and the presence of the storage unit allows storing energy generated by the PV systems when it is in excess regarding the local demand instead of immediately injecting these excesses back to the public grid.

Figure 6.18 shows the annual energy balance for the architectures with storage (SC_ST45) and without storage (SC_PV), considering the community energy demand and generation. It is possible to observe the increase of the community self-consumed energy in the simulation with storage system (SC_ST45). In what concerns the electricity injected back into the grid, it is lower in the scenario SC_ST45 as indicated above. As previously highlighted, in the overall energy generation, using the SC_ST45 architecture it is possible to have a better management of the energy generated by the PV panels. This means that the generation profile is more “aligned” with the demand profile than what occurs in the system without storage meaning that the self-consuming level is leveraged by the installation of the storage unit.

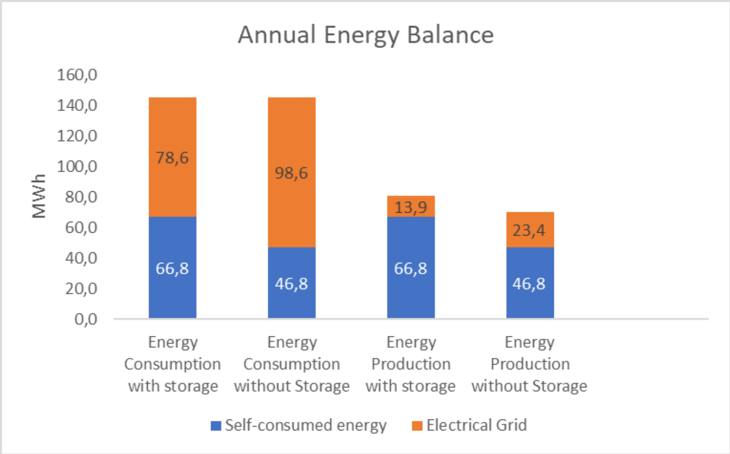


Figure 6.18. Community annual electricity demand and production (with and without storage)

Figure 6.19 presents the monthly distribution of the electrical energy for scenario SC_ST45. When compared with the monthly analyses for the architecture without storage, SC_PV, in Figure 6.7, it is possible to observe that the demand supplied by the public grid is lower in every month. Conversely, there is an increase in each month of the demand supplied by self-consumption. In this graph all the values are read in the left-hand side (LHS) vertical axis except for the electricity injected back in the public grid that is read in the right-hand side (RHS) vertical axis.

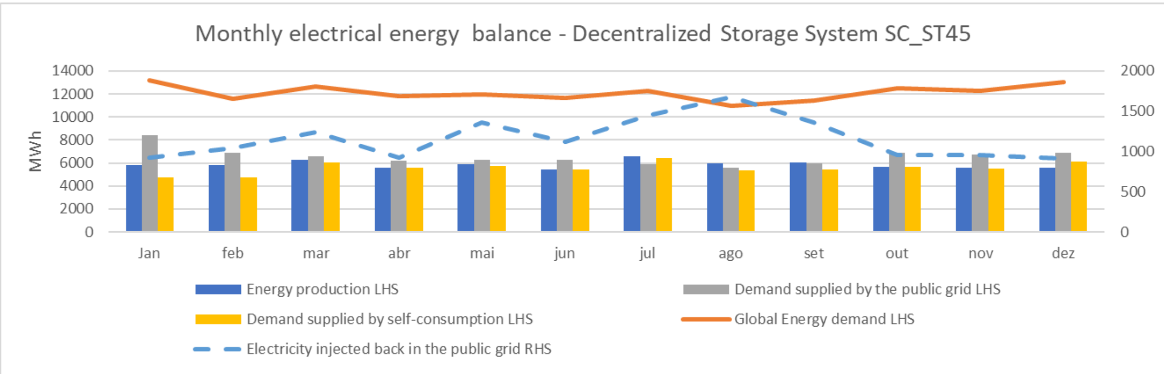


Figure 6.19. Monthly electrical energy balance for scenario SC_ST45

6.4.2. Optimization model analysis and results

The analysis to be presented in this section follows the structure of the one presented in Section 6.3.1. The developed model is based on the same strategy defined for the Q-Learning procedure, i.e., it was created based on identical pairs state-action behavior analysis. So, the Q-Learning states and actions are the same. The parameters λ, γ and ε to compute the Q-values will also be the same as the ones presented in Table 6.56. and are indicated in Table 6.21.

Table 6.21. Structure of the Q-matrix for Scenario SC_ST45

State/Action	a1	a2	a3	Parameter	
S1	Q1,1	Q1,2	Q1,3	λ	0,8
S2	Q2,1	Q2,2	Q2,3	γ	0,8
S3	Q3,1	Q3,2	Q3,3	ε	0,1
S4	Q4,1	Q4,2	Q4,3		
S5	Q5,1	Q5,2	Q5,3		

In order to facilitate the comparison with the analysis performed in Section 6.3.1, similar graphs will now be detailed. In this sense, Figure 6.20. presents the results for one year (52 weeks) simulation. When compared with the analysis with the architecture without storage (SC_PV) in Figure 6.8, one can observe that the submitted bids show a different trend regarding the ones that are presented in Figure 6.20. Nevertheless, the defined strategy is similar, and it contributes to increase the social welfare of the community members by reducing the cost of buying electricity from the grid and to increase the self-consumption level, considering now the storage equipment.

In Figure 6.20, the dark blue line represents the average bid price, and it is also possible to observe that the community agent was also exploring the environment by doing bid up and bid downs always above the C^{PV}. It is also interesting to observe that the agent has a different behavior regarding the results obtained for the SC_PV scenario. In fact, the submitted average bid price is often closer and more stable regarding the WSM price than the results presented for the SC_PV case. This means that the agent is responding in a more dynamic way to different environments.

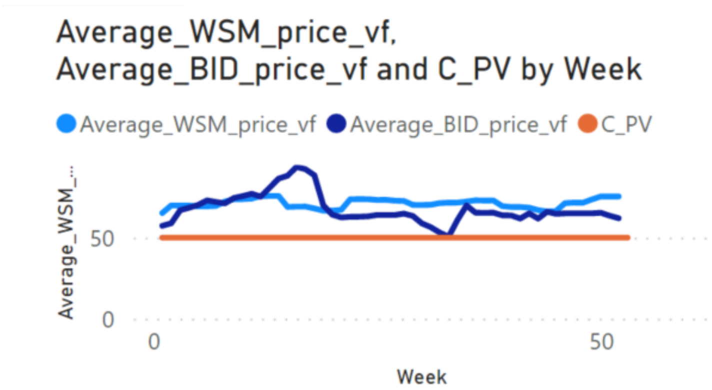


Figure 6.20. Bidding results for Case Study SC_ST45 (considering decentralized storage)

Figure 6.21 presents the WSM and the LEM average prices that were observed in the month of January. In this simulation, the bid strategy of the Market Community Agent reaches the WSM bid price at days 17 and 27. As comparison, in scenario SC_PV for the same month, the bid price only reached the WSM price on day 27. Notwithstanding the learning parameters are the same, this occurs because the agent was doing different explorations of the environment, which is different in this scenario, and consequently originated different behaviors although the same overall strategy was used.

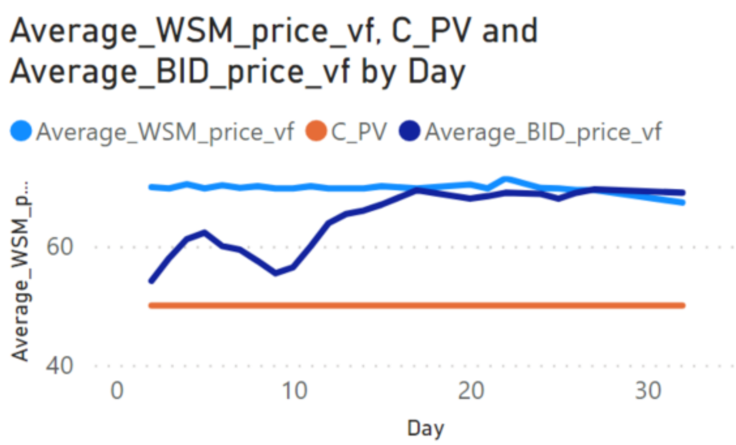


Figure 6.21. January average prices results for the Case Study SC_ST45

As shown in Figure 6.212, on January 27 the bid strategy of the agent reaches a value higher than the WSM price (@27/Jan 13h00). In this simulation, the WSM price was 69,46 €/MWh (obviously the same as in the simulation for SC_PV) and the bid price was set as 69,57 €/MWh. In this case, the revenue will be equal to the C^{PV} which was defined as 50,00 €/MWh and there is no additional profit. Figure 6.22 details the abovementioned results.

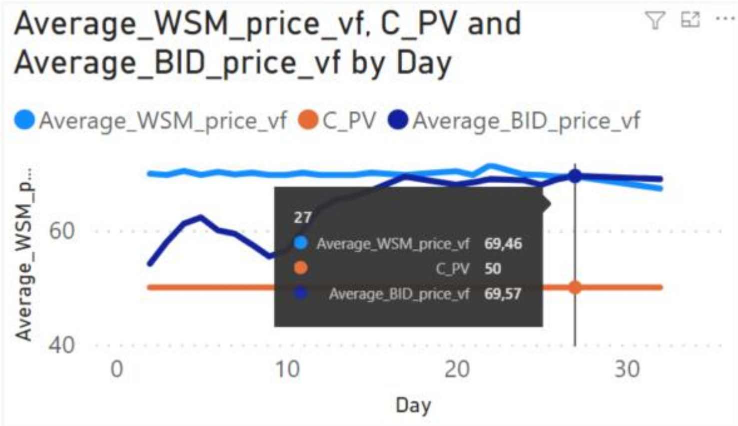


Figure 6.22. January average prices results for the Case Study SC_ST45 (highlight day 27)

By doing the same analysis of the behavior of the Market Community Agent regarding the actions and states that were selected, Table 6.22. shows the Q-matrix for the same day and period that was addressed in Table 6.7. for the Scenario SC_PV. As the Q-Learning parameters are the same, the agent has 90% probability (ε =0,1) of choosing the action which corresponds to maximum value of the Q-matrix. However, at hour 12, the action chosen was a_2, which doesn't correspond to the maximum value of the Q-matrix. Nevertheless, at hour 13 the performed action corresponds to the maximum value of the Q-matrix and in this way action a_3 was selected, which led to a bid up of +1 €/MWh regarding the bid price of the last iteration. So, at this hour the bid was 61,00 €/MWh (the previous bid at hour 12 was 60,00 €/MWh). Considering that there is an increase on the reward regarding the previous one (the difference between 61,00 €/MWh and 50,00 €/MWh - C^{PV} - is higher when compared with the difference between 60,00 €/MWh and 50 €/MWh), and it is possible to get more profit (increase until the WSM price, i.e., from 61,00 €/MWh until 70,65 €/MWh), state s_2 was therefore selected.

Table 6.22. Q-matrix for the scenario SC_ST45 - January 4

hour	BID_price_vf	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
10		68,44						
11	60,00	69,30	10,00	18,61	26,51	38,28	2	3
12	60,00	68,72	10,00	18,61	26,51	38,28	2	3
13	61,00	70,65	11,00	19,28	39,14	41,90	3	2
14	62,00	72,05	12,00	19,28	39,14	44,80	3	2
15	63,00	71,43	13,00	19,28	39,14	48,03	3	2
16		67,50						
17		67,78						

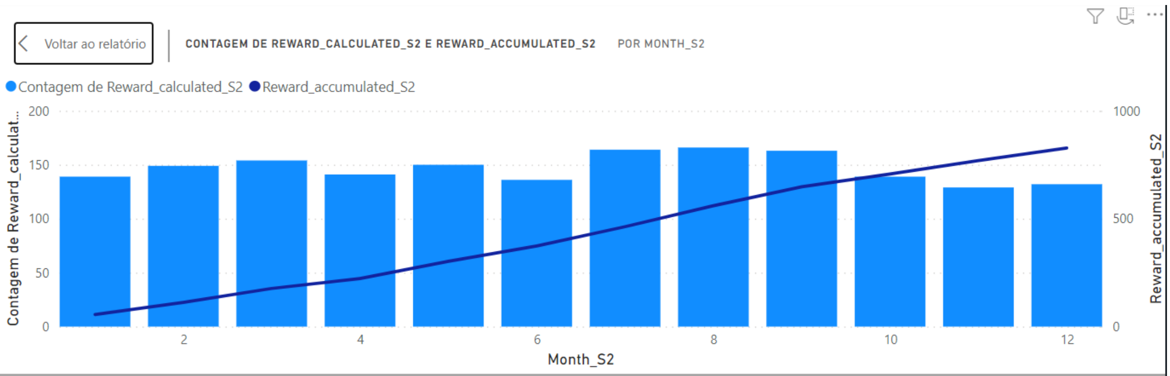
On hour 14 of January 4th, the agent keeps choosing the highest Q-matrix value, which corresponds to action a_3, leading to a bid up of +1 €/MWh regarding the previous value. In this way, the Market Community Agent performs a bid up to 62,00 €/MWh. As the agent obtained more profit and it continues to be possible to increase the profit, the Q-Learning state keeps in s_2. As it is possible to observe, the reward per MWh is the difference between the cleared bid price and the C^{PV} (e.g., at hour 14, the average bid price is 62,00 €/MWh and the reward is equal to the difference between 62,00 €/MWh and the C^{PV}, 50,00 €/MWh, i.e., 12,00 €/MWh).

Analyzing the behavior of the Market Community Agent on January 27, Table 6.23 presents the corresponding Q-matrix results. It is possible to observe that at hour 12 the agent chooses the action that corresponds to the higher Q-matrix value, action a_3. As a consequence, the bid price will increase by 1 €/MWh from 70,00 €/MWh till 71,00 €/MWh, which is higher than the WSM price (which is 69,72 €/MWh). In this sense, the reward at hour 13 is negative, i.e., the agent lost the opportunity of having a reward of 19,82 €/MWh (difference between WSM price and the C^{PV} price).

Table 6.23. Q-matrix for Case Study SC_ST45 - Day 27

hour	BID_price_vf	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
12	70,00	70,18	20,00	25,44	20,97	41,75	3	1
13	71,00	69,82	-19,82	38,17	26,21	35,86	3	5
14	70,00	68,72	-18,72	25,44	20,97	16,92	1	1
15	69,00	67,34	-17,34	7,50	20,97	16,92	1	1
16	69,00	66,59	-16,59	7,50	4,34	16,92	2	1
17		67,85						

Analyzing the economical results for the scenario SC_ST45, considering a period of 12 months, Figure Table 6.23. presents the monthly reward values and the accumulated value throughout the year.



Month_S2	Contagem de Reward_calculated_S2	Reward_accumulated_S2
1	139	55,98
2	149	112,20
3	154	176,87
4	141	222,79
5	150	302,68
6	136	373,72
7	164	463,21
8	166	560,50
9	163	648,25
10	139	707,71
11	129	769,54
12	132	827,80

Figure 6.23. Scenario SC_ST45 - calculate reward by month and accumulated reward (€)

Similarly, to the analysis for the scenario SC_PV, this graph shows the calculated rewards per month and the accumulated reward. In this case, the accumulated reward corresponds to almost 830 €. When compared to the accumulated reward assessed for Scenario SC_PV (Figure 6.1Figure 6.141), it is possible to verify a significant reduction. This is justified by the strategy that was performed, which prioritizes self-consumption and storage, instead of selling energy in the market which in the end reduces the revenues from selling electricity in the WSM. This allows storing a larger volume of energy coming from the PV panels in the periods in which the demand is more reduced than the PV generation. However, the months in which the rewards are higher, are the same than the presented in Scenario SC_PV and corresponds to July, August and September. This is justified by that fact that these months are the months with more irradiation in Portugal and so the PV generation is higher and consequently more energy is sell into the WSM.

6.4.3. Economic assessment of the scenario SC_ST45

In a similar way regarding what was done for the Case Study SC_PV, the results for the economic evaluation for this architecture will now be analyzed. The same comparison with the system without self-consumption, termed Normal Exploration, will also be made. For the Normal Exploration situation, the values obtained for the energy cost and access tariff are the same as the ones indicated in Section 6.3.3.

As previously mentioned, the SC_ST45 architecture considers a system with three 15 kWh *sonnenBatterie* modules [325] and the same analysis will be done.

The tariffs considered in this work are detailed in Annexes B1, B2.1, B2.2 and B2.3. They were published by ERSE in Portuguese Diário da República (Diretiva n.º 5/2020, of March 20 and Diretiva n.º 15/2020, of October 7) [323].

Table 6.24 presents a comparison of the energy acquisition costs and the access tariffs between the Normal Exploration (without self-consumption and all the electricity to supply demand is taken from the grid) and considering this decentralize storage architecture, SC_ST45. The overall costs reduced by 39,2%, with a reduction on the access tariffs of 41,3%, which is aligned with the increase of the self-consumption level of the installation.

Table 6.24. Comparison of access tariffs and electricity acquisition for SC_ST45 and Normal Exploration

Costs	Scenario SC_ST45	Normal exploration	Savings	
Access Tariffs	4.770,47 €	8.135,26 €	3.364,79 €	41,36%
Electricity acquisition	6.385,94 €	10.218,71 €	3.832,77 €	37,51%
Total	11.156,41 €	18.353,97 €	7.197,56 €	39,22%

Figure 6.24 and 6.25 present the related costs and their distribution in both cases, i.e., Normal Exploration and self-consumption exploration for a decentralized storage architecture system, SC_ST45. It is possible to observe that access tariff in the Normal Exploration case represents almost 50% of the total.

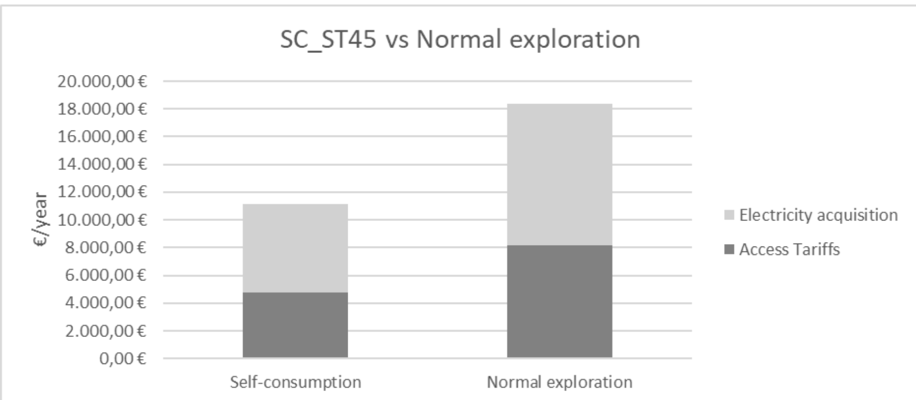


Figure 6.24. Self-consumption SC_ST45 and Normal Exploration costs

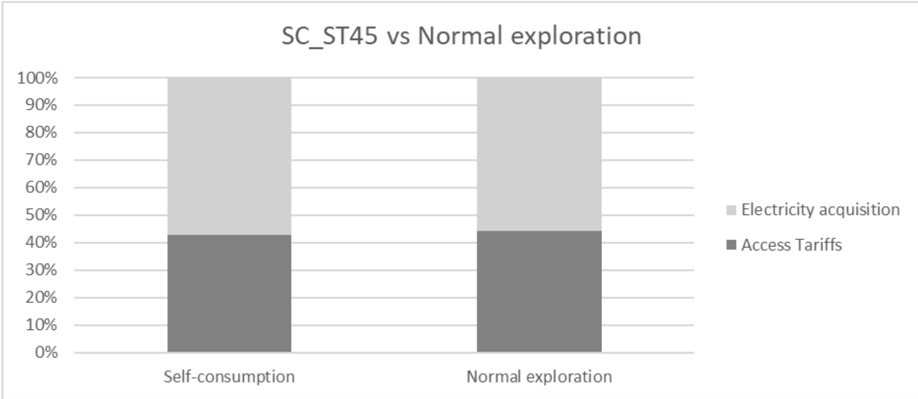


Figure 6.25. Breakdown of self-consumption SC_ST45and Normal exploration costs

In order to access the behavior of the developed optimization model and the applied learning strategy, Table 6.25. presents the global annual energy costs considering the revenues obtained from selling energy in the WSM, admitting that the Q-Learning approach was used and not used. For this, the right column considers the SC_ST45 scenario where the surplus energy generated by the PV, regarding the demand and the stored energy is paid at the bilateral contract price, C^{PV}, set at 50,00 €/MWh and the energy supplied by the public network is paid at the market price so that no optimization strategy is used. In this case, the energy sold in the market leads to a revenue of 695,03 €/year. On the central column, the selling bids consider the values followed by the applied learning strategy, i.e., if the storage energy plus the PV generation is sufficient to feed the demand, and there is still some surplus, the energy in excess will be sold to the market following the optimization strategy. The application of the optimization model enables increasing the annual revenues to 936,61 €/year. As it is possible to observe, the application of the developed optimization methodology originates an increase on the selling energy revenues by 26%, which has a significant impact in the overall energy annual costs.

Table 6.25. Energy annual costs for SC_ST45 using and not using the Q-Learning approach

Costs	Optimization model	Without optimization
Access Tariffs	4.770,47 €	4.770,47 €
Electricity acquisition	6.385,94 €	6.385,94 €
Selling energy	-936,61 €	-695,03 €
Total	10.219,81 €	10.461,38 €

To access the economic value of this architecture, the NPV methodology will also be used, considering the same assumptions as detailed in Section 6.3.3.

The initial investment cost will now consider a configuration with self-consumption with PV units, and with the already mentioned storage system. The selected photovoltaic system is the same as the one used in Section 6.3.3. which corresponds to 17.280 € of CAPEX and 364,5 €/year of OPEX investment and considers 20% with equity.

Considering current battery cost and its breakdown, the data to be used follows the same reference that was considered for the PV investment analysis [310]. The assumptions for the storage system investment analysis consider data for 2020. Table 6.26 presents the reference costs considered for the storage system investment analysis [310].

Table 6.26. Battery reference costs used for the economic assessment calculation

Reference Cost	
CAPEX	0,209 €/Wp
OPEX	6,0 €/kWp/year

In this sense, for a storage system with a capacity of 45 kWh, the cost is about 9405 € for CAPEX and 270 €/year for OPEX. So, the overall investment associated to SC_ST45 (PV and storage system) for 20 years is 26.685 € for CAPEX and 634,5 €/year for OPEX.

In order to access the impact of the optimization strategy in this scenario, the NPV calculation is now provided in Table 6.27. It considers the results provided in Table 6.25, i.e., the different annual energy costs regarding the application or not of the optimization model. In this sense, for a 20-year analysis, the NPV will be -211.198,00 € without considering the application of the optimization strategy and -207.432,00 € regarding the application of the optimization strategy.

Table 6.27. Comparison of the Net Present Value for the SC_ST45 scenario, using and not using the Q-Learning approach

	Scenario SC_ST45 without optimization strategy	Scenario SC_ST45 with optimization strategy
NPV	-211.198,00 €	-207.432,00 €

For an architecture which considers a PV and a decentralized storage system (scenario SC_ST45), the NPV increases by 3766 € to -207.432,00 €, i.e., it gets less negative, when following the implementation of the optimization Q-Learning strategy. This means a reduction of 2% which is considerable in an investment decision analysis. It should be again mentioned that without the application of the optimization strategy, the surplus of energy is paid at the defined C^{PV} and the energy supplied by the grid is paid at the WSM price. When the optimization strategy is applied, the surplus of energy is paid at the submitted bid price (if the bid price is lower than the WSM price) or at C^{PV} (if the bid price is higher than the WSM price).

The presented analysis shows the benefits of investing in storage systems. When integrated in communities with its own PV generation, not only the dependence on the electrical grid decreases, but also the benefits from selling eventual surplus of electricity became important in terms of taking a decision on this type of investment.

6.5. Centralized storage – scenario SC_ST300 description and results

6.5.1. Scenario description and energy balance

In this section, a new architecture of an energy community will be simulated. It consists of an architecture with a storage system located at the Low Voltage side of the MV/LV substation that supplies a set of buildings. This architecture is termed Centralized Storage and it is illustrated in Figure 6.26. In stand of having one storage system per building as in the previous situation, we will now have just one storage equipment at the LV busbar of the MV/LV substation and with a larger storage capacity. The dataset used in this simulation is the same as in the previous one but it is replicated to a combination of 3 collective buildings with the same demand and PV generation profiles [319]. That is, the demand and the PV generation have an increase of 3 times.

Considering the usage of the public grid for self-consumption purposes, different simulations will be performed taking into consideration the impact of having or not exemptions on network tariffs, namely regarding the CIEG component of the Access Tariffs. The corresponding simulations allow getting insights about the impact of paying the grid tariffs considering the utilization of the public grid [305] and, in this sense, assess the economic performance of the entire installation, namely considering the storage system, in this architecture.

The bidding strategy of the Market Community Agent will be the same and we will also consider the same range of SOC values already defined for the batteries used in the previous scenario (SC_ST45) and their three possible operation modes, charging, discharging or idle. They will be in the charging mode if there is a surplus of PV generation regarding the demand and in the discharging mode if the community demand is higher than the local PV generation. However, and if the stored energy is sufficient to supply the demand, and if there is still some surplus, the remaining energy will be sold to the market following the optimization strategy defined in this work.

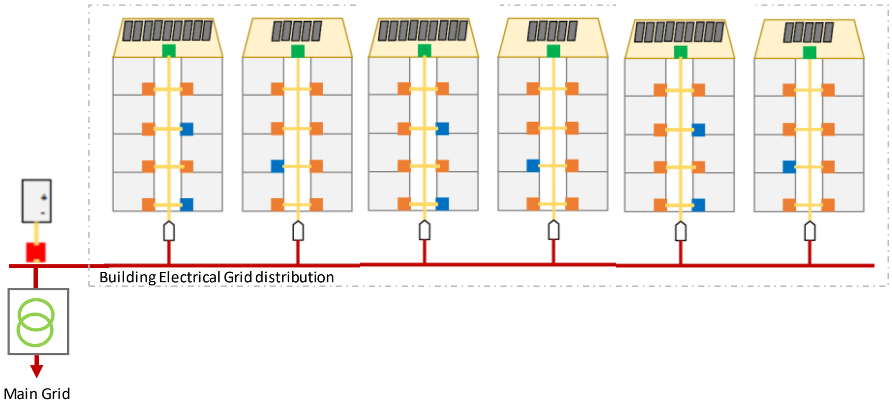


Figure 6.26. Illustration of the collective self-consumption installation with centralized storage system (scenario SC_ST300) located at the same voltage level (adapted from DGEG [318])

The PV generation is constituted by a system 3 times larger than the one that was used in previous scenarios, i.e., it has a peak power of 135 kWp. A 300 kWh storage system was considered in this simulation. Yet, the chosen system can be paralleled with other modules for scalability of power and capacity [327, 328]. The SOC limits are the same as for the 45 kWh batteries used in the previous simulation, that is a range from 20 to 80% of the nominal capacity.

The demand and PV renewable generation profiles were built using the same dataset mentioned in Section 6.2. The annual energy community balance, considering now the centralized ESS system, is presented in Table 6.28. This table includes the global energy demand (which corresponds to three times the one in the previous simulation since in this case we considered three collective buildings, each one equal to the one used previously), the demand supplied by the grid and by self-consumption, as well as the electricity injected back to the public grid.

Table 6.28. Annual Energy Community balance (with centralized ESS)

	MWh
Global Energy demand	436,2
Demand supplied by the public grid	212,1
Demand supplied by self-consumption	224,1
Electricity injected back in the public grid	4,9

The demand supplied by the public grid represents 212,1 MWh for a global energy demand of 436,2 MWh which means that 49% of the demand is supplied by the public grid. On the other hand, the demand supplied by self-consumption is 224,1 MWh which is 51% of the global energy demand.

Comparing with the simulation without storage (SC_PV, Table 6.3), the demand supplied by the grid represented 68% of the global energy demand (i.e., 98,6 MWh out of 145,4 MWh), whereas the demand supplied by self-consuming accounted for 32% of the global energy demand (i.e., 46,8 MWh out of 145,4 MWh). When compared with the decentralized storage system (SC_ST45, Table 6.20), the demand supplied by the public grid represented 54% of the global energy demand (i.e., 78,6 MWh of 145,4 MWh) and the demand supplied by self-consumption represented 46% of the global energy demand (i.e., 66,8 MWh of 145,4 MWh).

The results also show that the energy injected back into the grid decreases when going from SC_ST45 to SC_ST300, where the share of energy injected back into the grid decreases almost to zero in SC_ST300. This is related with the capacity of the storage equipment used in this case that is more than 6 times larger than the one that was used in case SC_ST45. This allows storing a larger volume of energy coming from the PV panels in the periods in which the demand is more reduced than the PV generation. These excesses can now be stored rather than being injected back in the grid as it occurred more frequently in scenario SC_ST45. Table 6.29 makes a resume of the aggregated results for comparison purposes.

Table 6.29. Relative global Energy Community demand and electricity injected back in the public grid (scenarios SC_PV, SC_ST45 and SC_ST300)

	SC_PV	SC_ST45	SC_ST300
Demand supplied by the public grid	68%	54%	49%
Demand supplied by self-consumption	32%	46%	51%
Electricity injected back in the public grid	23,4 MWh/year	13,9 MWh/year	4,9 MWh/year

Figure 6.27 presents the annual energy balance for the architectures with Centralized (SC_ST300) and Decentralized Storage (SC_ST45) and without Storage (SC_PV), considering the community energy demand and production.

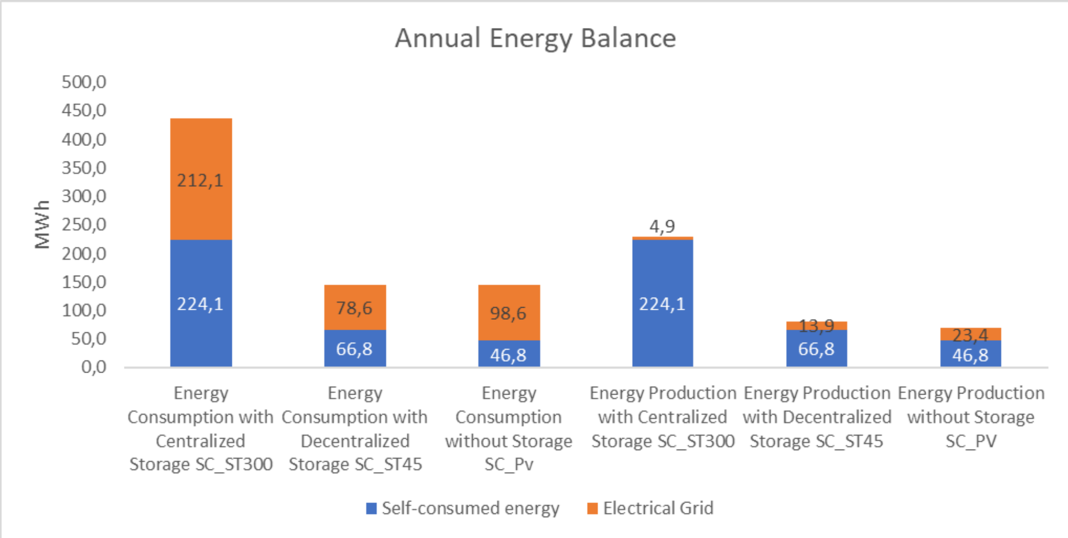


Figure 6.27. Community annual electricity demand and production (for Decentralized SC_ST45, Centralized Storage SC_ST300 and without Storage SC_PV scenarios)

Figure 6.28. presents the monthly distribution of electrical energy. In this graph all the values are read in the left-hand side (LHS) vertical axis, except the values of the energy injected back to the public grid that are read in the right-hand side (RHS) vertical axis. When compared with the same monthly analyses for the architecture with decentralized storage, SC_ST45, in Figure 6.19, it is possible to observe that the demand supplied by the public grid is proportionally lower in every month. On the other hand, the demand supplied by self-consumption has larger shares in every month. The electricity injected back into the public grid has a behavior in line with the philosophy and strategy previously mentioned, that is, the energy is firstly self-consumed, followed by charging the storage system and the remaining will be considered as a surplus. Because the storage capacity is higher in this scenario, the electricity injected back into the public grid achieves much lower values as previously explained.

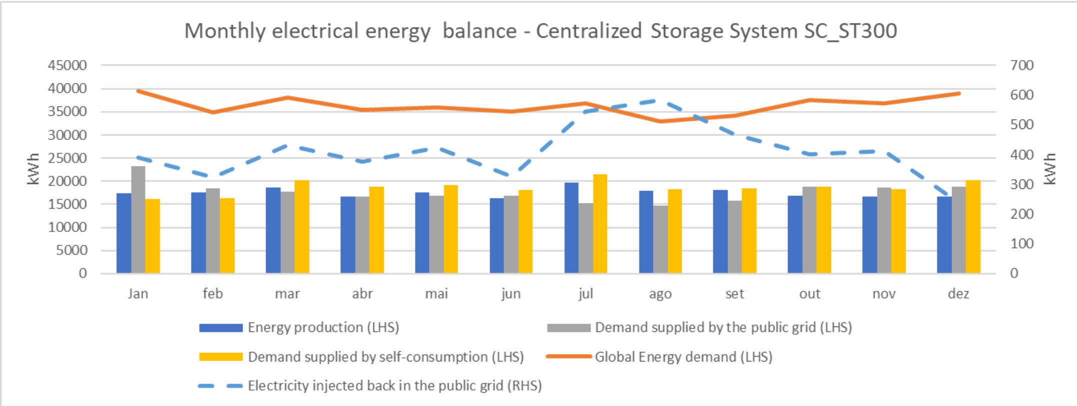


Figure 6.28. Monthly electrical energy balance for scenario SC_ST300

6.5.2. Optimization model analysis and results

The analysis to be presented in this section is similar to the one presented in Sections 6.3.1 and 6.4.2. The developed model is based on the same strategy defined for the Q-Learning procedure, i.e., it was created based on identical pairs state-action used in the previous analysis. So, the Q-Learning states and actions are the same as the ones used previously. The learning rate, λ, discount factor, γ, and greedy police, ε, parameters used to obtain the Q-values are also the same as the ones presented in Table 6.6. and Table 6.21., which were used for the simulation of scenarios SC_PV and SC_ST45. They are now replicated in Table 6.30.

Table 6.30. Structure of the Q-matrix for the Scenario SC_ST300

State/Action	a1	a2	a3	Parameter	
S1	Q1,1	Q1,2	Q1,3	λ	0,8
S2	Q2,1	Q2,2	Q2,3	γ	0,8
S3	Q3,1	Q3,2	Q3,3	ε	0,1
S4	Q4,1	Q4,2	Q4,3		
S5	Q5,1	Q5,2	Q5,3		

Figure 6.29 presents the results for one year (52 weeks) simulation. When compared with the same analysis done for the architecture without storage (SC_PV) in Figure 6.8. and with decentralized storage (SC_ST45) in Figure 6.20, we observe that the average bid price is different. In this case, the fact of having larger capacity of stored energy conjugated with the defined strategy, where the agents prioritize the self-consumption instead of selling the surplus into the market, the electricity injected back into the public grid achieves much lower values. This fact explains the agent behavior,

namely the fact of the bid price that is much closer to C^{PV} value when compared with Scenarios SC_PV and SC_ST45. However, the strategy behind this behavior is the same since the agent is always trying to increase its bid prices in order to get closer to the WSM prices. This observation highlights the previous conclusion, indicating that the Market Community Agent is responding in a dynamic way to different environments.

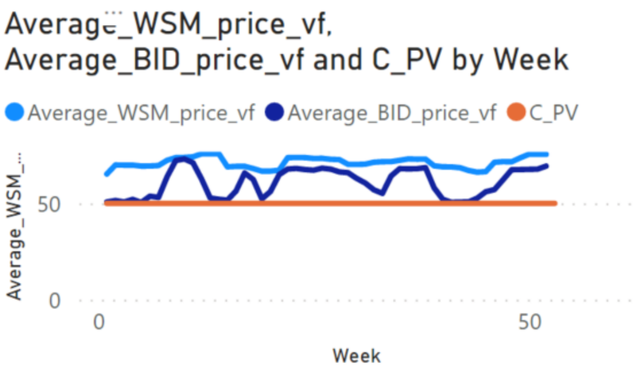


Figure 6.29. Bidding results for Scenario SC_ST300 (considering centralized storage)

Figure 6.30 presents the WSM and the LEM average prices that were observed in the month of January. In this simulation, the bid strategy of the Market Community Agent doesn't reach the WSM bid price in January, as it occurred in SC_PV and SC_ST45. Although the Q-Learning parameters are the same, this difference occurs because the Market Community Agent is doing different explorations of the environment which originate different behaviors but keeping the same philosophy. In this sense, Figures 6.31 and 6.32 extend the analysis until February so that it is possible to see that the agent reaches the WSM bid price on day 59. In this day, the WSM price was 72,38 €/MWh (defined by 2019 WSM price dataset) and the bid price was set as 73,00 €/MWh. In the same way, in this case the revenue will be equal to the C^{PV} value which was defined as 50,00 €/MWh and there is no additional profit.

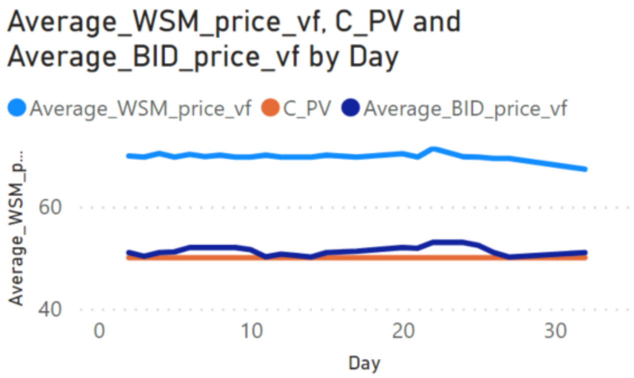


Figure 6.30. January average price results for the scenario SC_ST300

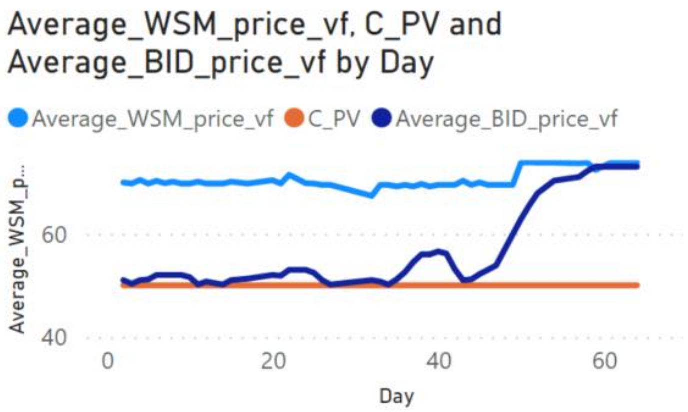


Figure 6.31. January and February average price results for the scenario SC_ST300

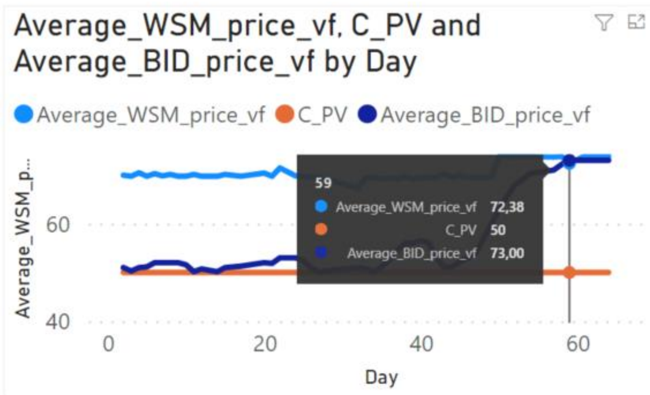


Figure 6.32. January and February average prices results for the scenario SC_ST300 highlighting the values obtained for day 59

Analyzing now in more detail the behavior of the Market Community Agent regarding the actions and the states that were considered, Table 6.31 shows the Q-matrix for day 54 between hours 14 and 16. We will now make an analysis similar to the ones in Sections 6.3. and 6.4. Given there is an energy surplus in this period (after supplying the local demand and charging the storage system, that is after self-consuming), the surplus will be traded considering the defined coordination between the WSM and LEM. The agent has 90% probability (ε=0,1) of choosing the action which corresponds to the maximum value in the Q-matrix. At hour 14 the action that is chosen corresponds to the Q-matrix highest value and so it was performed action a_3 which corresponds to a bid up of 1 €/MWh (from 70,00 €/MWh to 71,00 €/MWh). However, at hour 15 the chosen action doesn't correspond to the highest value of the Q-matrix and the agent doesn't select action a_3 but in fact action a_1 is used. This behavior originates that the agent decreases the bid from 71,00 €/MWh to 70,00 €/MWh. Consequently, and because the reward decreases from 21,00 €/MWh to 20,00 €/MWh, the state obtained was s_4. In hour 16, the agent chooses action a_3 and the bid price increases 1 €/MWh to 71,00 €/MWh. As the reward also increases and it is possible to get more profit, since the WSM price is 73,28 €/MWh, the state that was obtained was s_2.

Table 6.31. Q-matrix for Case Study SC_ST300 – Day 54

hour	BID_price_vf	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
14	71,00	71,95	21,00	21,21	19,68	80,21	3	2
15	70,00	72,38	20,00	16,41	16,14	20,24	1	4
16	71,00	73,28	21,00	33,20	19,68	80,21	3	2
17		74,23						

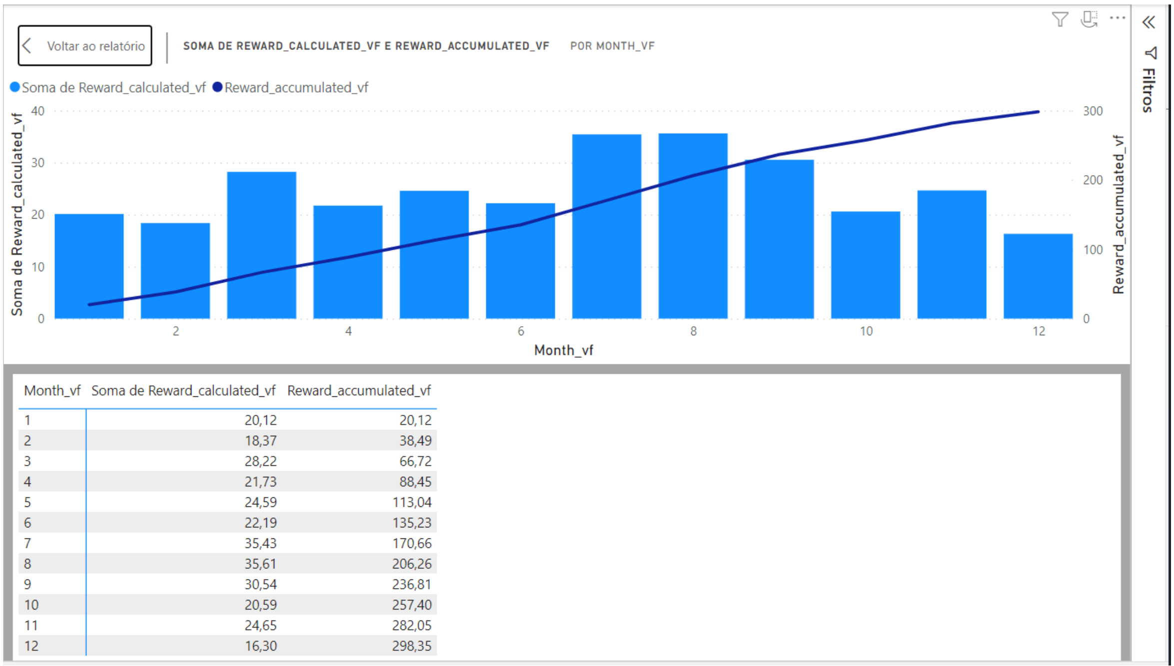
Analyzing the behavior of the Market Community Agent at day 62, Table 6.32 presents the corresponding Q-matrix results. At hour 14 of day 62, the agent doesn't choose the highest Q-matrix value, which corresponds to the action a_1, but chooses and performs action a_3 which led to a bid up of +1 €/MWh regarding the previous one. In this way, the Market Community Agent performs a bid up to 73,00 €/MWh. As the agent obtained a bid with a value higher than the WSM price, which was 71,95 €/MWh, the reward was negative, and the profit decreased. In this way it wasn't possible to get more profit and the Q-Learning state changes to s_5. In hour 15 the agent selects again action a_3 and increases its bid price from 73,00 €/MWh to 74,00 €/MWh. As this bid price continues higher than the WSM price, the reward remains negative, and the state continues in s_5. In hour 16, the agent chooses the Q-matrix highest value and performs action a_1 which originates a bid decrease from 74,00/MWh to 73,00 €/MWh. As the bid price reached a value lower than the WSM price, the reward changed to positive. The state of the Q-Learning at hour 16 is now the state s_1. This means that the reward increased regarding the previous bid (from -22,38 €/MWh to +23,00 €/MWh), but it isn't possible to get more profit because the WSM price is 73,28 €/MWh and the bid price of 73,00 €/MWh is very close.

Table 6.32. Q-matrix for Case Study SC_ST300 - Day 62

hour	BID_price_vf	WSM price	Reward	Q(s,1)	Q(s,2)	Q(s,3)	Action	State
13	72,00	73,76	22,00	16,41	16,14	72,18	1	4
14	73,00	71,95	-21,95	31,42	-24,91	7,68	3	5
15	74,00	72,38	-22,38	31,42	-24,91	3,74	3	5
16	73,00	73,28	23,00	65,03	-25,29	-25,31	1	1
17		74,23						
18		76,89						

Figure 6.33. presents the monthly rewards and its accumulate values for the Case Study SC_ST300, considering a period of 12 months. It is possible to observe the calculated rewards per month and the accumulated reward. As it is possible to see, the accumulated reward is close to 300 €. Since the quantity of energy traded in the market in this scenario is lower than in the previous scenarios, the accumulated reward also decreases. This was expected to occur because the adopted strategy prioritizes self-consumption instead of selling energy in the market an also because of the capacity of the storage system.

It is also possible to observe that the months in which the rewards are larger correspond to July, August, and September. These are the months in which PV generation is larger (sunny months in Portugal) and the quantity of generated electricity is sufficient to supply de demand, charge the storage equipment and injected the surplus back to the network.



Month_vf	Soma de Reward_calculated_vf	Reward_accumulated_vf
1	20,12	20,12
2	18,37	38,49
3	28,22	66,72
4	21,73	88,45
5	24,59	113,04
6	22,19	135,23
7	35,43	170,66
8	35,61	206,26
9	30,54	236,81
10	20,59	257,40
11	24,65	282,05
12	16,30	298,35

Figure 6.33. Scenario SC_ST300 - calculate reward by month and accumulated reward (€)

6.5.3. Economic assessment of the scenarios SC_ST300_A, B and C

Similarly, to what was done for scenarios SC_PV and SC_ST45, the economic results for the simulation for SC_ST300 will now be analyzed. However, and since the storage system is connected to the public grid, the network tariffs applied for self-consumption will now be considered. Therefore, these simulations were done considering the impact of having or not exemptions on network tariffs, namely for the CIEG component of the Access Tariffs.

Table 6.33. presents the annual energy costs, the Access Tariffs and the self-consumption tariff. For a system without self-consumption (Normal Exploration), the costs to supply the demand, which includes the applicable Access Tariffs and electricity acquisition costs, are higher than 55.000 € as indicated in Regarding SC_ST300_A, Table 6.33 presents the annual energy costs, the access tariffs, and the self-consumption tariff. It should be notice that the self-consumption tariff is related to the fact that in this scenario, the location of the battery it is not inside the community itself and it is located at a Low Voltage side of the MV/LV substation that feeds the set of buildings. In this sense, it is applied the related tariffs (see Annex B2.1 – without CIEG exemption). In other hand and considering that the battery storage system used in scenario SC_ST45, is located at the building level, and the community does not use the public grid, these tariffs are not applied in this scenario.

Regarding SC_ST300 we considered three variations as follows:

- SC_ST300_A with no CIEG exemption, that is, the full Access Tariffs are considered;
- SC_ST300_B with 50% of CIEG exemption;
- SC_ST300_C with full CIEG exemption.

Regarding SC_ST300_A, Table 6.33 presents the annual energy costs, the access tariffs, and the self-consumption tariff. It should be notice that the self-consumption tariff is related to the fact that in this scenario, the location of the battery it is not inside the community itself and it is located at a Low Voltage side of the MV/LV substation that feeds the set of buildings. In this sense, it is applied the related tariffs (see Annex B2.1 – without CIEG exemption). In other hand and considering that the battery storage system used in scenario SC_ST45, is located at the building level, and the community does not use the public grid, these tariffs are not applied in this scenario.

Table 6.33. Comparison of access tariffs and electricity acquisition, for scenario SC_ST300_A and for Normal Exploration

Costs	Without CIEG exemption			
	SC_ST300_A	Normal Exploration	Savings	
Access Tariffs	12.818,43 €	24.404,29 €	11.585,86 €	47,47%
Self-Consumption Tariff	10.819,64 €	----	----	----
Electricity acquisition	17.410,63 €	30.650,76 €	13.240,13 €	43,20%
Total	41.048,70 €	55.055,05 €	14.006,35 €	25,44%

The implemented architecture is designed to prioritize self-consumption in such a way that the demand supplied by self-consumption is higher than the one supplied by the public grid as indicated in Table 6.28. So, notwithstanding the costs related with the utilization of the public grid for self-consumption purposes (self-consumption tariff - DL 15/22 Art. 212 1) [54], which doesn't exist in the Normal Exploration mode, the overall savings are almost 26%. This is also an expected result since we have less electricity acquisition from the grid and lower access tariffs in the SC_ST300_A when compared with the Normal exploration mode.

Figures 6.34. and 6.35. presents the related costs and their distribution in both cases, i.e., Normal Exploration and self-consumption exploration without exemption of the CIEG for a centralized storage architecture system, SC_ST300_A.

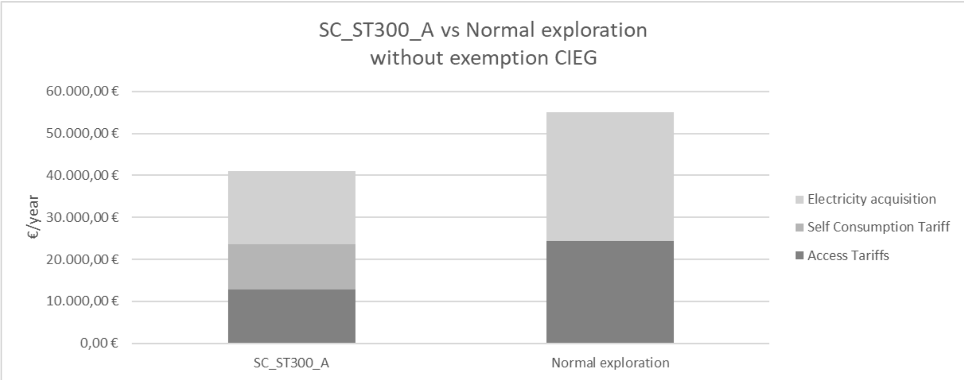


Figure 6.34. Comparison of costs for SC_ST300_A versus Normal exploration

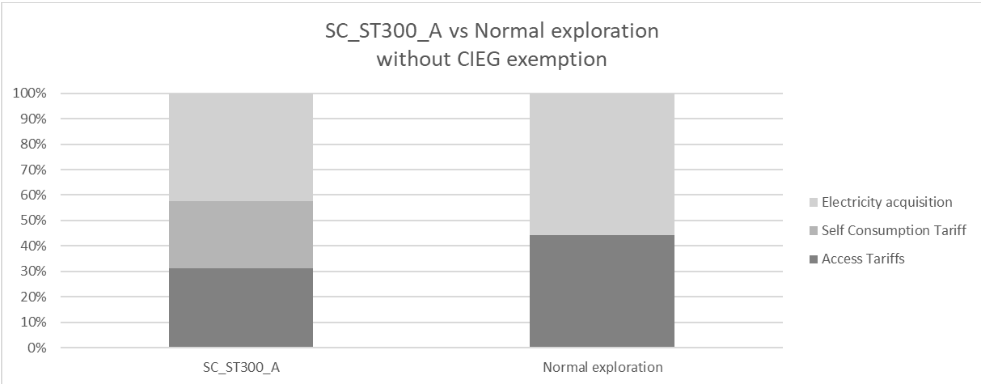


Figure 6.35. Breakdown of costs for SC_ST300_A versus Normal exploration cost

In Normal Exploration the access tariffs represent 44% of the total costs. When the exploration is in the self-consumption mode, these costs only represent 31% of the total.

Table 6.34. presents the global annual energy costs considering the revenues of selling energy in the WSM, for a simulation with and without using the optimization Q-Learning model. It is possible to observe that the application of the developed optimization methodology originates a residual variation of the selling energy profits. This is in line with the lower quantity of electricity injected back into the grid and sold in the WSM.

Table 6.34. Scenario SC_ST300_A - energy annual costs using and not using the optimization approach

Costs	Optimization model	Without optimization
Access Tariffs; Self consumption Tariffs	23.638,07 €	23.638,07 €
Electricity acquisition	17.410,63 €	17.410,63 €
Selling energy	-299,93 €	-246,17 €
Total	40.748,78 €	40.802,53 €

Let now us analyze the impact of introducing an exemption of 50% of the CIEG component for an architecture with centralized storage system, that is, scenario SC_ST300_B. The community under analysis now saves almost 34% of the total cost when compared with the same scenario with Normal exploration as indicated Table 6.35. Making a similar comparison with the centralized architecture without exemption CIEG, that is for SC_ST300_A (Table 6.33) the savings correspond to 8,5%.

Table 6.35. Comparison of access tariffs and electricity acquisition costs for scenario SC_ST300_B and for Normal Exploration

Costs	With 50% CIEG exemption			
	SC_ST300_B	Normal Exploration	Savings	
Access Tariffs	12.818,43 €	24.404,29 €	11.585,86 €	47,47%
Self-Consumption Tariff	6.154,57 €	----	----	----
Electricity acquisition	17.410,63 €	30.650,76 €	13.240,13 €	43,20%
Total	36.383,64 €	55.055,05 €	18.671,41 €	33,91%

Figures 6.36 and 6.37 present distribution of the costs for the centralized system with an exemption of 50% in the CIEG component, ST_SC300_B, versus the Normal Exploration mode. It is verified a very significant reduction of the total cost, despite the presence of the self-consumption tariff in the architecture with the centralized storage system.

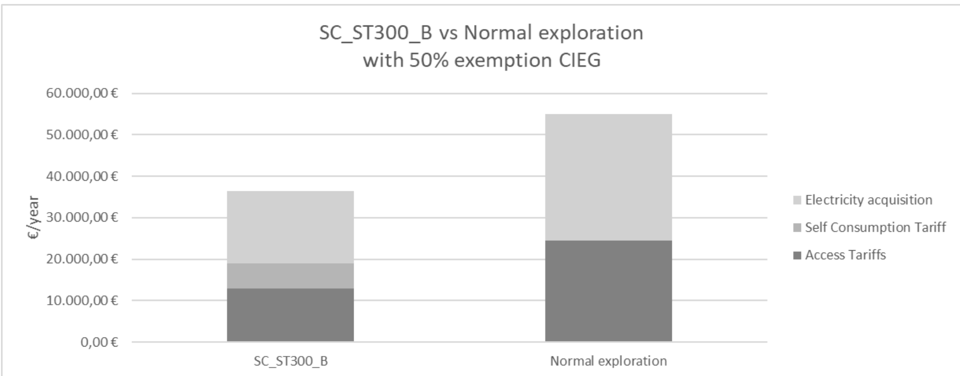


Figure 6.36. Comparison of costs for SC_ST300_B versus Normal Exploration

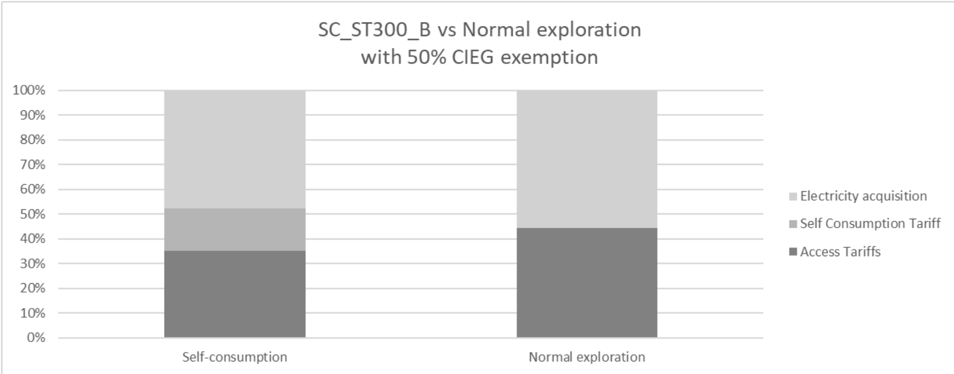


Figure 6.37. Breakdown of costs for SC_ST300_B versus Normal Exploration

Table 6.36 presents the global annual energy costs which includes the revenues of selling energy in the WSM, for a simulation with and without using the Q-Learning optimization model.

Table 6.36. Scenario SC_ST300_B - energy annual costs using and not using the optimization approach

Costs	Optimization model	Without optimization
Access Tariffs; Self consumption Tariffs	18.973,00 €	18.973,00 €
Electricity acquisition	17.410,63 €	17.410,63 €
Selling energy	-299,93 €	-246,17 €
Total	36.083,71 €	36.137,47 €

Finally, we will now analyze the impact of introducing an exemption of 100% of the CIEG component for an architecture with centralized storage system, that is, scenario SC_ST300_C. Table 6.37 presents the comparation of the total costs of SC_ST300_C regarding the Normal Exploration mode. In this case, the total savings almost reach 42% when comparing the centralized storage system with the Normal Exploration mode. As it is possible to observe, the cost associated with the Self Consumption Tariff is approximately 1500 €/year, which is less than 5% of the total costs.

When compared with scenarios SC_ST300_A and SC_ST300_B, the savings in the total costs in scenario SC_ST300_C are, respectively, of 23% and 13%. These numbers highlight the impact that the exemption levels in the access tariffs can reach, namely in architectures with storge systems.

Table 6.37. Comparison of access tariffs and electricity acquisition costs for scenario SC_ST300_C and for Normal Exploration

Costs	With 100% CIEG exemption			
	SC_ST300_C	Normal Exploration	Savings	
Access Tariffs	12.818,43 €	24.404,29 €	11.585,86 €	47,47%
Self-Consumption Tariff	1.475,98 €	----	----	----
Electricity acquisition	17.410,63 €	30.650,76 €	13.240,13 €	43,20%
Total	31.705,04 €	55.055,05 €	23.350,01 €	42,41%

Figures 6.38 and 6.39 present the related costs and their distribution for Normal exploration mode and for SC_ST300_C.

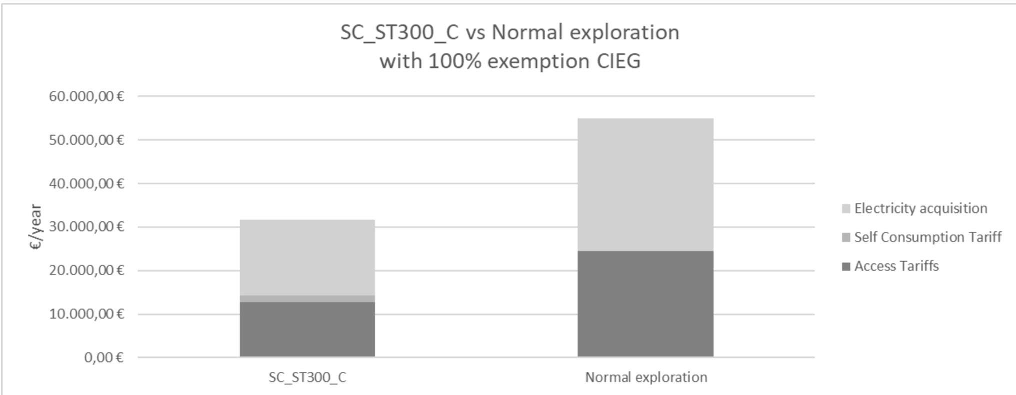


Figure 6.38. Comparison of costs for SC_ST300_C versus Normal Exploration

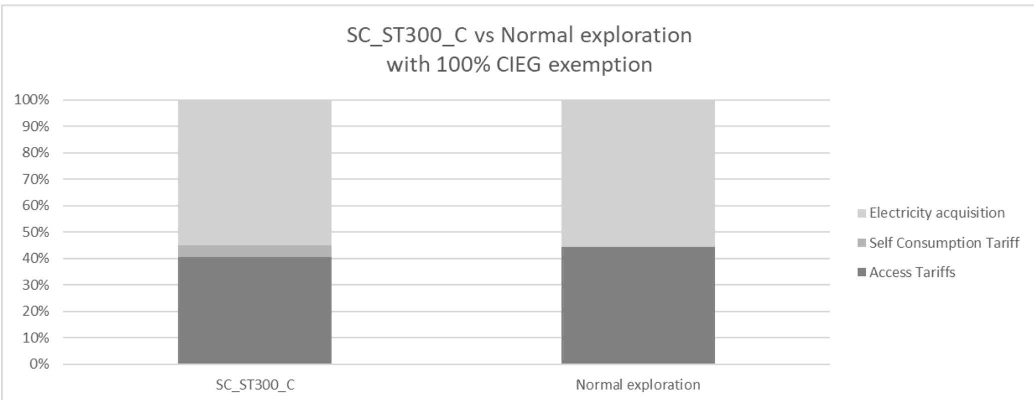


Figure 6.39. Breakdown of costs for SC_ST300_C versus Normal Exploration

Table 6.38. presents the global annual energy costs which includes the revenues of selling energy in the WSM, for a simulation with and without using the Q-Learning optimization model.

Table 6.38. Energy annual costs (optimization and non-optimization models scenario SC_ST300_C)

Costs	Optimization model	Without optimization
Access Tariffs; Self consumption Tariffs	14.294,41 €	14.294,41 €
Electricity aquisition	17.410,63 €	17.410,63 €
Selling energy	-299,93 €	-246,17 €
Total	31.405,12 €	31.458,87 €

Similarly, to what was done for scenarios SC_PV and SC_ST45, we will now access the economic value of this architecture. Accordingly, a 20-year cash flow analysis was developed considering the demand equal for all the years along the period under analysis. The discount rate was set at 2,5%. The same CAPEX and OPEX costs will be considered, which are detailed in Table 6.18 for the PV system and in Table 6.26 for the storage system. However, the capacity of the storage energy considered in this scenario is 300 kWh and for the PV system is 135 kWp peak power. So, the total costs for a centralized storage architecture with a battery of 300 kWh and a PV system with 135 kWp, will be 114.540 € for CAPEX and 2.893,50 €/year for OPEX costs. Reference [310] contains the values that are used in this economic analysis as for the analysis of scenarios SC_PV and SC_ST45.

The Net Present Values for the different CIEG exemptions levels are now presented in Table 6.39. Considering a scenario without CIEG exemption and without the application of the optimization strategy, the NPV is -794.702,00 €. On the other hand, when applied the optimization strategy, the NPV is -793.864,00 €. For the scenarios with optimization strategy and with 50% and with 100% of CIEG exemptions the NPV is -726.670,00 € and -653.735,00 €. This means an increase of the NPV by 8,4% and 17,7% respectively compared in scenario with optimization strategy and without CIEG exemption. Notwithstanding the residual profit of selling energy in all of these scenarios with centralized storage, the impact of the exemption level of the CIEG component on the overall NPV is very significative. This impact is very relevant when investors have to assess their final investment decisions processes.

Table 6.39. Net present value for scenarios SC_ST300_A (with and without optimization strategy), SC_ST300_B and SC_ST300_C (PV and Centralized Storage system)

	Scenario SC_ST300_A (without CIEG exemption)	
	without optimization strategy	with optimization strategy
NPV	-794.702,00 €	-793.864,00 €
	Scenario SC_ST300_B	**Scenario SC_ST300_C**
	with optimization strategy (50% CIEG exemption)	with optimization strategy (100% CIEG exemption)
NPV	-726.670,00 €	-653.735,00 €

The exemptions on the CIEG component have a significant impact in the improvement of the NPV. By adopting this incentive policy associated with exemptions of the CIEG component of the Access Tariff, and considering investments in PV and storage systems, the improvement of the NPV is large. The NPV remains negative (due to the initial investment cost in new equipment and also due to the acquisition energy costs and the remaining access tariff components) but it moves towards the positive direction meaning that there is a reduction of the costs to be incurred by the consumers during the entire horizon.

6.6. Final comparisons and sensitivity analysis

As mentioned, the developed ABM model was applied to real data of consumption, PV generation and 2019 WSM prices of the Iberian Electricity Market. The demand data considers 16 consumers for each collective building (15 apartments plus common services) and the simulations also consider generation using PV systems, and storage units (decentralized with 45 kWh and centralized with 300 kWh capacities). In the centralized storage scenario, the dataset used was the same, however replicated to a combination of 3 collective buildings.

Table 6.40. presents the global energy demand, the demand supplied by the public grid, the demand supplied by the self-consumption and the electricity injected back to the grid for the three analyzed cases using the Q-Learning approach, that is for the scenarios SC_PV, SC_ST45 and SC_ST300.

Table 6.40. Annual Energy Community balance for the three analyzed scenarios

MWh	SC_PV	SC_ST45	SC_ST300
Global Energy demand	145,4	145,4	436,2
Demand supplied by public grid	98,6	78,6	212,1
Demand supplied by self-consumption	46,8	66,8	224,1
Electricity injected back into the grid	23,4	13,9	4,9

When compared with the SC_PV, these results show that the SC_ST45 case has a lower amount of energy injected back into the grid namely due to the installation of batteries. This is line with the fact that the demand supplied by the public grid decreases and the demand supplied by self-consumption increases in case SC_ST45. These results also show that the operation strategy that was used is successful in terms of maximizing the energy community self-energy consumption. Case SC_ST300 is also designed to prioritize self-consumption in such a way that the demand supplied by self-consumption is higher than the one supplied by the public grid.

Figure 6.40 presents the distribution of the energy demand for these 3 scenarios. It is possible to observe that in scenarios SC_ST45 and SC_ST300 there is an increase of the demand that is fed by self-consumption, due to the existence of the storage system. This difference is more relevant in scenario SC_ST300, since it has a larger storage capacity and consequently it can store more energy surplus. Apart from the increase of the capacity of the storage units, this evolution is a consequence of the maximization of the self-consumed energy by the optimization of the use of the storage equipment through the adequate selection of its charging and discharging periods. However, and if the stored energy is sufficient to feed the demand, and there is still some surplus, these additional quantities will be injected back into the grid and will be used in the selling bids strategy of the Market Community Agent.

In Figure 6.41 we can observe the increase of the percentage of energy that is self-consumed regarding the energy that is locally generated as well as the percentage of energy that is injected back to the grid regarding the local generation (in SC_ST45 and in SC_ST300, when compared with SC_PV in which there is no storage systems). It should also be noted that the energy surplus injected back into the grid decreases when going from SC_ST45 to SC_ST300. When comparing SC_ST45 with SC_ST300, the share of energy injected into the grid decreases almost to zero in SC_ST300. This is related with the capacity of the storage system that, in this case, has a capacity larger than 6 times the one that was used in SC_ST45. This allows storing a larger volume of energy coming from the PV panels in periods in which the demand is more reduced than the PV generation. These excesses can now be stored in SC_ST300 rather than being injected back in the grid as it occurred more frequently in SC_ST45.

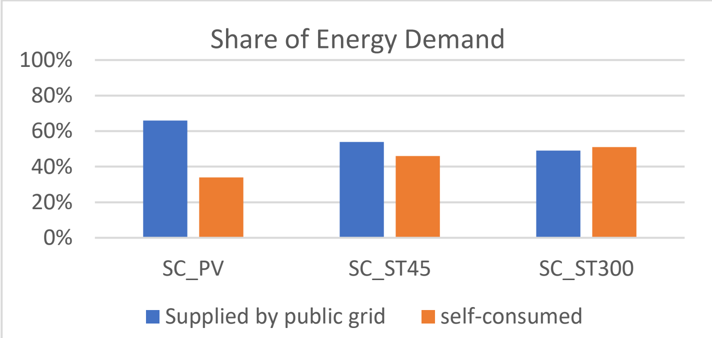


Figure 6.40. Share of Community Energy Demand

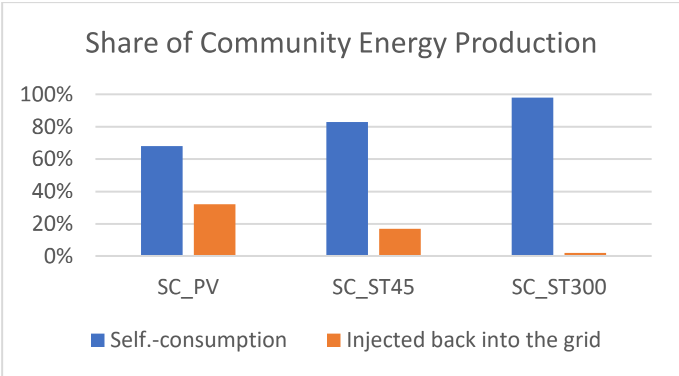


Figure 6.41. Percentage of self-consumed and injected back energy regarding local generation

The overall results of these simulations show a very good performance of the proposed Agent-Based Model. Table 6.41 presents the results for the real WSM annual average price for 2019, the selling value of the PV generation excess without using the bidding strategy, that is the C^{PV} value, and the average values using the LEM strategies for SC_PV, SC_ST45 and SC_ST300. Despite the annual average price in the WSM is 71,1 €/MWh, these results show that if the LEM strategy is applied, the LEM average market price gets closer to the WSM price. This improvement regarding the initial C^{PV} value (50,00 €/MWh) is explained because of the use of the ABM model incorporating the Q-Learning approach with bid up/bid-down strategy. In all the scenarios, the improvement achieves values higher than 15% of the selling bilateral contract price that was defined.

Table 6.41. Results for the annual average selling price

Scenario	**Annual average selling price €/MWh**
Real WSM price data	71,1
Selling price without LEM strategies (C^{PV})	50,0
Selling price with LEM strategies SC_PV	62,04
Selling price with LEM strategies SC_ST45	59,20
Selling price with LEM strategies SC_ST300	59,35

Figure 6.42 shows the average weekly prices of the WSM and of the LEM after using the bidding strategy, as well as the bilateral contract price C^{PV}. As we can see, when using the bidding strategy, independently of the simulated case, the agent in LEM tries to increase its prices in order to get closer to the WSM prices (curves BID Strategy SC_PV, BID Strategy SC_ST45 and BID Strategy SC_ST300). This reflects the learning capability that the agents have since the start of the process.

Regarding the impact of the application of the optimization model, the profits by selling the electricity surplus using the learning approach, presents an improvement of 25% in scenario SC_PV (Table 6.17), 34% in scenario SC_ST_45 (Table 6.25) and 22% in scenario SC_ST_300 (Table 6.34). Notwithstanding the difference verified, due to different behaviors of agents, the impact is significative in the overall profits. Recall that the excess of generated electricity regarding the demand is paid at a minimum of C^{PV} price or at a LEM price as a consequence of the bidding strategy. So, the reward will be higher as lower is the difference between the WSM and the LEM price (considering a minimum value for C^{PV}).

To access the economic value of the different scenarios, the NPV methodology was used. As mentioned in Section 5.5.2, the NPV is the sum of the present value of a series of present and future cash flows, considering a discount rate. Because NPV accounts for the time value of money, it provides a way to evaluate and compare products with cash flows spread over many years, as in loans, investments, payouts from insurance contracts and so on. Figures 6.43, 6.44 and 6.45 present the resulting accumulated cash flows for scenarios SC_PV, SC_ST45 and SC_ST300, considering the application of the optimization strategy and the initial investment costs. The expected economic benefits are constant along the years and depend on the energy that is sold to the market. The NPV reflects the total operating costs, exchanges with the grid as well as the attributable investment costs for a 20-year analysis. The updated accumulated cash flow represents the discount rate of the project considering the NPV (see equation 5.29).

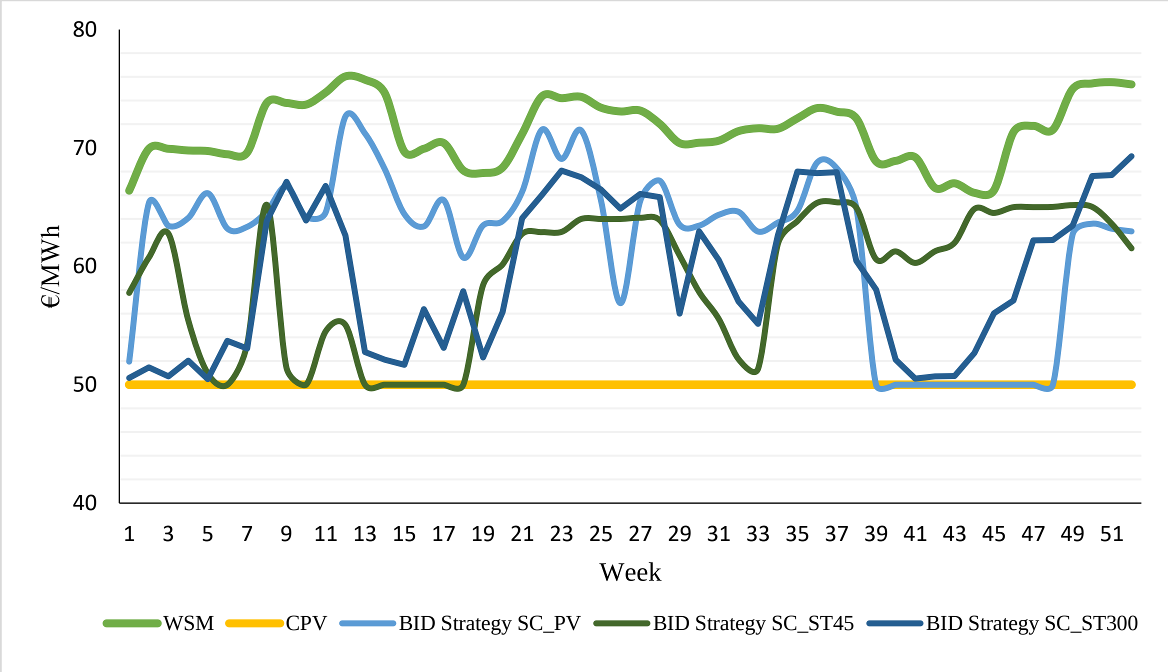


Figure 6.42. Average weekly prices for the WSM and the LEM markets for the different analyzed scenarios

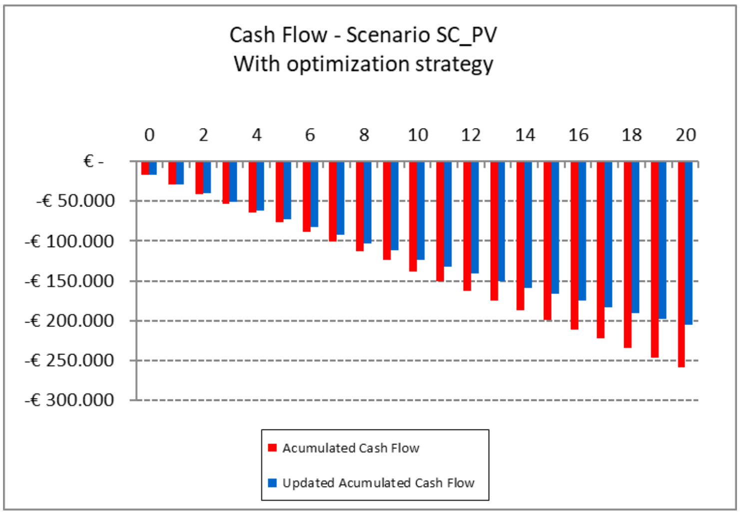


Figure 6.43. Scenario SC_PV - cash flow over 20 years

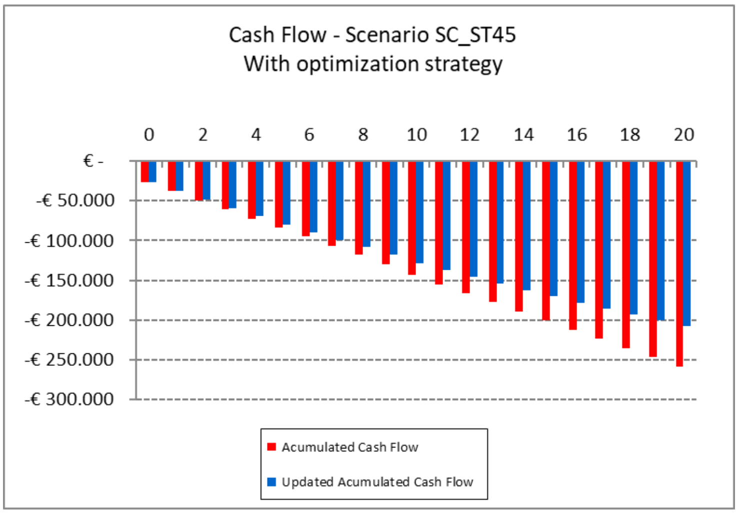


Figure 6.44. Cash flow over 20 years – Scenario SC_ST45

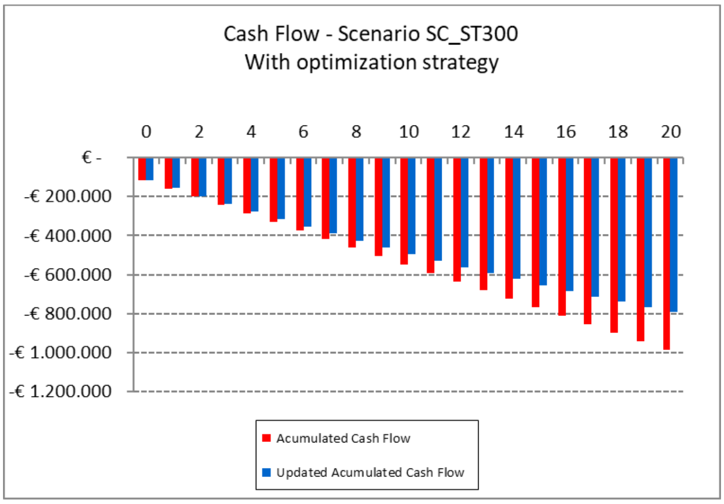


Figure 6.45. Cash flow over 20 years – Scenario SC_ST300

Analyzing now the impact of the CIEG exemptions on the NPV, Figure 6.46 presents the NPV for scenarios SC_ST300_A, SC_ST300_B and SC_ST300_C. It is possible to observe that as the exemption level increases, from a scenario without exemption till a scenario with 100% of exemption, the NPV evolves in the positive direction, meaning that it gets less negative and so the consumers obtain important savings. The results that were obtained indicate that a 50% exemption increases the NPV by 10% while a scenario with total exemption increases it by 20%, when compared with scenario without CIEG exemptions.

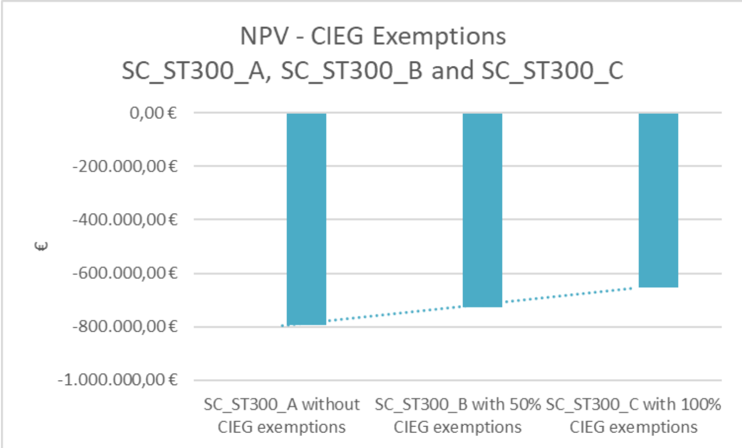


Figure 6.46. Impact of the CIEG exemptions on scenarios SC_ST300_A, SC_ST300_B and SC_ST300_C

To better understand the impact of several factors on the overall value of the installation of PV and storage units for self-consumption purposes, a sensitivity analysis is now conducted. We considered different changes affecting different parameters used in the simulations:

- Investment cost of the PV units and storage devices:
    - Based on the forecasted values for the CAPEX and OPEX of PV units and batteries, [310] presents the expected evolution until 2050. For instance, regarding the prices in 2022, the cost of PV units is expected to be reduced by 28% for the CAPEX and by 21% for the OPEX in the year 2030. For 2050, these reductions are respectively of 57% and 48% when compared with 2022. In what concerns storage, the expected reductions are 44% and 25% for CAPEX and OPEX for the year 2030 and 69% and 44% for the year 2050. So, regarding the cost reduction forecasts, we analyzed the impact of 25%, 50% and 75% reductions on investment costs in PV and storage systems. All scenarios, Ref-Case, SC_PV, SC_ST45 (Figure 6.47) and SC_ST300_A, SC_ST300_B and SC_ST300_C (Figure 6.48), were assessed;
- Electricity acquisition costs:
    - Figure 6.49. presents the impact of the variation on the electricity acquisition cost which is related to possible changes in the WSM prices. It was analyzed the impact of both the increase and the decrease of the cost of electricity acquisition (in steps of 25%).

On the right side of Figure 6.47 the NPV values for 0% cost reduction were obtained using the reference prices in Tables 6.19. and 6.27, that is no reduction of the investment cost are used. It is possible to observe, when we consider the reference prices, the scenario Reference Case presents the lower NPV. When comparing the scenario SC-ST45 with the scenario SC_PV, this last presents a less negative NPV which is related to the investment in the storage systems in scenario SC_ST45.

Analyzing now the impact of reductions of 25% of the investment cost, it is observed a change in the relative position between the SC_ST45 and the SC_PV scenario, which presents in this case a less negative value. It is interesting to observe that with a reduction of 75% on the investment costs, scenario SC_ST45 presents a less negative NPV than the Ref-Case and SC_PV scenarios. This change highlights the relevance of the investment costs in PV and storage systems so that a reduction of these costs will certainly be important when selecting an investment decision. So, we can conclude that reductions of 50% and 75% on CAPEX and OPEX for PV and storage systems make investments in PV and storage systems more competitive, namely when compared with the Ref-Case in which no such equipment is considered.

So, despite the appearance of battery costs in the SC_ST45 scenario, the NPV value does not degrade. And this fact is related to the increase in self-consumption in SC_ST45 and, consequently, a reduction in network tariff payments.

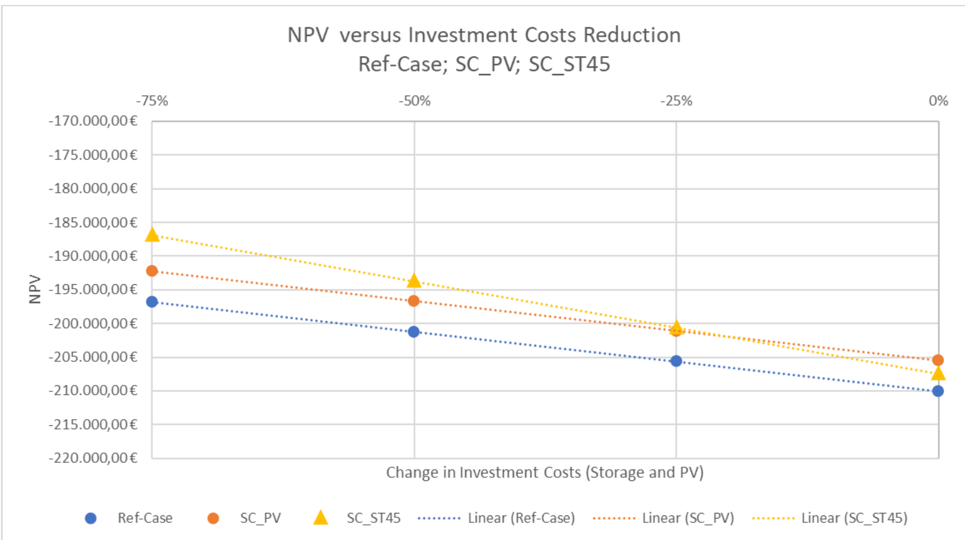


Figure 6.47. NPV versus investment costs reduction for scenarios Ref-Case, SC_PV and SC_ST45

In Figure 6.48 the same analysis is done now for scenarios SC_ST300_A, SC_ST300_B and SC_ST300_C. These results show that the NPV increases, or gets less negative, by approximately 4%, 8% and 11% as the investment cost is reduced respectively by 25%, 50% and 75%.

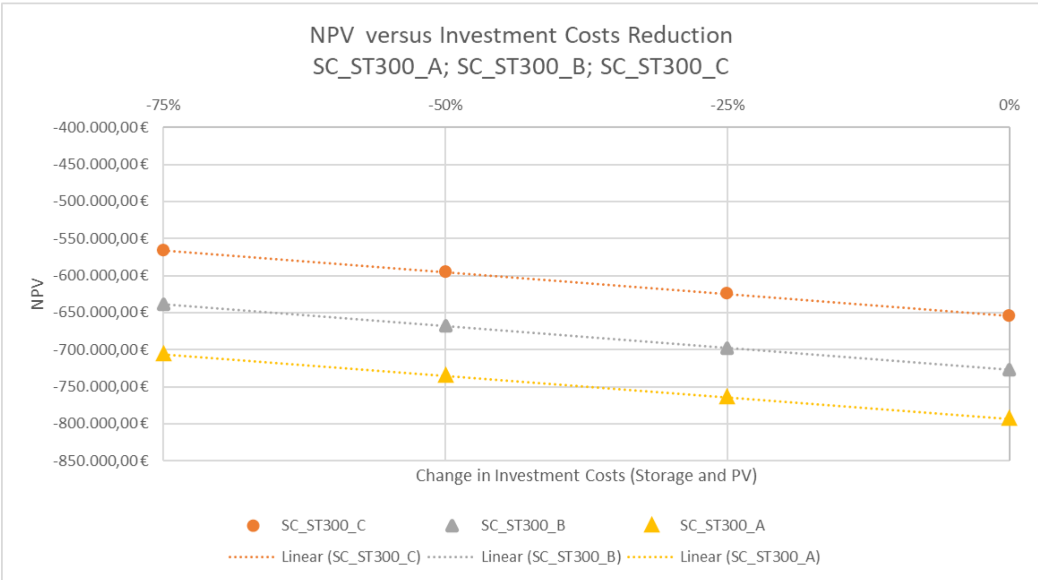


Figure 6.48. NPV versus investment costs reduction for scenarios SC_ST300_A, SC_ST300_B and SC_ST300_C

Figures 6.49 and 6.50 present the impact on the NPV of the scenarios Ref-Case, SC-PV, SC_ST45, SC_ST300_A, SC_ST300_B and SC_ST300_C, if the electricity acquisition cost changes. By observing Figure 6.49, it is possible to observe that NPV changes by approximately 30% if the energy acquisition costs change by 50%. When considering a larger storage system, i.e., in scenarios SC_ST300_A, SC_ST300_B and SC_ST300_C, the variation of 50% on the energy acquisition costs has an impact on 22% on the NPV (Figure 6.50). This is explained by the fact that in these scenarios, the storage allows having higher quantities of self-consumed energy and consequently lower energy imported from the grid.

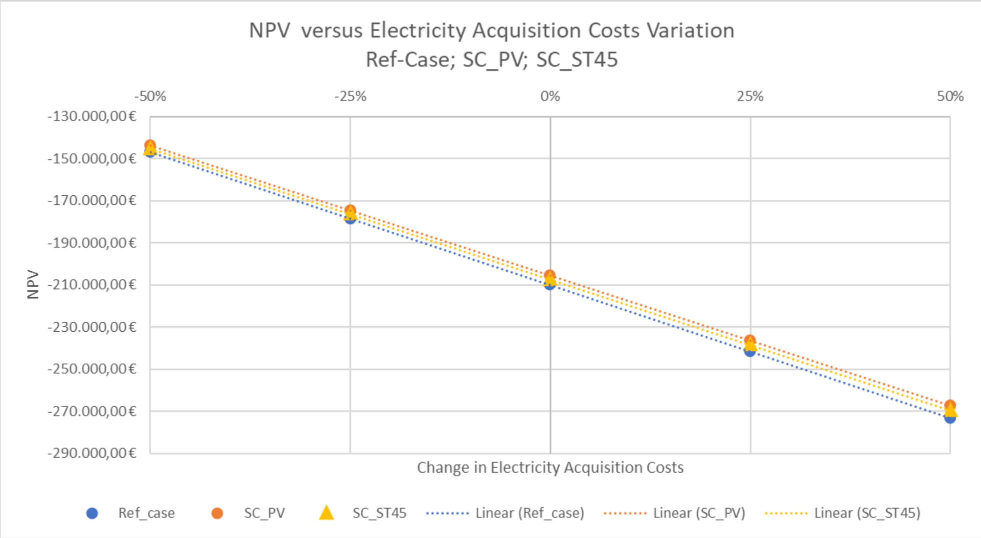


Figure 6.49. NPV versus variation of the energy acquisition cost for (scenarios Ref-Case, SC_PV and SC_ST45

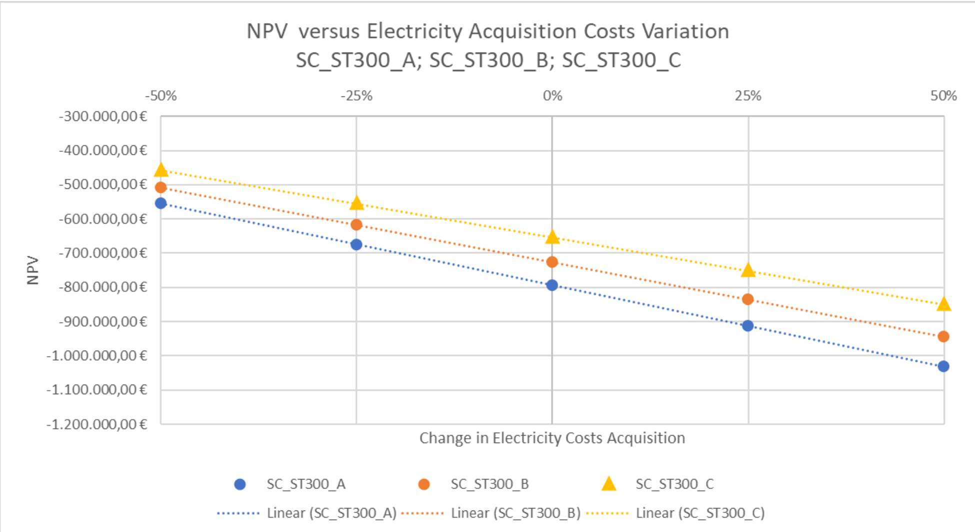


Figure 6.50. NPV versus energy acquisition cost variation for scenarios SC_ST300_A, SC_ST300_B, and SC_ST300_C

Analyzing the overall results, it is possible to conclude that the investment in PV systems, allowing to inject in the public grid an eventual surplus of generated electricity, has an impact of 2% on the NPV when compared to a system without PV. So, although investment, operation and maintenance costs of the PV systems are internalized in the calculation, the NPV evolves in the positive direction, meaning that it gets less negative and so the consumers obtain important savings.

The same analysis and the same impact are verified when the architecture considers a PV and a storage system. When compared with the same reference case (architecture without PV), the NPV continues to get less negative which reveals that exists benefits in investing in both PV and storage systems. In this case, the impact on the NPV is lower, around 1,3%, which is obviously related to the investment in both technologies (PV and storage) (Table 6.42).

Table 6.42 Net present values for the Ref-case, SC_PV and SC_ST45 scenarios

	Ref-Case	SC_PV	SC_ST45
NPV	-210.085,00 €	-205.510,00 €	-207.432,00 €

When integrated in communities, not only does the dependence of the electrical grid decreases, but also the benefits from selling surplus of electricity become important in terms of investment decisions. As bigger is the dimension of the storage systems, lower will be the demand supplied by the public grid and higher the demand supplied by self-consumption. Considering the architecture with a centralized storage system (where the location of the battery is not inside the community itself and it is located at the Low Voltage side of the MV/LV substation), the self-consumption tariff should be applied. However, the cost savings in tariffs are almost of 26% when compared to the same architecture but with batteries located at the electrical building level (Table 6.33). If it is considered an exemption of 50% and 100% of this component of self-consumption tariffs (CIEG), the savings will be respectively almost 34% and 43%. (Tables 6.35. and 6.37). These exemptions are significative and have an important impact in the improvement of the NPV, that is it increases by 10% and 20% for respectively 50% and 100% of CIEG exemptions. It was possible to conclude that a reduction of, at least 50% on CAPEX and OPEX for PV and storage systems, turns these architectures more competitive when compared for architectures only with PV systems.

By observing Figures 6.49 and 6.50, it is possible to conclude that electricity acquisition cost is the parameter that has a larger impact on the NPV. However, this conclusion doesn't underestimate the overall impact of the other parameters, namely investment costs and the CIEG component, which obviously have also a significant influence. Furthermore, if several of these parameters are reduced in a simultaneous way, the NPV would become less negative turning the investments more economically attractive.

Finally, let us discuss the computational performance of the developed model. To emulate the optimization problem, the Spyder Integrated Development Environment © [329] was used. For one year simulation and using a computer having 16 GB of RAM and with a processor of 3.0 GHz, the simulation for scenario SC_ST300 runs in approximately 39,3 seconds. As a final indication, the results of the Q-Learning model were treated using the Power BI © namely to build the graphs presented along this chapter [330].

Chapter 7

7. Conclusions and Future Work

7.1. Main conclusions

Power systems are evolving very rapidly namely in what concerns the technologies used to generate electricity, the diversification of commercial relationships which involves different agents and more specifically the empowerment of consumers. Otherwise, regarding the new paradigm with bi-directional power flow between production and demand prosumers and producers, as well as with the increasing of renewable energy penetration, several countries have enacted new legislation. These acts are aimed at promoting the establishment of renewable energy communities and increasing the self-sufficiency of end-users. In this sense, new players and architectures, such as LEM, are gradually entering into the electricity markets. However, the way these new frameworks interacts with the conventional ones, such as the integration of LEM into WSM, is not yet fully established.

To this end, the present PhD thesis addresses a design and an optimization model to increase the mentioned self-sufficiency level, to better manage the energy produced locally, also admitting the installation of battery storage units, and to profit as much as possible of them. It is proposed a new Agent-Based modelling with a special focus on the Energy Communities purposes. The general overview presented in Chapter 2, allowed to describe the electricity market in the past till nowadays and link it to the State of The Art of Legislation that support European Climate and Energy policies, namely in what concerns Energy Communities. The electricity sector is characterized by multiple and interconnected markets: day-ahead and intraday markets, bilateral trading, ancillary services markets, emissions allowances, and fuel (namely Natural Gas) markets. In this sense, with the increase of the participation of new actors in the electricity markets, the identification of the most adequate trading strategies turns it more complex. Considering this complexity, and to complement this decentralized and open energy market, Agent-Based Models are being used as a new research paradigm that allows adaptive approaches to provide adequate decisions to support in view of the complexity of the problems to handle.

Thus, it has become a core interest for all the participants in electricity markets, to develop new simulation models that takes into account this "democratization of energy". Since Agent Based Models simulate the interactions and actions of autonomous agents, it is widely used in the electricity market simulations field. In line with that, the main goal of this work was to develop a computational tool, using an Agent-Based Model, to help Energy Communities participants to build an optimal trading strategy, taking into account the regulations and limitations behind these local architectures. The developed model was based on an Energy Community constituted by different type of agents, such as consumers or prosumers, focused mainly of maximizing its self-energy consumption and profit in consequence of selling at the best price the energy surplus. The developed framework considers that the Energy Community deficit or surplus in each trading period will be traded between a Market Community agent and Aggregator through a bilateral contract.

The concept of an Agent-Based Model allows agents to take their decisions based on their past experiences with other agents and through the interaction with the environment. This type of model allows the market participants to develop their own strategies and preferences as adaptive agents. The electricity markets complexity contributes to create dynamic and adaptive systems. In this circumstance, the Q-Learning strategy was used in this work. However, and to assess the impact of the different parameters used in the developed Q-Learning methodology, several simulations were done considering different learning parameters. When was changed the greedy police parameter, ε, it was possible to verify that the "greedy" selection strategy had impact on the exploration strategy since with lower values didn't allow the process to be more effective by experimenting all the actions even if they were worse at a given step of the learning process. By decreasing the discount factor, Υ, i.e., the weight given to future reinforcements, we conclude that the agent finds new strategies in each hour and did not have in consideration the impact of its decisions in future rewards. Otherwise, when was changed the learning rate parameter λ, to lower values, the agent did not completely explore its bid ups and bid downs considering its experience. In this sense, and since the markets dynamics are continuously changing, it was considered a higher value for the learning rate.

The results that were obtained in this work indicates that the proposed Agent-Based model can be a very important tool to help LEM participants to follow the best strategy regarding self-consumption purposes and to increase the revenues that are coming from selling energy surplus into WSM. The simulation results, considering a Community with PV generation, reveals that when it was applied the optimization strategy, the revenues by selling the electricity surplus, was 25% higher than in the case that wasn't consider any optimization strategy.

When the developed model simulates energy trading between LEM and WSM, but also considering storage systems, two architectures were proposed. As established by the European Directives, Energy Community business models can include not only local generation trading and aggregation, but also storage. To understand how Energy Storage Systems can add value to a LEM, the two developed architectures were located at different Community locations – a decentralized located at the community building level and a centralized located at the substation near the community. It was also possible to observe that the application of the optimization model enables increasing the annual profits. The application of the optimization methodology originates an increase on the selling profits by 26% in both scenarios.

Besides the design and the optimization model developed, which aimed to increase the community self-sufficiency level and the revenues that are coming from selling energy surplus, the Energy Storage Systems had impact in the Energy Communities business models and in its investment decisions. Considering the usage of the public grid for self-consumption purposes, different simulations were performed taking into account the consideration the impact of having or not exemptions on network tariffs. These allows to getting insights about the impact of paying grid tariffs considering the utilization of the public grid and, in this sense, was assessed the economic performance of the entire installation, namely considering the storage systems. The results that were obtained reveals that the exemption in some elements of the Access Tariffs, namely in the CIEG component, had a significant impact in the improvement of the Net Present Values. For scenarios with 50% and 100% of exemption on CIEG components, the NPV increased, respectively, by nearly 10% and 20% when compared with a scenario without exemption.

The level of exemptions of the access tariffs, as well as the electricity purchase costs and the investment costs of PV and storage systems, are among the factors that will determine the massification of RECs. A sensitivity analysis performed in this work concludes that reductions on CAPEX and OPEX for PV and storage systems, turn investments more attractive. For instance, if investment costs are reduced by 25%, 50% and 75%, the NPV increases by 4%, 8% and 11%, respectively. In what concerns electricity acquisition costs, we concluded that this parameter had a larger impact on the NPV. If the electricity costs decrease by 50%, the NPV was reduced by approximately 30%. So, we concluded that the overall impact of tariffs exemptions, electricity acquisition costs and investment costs will induce the penetration and massification on electric power systems.

The main contributions of this work will be presented in Section 7.2. Then Section 7.3 aims to answering to the Research Questions presented in Chapter 1 and finally, Section 7.4 includes suggestions for future work.

7.2. Contributions

The following paragraphs presents the major contributions of this PhD Thesis, specifically what covers each chapter.

Chapter 2 presents a background and the state of the art about the main topics approached n this thesis, namely an overview of electricity markets, different national frameworks for Energy Communities and P2P and VPPs models. Regarding the development of this work, with Agent Based Models, some modelling methods to simulate electricity markets, Machine Learning Methodologies and ABM in Power systems simulators, were presented in Chapter 3.

Considering the operations strategies under Energy Communities, Chapter 4 presents the structure of the model that was developed. It was presented an ABM as a decision tool to support energy transactions between the LEM and the WSM. In the developed ABM model, the market participants were modeled as adaptive agents with main purpose of maximizing the profits resulting from the reduction of the generation cost, the increase of self-consumption, and of selling the energy surplus in the Wholesale Market. The Market Community Agent purchased the energy to balance the Energy Community electricity deficit from the Aggregator Agent and sell the excess electricity considering specified price limits. In order to evaluate the performance of the optimization tool, it was defined a utility function as a numeric representation of how good some sort of possible residence state of a system under analysis was. It consists of the ratio between the Market Community Agent Bid (C^{Bid}) and a bilateral contract predefined (C^{PV}). The higher this ratio is, the higher will be the community profits by applying the optimization model. If the WSM price (C^{agg}) is lower than C^{PV}, the Market Community Agent will receive the guaranteed reward defined by the bilateral contract, that is C^{PV}. Otherwise, and if the C^{Bid} is lower than the $C^{agg}$and higher than C^{PV}, the reward will be equal to the difference between $C^{Bid}$and C^{PV}. Regarding the strategy adaptation tool, it was developed an ABM associated to the reinforcement Q-Learning approach to simulate the LEM market and its interactions namely with the WSM. The Q-Learning procedure, evaluates the payoff that can be obtained for a given state-action pair *Q(s,a)*. In this sense, the state's definition developed was in line with energy communities' perspective, i.e., to enhance the self-supply capacity and to minimize the dependency of the grid. In the learning approach it was considered 5 states and an adaptation of the derivative-following strategy, where the Market Community Agent increases or decreases its bid price in an attempt to increase the overall profit.

Chapter 5 was directed to an electricity market design, similar to the previous one, but now considering prosumers and energy communities with ESS, namely batteries. The operation strategy implemented was similar than the previous one, however it aimed at benefiting the community members by storing the excess of electricity for their internal consumption or to sell in the LEM. Regarding the system structure, two architectures were presented. One, where ESS was placed anywhere in the community (named as decentralized) and located not inside the community (termed as centralized). The operation strategy of the batteries, consider charging and discharging mode operation. The first one, was if there was any surplus of PV generation regarding the local demand and in discharging mode if the community demand was higher than local generation. However, and if the stored energy was sufficient to feed the demand, and it also had some surplus, those additional quantities was considered in the selling bids optimization strategy of the Market Community Agent. This Chapter also presented an overview of different energy storage technologies and explained how the proposed ESS was modelized. However, it was similar to the model developed in the previous Chapter but considered its technical characteristics. Besides the implemented legal framework and the incentives for the deployment of Energy Communities, in this Chapter, it was also detailed the legal frameworks that impacted in the economic viability of the investments and operation of Renewable Energy Communities, namely tariffs, charges and some kind of exemptions.

Chapter 6 presents the simulations, the results, and discussions regarding the main outcomes. The first simulation considers a collective self-consumption with PV system integrated into a Portuguese collective building. All the data used were real data. The second scenario consider the same community, however with a decentralized storage system (not a fully decentralized approach in which each consumer/prosumer would have its own small storage unit). Such level of decentralization was not considered in this study because the current investment cost in storage systems is still large enough to prevent this type of dissemination. The third architecture simulated, consider a storage system located not inside the community, but located at a Low Voltage side of the MV/LV substation that feeds the set of the buildings. In this last architecture, it was possible to get insights related with the payment of grid tariffs and in particular with the CIEG component applied to self-consumption that used the public grid. Other contribution of this Chapter was to access the dependence of the external grid in systems with its own generation but also, the benefits of the developed optimization tool regarding the application of its bidding strategy. An economic assessment was made, for all the proposed scenarios, using the NPV methodology. It reveals that the optimization strategy that was used, the levels of exemptions on the CIEG component, and the CAPEX, OPEX and electricity costs acquisition impact on the NPV. The final contribution was related to sensitivity analysis made considering changes on the investment and electricity acquisition costs.

7.3. Answering the Research Questions

In this section, the research questions raised in Chapter 1 are answered.

Research Question 1:

1. Are the Agent-Based Models capable of handling Energy Communities' main purposes?

Energy Communities and Renewable Energy Communities introduce new concepts and business models, where small scale producers and end users can participate in the electricity trading systems. This new energy paradigm gives new roles and opportunities for citizens, having more choices in their homes as well as flexibility to reduce their energy use when it is expensive and consume or store it when it is cheap. This type of framework also contributes to the appearance of markets, such as LEM, where new agents can interact, not only locally, but also be integrated with conventional markets.

As referred in Chapter 3, the traditional market analysis models, such as equilibrium models, do not incorporate strategic behavior of market participants and have unrealistic design when assuming that market participants have all relevant information about the characteristics and behavior of competitors. The answer to this research question may rely, among other issues, on the development of new computational tool based on Artificial Intelligence to deal with the increase complexity of the participation of new actor in local energy markets. With new computing technologies, those new actors can use Artificial intelligence models with learning capabilities to solve more complex problems. In this sense, Agent Based Models are a new paradigm that allows the developing of tools that can represent and model, in a more realistic way, Energy Communities frameworks and Local Energy Markets.

Research Question 2:

2. How should the Energy Communities' actors be organized, regarding integration with conventional electricity markets?

This framework behind Energy Communities aims at increasing the renewable-based decentralized generation and empowering consumers as important decision makers in the energy markets. It is also designed to allow smaller energy retailers to develop and offer innovative electricity supply packages, making room for new Energy Business Models to emerge. One of these standpoints is the Energy Community business models, where all the members should be considered in the overall arrangement design, implementation, and operation. As advocated by the European Directives, Energy Community Business Models 'key activities' include local generation, supply, storage, consumption, trading, aggregation, e-mobility, and energy related services, as well as system administration. To address some of these challenges, LEM emerges as a new energy business model where consumers have access to a joint market platform to trade locally produced electricity among each other.

So, considering the appearance of new agents and new energy business models, Energy Communities actors should be organized in LEM in order to consider the community agents participation and their interaction with the conventional electricity market design, namely WSM.

As mentioned in Chapter 4, the energy sharing concept is at the root definition of Energy Communities where any member of the community can buy and sell its electricity within the community boundaries. In this sense, LEM are emerging mechanisms to enable local energy trading in Energy Communities regarding its integration with conventional markets. The developed LEM presented in Chapter 4, describes different types of agents and a Market Community Agent which was in charge of maximizing self-energy consumption and the profit in consequence of selling the energy surplus. To balance supply and demand in the community, it communicates with an aggregator, who operates as a traditional retailer regarding the market clearing mechanism in the WSM.

Research Question 3:

3. What is the influence of including not only generation trading and aggregation in Energy Communities, but also storage systems?

As established by the European Directives, Energy Community business models can include not only local generation trading and aggregation, but also storage. To understand how ESS can add value to a LEM, in Chapter 5 was proposed an electricity market design which considers two different architectures regarding the integration of storage systems. The first one was a decentralized architecture, where storage was located at the building level, while the second one was a centralized architecture within the community. Specifically, the value of battery storage and associated architectures in combination with LEM were examined. To understand the value of local markets and battery flexibility, we compared the outcomes of the two proposed market designs against a reference case that did not incorporate storage systems.

The results show that when compared with a scenario without storage, the decentralized architecture had a lower amount of energy injected back into the grid. This is in line with the fact that the demand supplied by the public grid decreases and the demand supplied by self-consumption increases due to integration of the storage systems. In the case of the centralized architecture where self-consumption was also prioritized, the demand supplied by self-consumption was also higher than the one supplied by the public grid. When comparing both storage scenarios, the centralized architecture, since it had a larger storage capacity of the storage units, stored more energy than the decentralized architecture. Apart from the increase of the capacity of the storage units, this evolution was consequence of the maximization of the self-consumed energy by the optimization of the use of the storage equipment through the adequate selection of its charging and discharging periods. However, and if the stored energy was sufficient to feed the demand, and there was still some surplus, those additional quantities were injected back into the grid and used in the adopted selling bids strategy. In this sense, it could increase the community profits.

Research Question 4:

4. Can the regulatory context induce the massification of Energy Communities?

Besides the implemented legal framework and the incentives for the deployment of RECs, the economic viability of the investments (namely in storage systems) and operation of RECs, specifically considering different tariff and charge exemption designs, can induce the massification of Energy Communities.

The legislation stated that CSC and REC should receive a remuneration for the surplus energy injected back into the grid and which can be commercialized by an independent aggregator or utility company. However, and in the case of Portugal, it is also stated that the charges associated with CIEG (Costs of General Economic Interest), a component of the grid tariffs paid by end consumers, could be totally or partially deducted from the grid access tariffs. On 19th June 2020, a Portuguese government dispatch, n. º 6453/2020, stated that CSC and REC projects, starting operation till the end of the calendar year 2021, benefit from an exemption regarding the payment of the CIEG component of the access network tariffs for seven years. More recently, it was passed the DL 15/2022 of January 14 corresponding to new Portuguese electricity law.

This provision is intended to induce the wider deployment of self-consumption and of Energy Communities. When the public grid is used for self-consumption purposes, namely when storage systems are located outside the electrical network of the buildings where the consumers are installed, the exemptions of grid tariffs have impacts on the final investment decisions processes. In this work, it was possible to observe in Chapter 6, that as the exemption level increases, from a scenario without exemption till a scenario with 100% exemption, the NPV evolves in the positive direction, meaning that it gets less negative and so the investors obtain important savings.

However, and as stated in Chapter 5, from a regulatory point of view, enlarging the charge reductions or exemptions so that more and more network users benefit from them, originates an important regulatory problem. In fact, the Access Tariffs are designed to provide the amount of regulated revenues defined in the Tariff Code and required to finance several regulated activities as network distribution and transmission and the system control and management as well as several public policies that are designed to benefit all the society on the long term. As the number of consumers or network users benefiting from charge reductions or exemptions increases, the consumers that at the end will pay the complete regulated Access Tariffs reflecting the mentioned regulated revenues gets more and more reduced which means that each of them would pay more for the access to the system. This is a major concern as the number of RECs increases and clearly shows that these charge reductions or exemptions should be cautiously set and should only be accepted as a transitory provision to help induce the development of this new business case.

7.4. Future work and Research Opportunities

Power systems are an area that has been and will be in continuously development. Consequently, its optimization will remain to be a concern for all the actors enrolled in this sector, namely electrical companies as well as researchers dedicated to this topic. In this section, we identify further research areas related to the work developed in this PhD Thesis.

Chapter 3 presents some modelling methods to simulate electricity markets. In this work a Q-Learning procedure was developed and showed to be as an efficient approach to perform the bidding strategy behind local energy markets. Nevertheless, because of the increasing complexity of power systems, for instance by considering an aggregation of several energy communities, the Q-Learning strategy can lead to a slow convergence of the Q-values. For this reason, hybrid methodologies and techniques using Deep Learning should be considered. However, another modelling methods for optimizing the bidding process, namely traditional methods and another agent-based method of optimization could be developed for further comparison with the develop model presented in this work.

The models proposed in Chapters 4 and 5, presents a structure considering an energy community constituted by consumers and prosumers. In these models there are some improvements that can be considered and implemented. The first one is related with the potential of Energy Communities by demand-side solutions to reduce energy demand and foster demand-side flexibility. Demand response will be an opportunity for consumers to play a more significant role in the operation of the power systems by reducing or shifting their electricity consumption during peak periods in response to price variations or other forms of financial incentives (e.g., capacity markets). Other research area to explore is the storage arbitrage price strategy, that is, by moving the time intervals in which electricity would have to be bought to some other periods in which the price is lower or to store electricity when local generation is in excess in order to sell it in periods in which the price is higher. These improvements can have a significant impact in the local energy market prices, meaning that these agents should have a bidding strategy that consider these issues.

As presented in this work, local electricity markets give end-users the ability to trade electricity at different voltage levels, namely at the distribution level. However, distributed energy transactions can threaten the correct operation and stability of the grid since it impacts on the control, operation, and planning of electricity distribution systems. For this reason, a power flow assessment should be developed considering the presence of new consumers and prosumers (electric vehicles, heat pumps, rooftop photovoltaic panels, large scale, and local storage systems, etc). The co-optimization/simulation of real-time intraday markets and ancillary services and capacity markets should be considered in this assessment.

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Annex A

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Agent-Based Models in Power Systems – A Literature Review

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Abstract
In the last two decades, power systems have experienced several changes, mainly related to organizational and operational restructuring. The appearance of new actors contributes to developing new business models and modifies its traditional operation activities. As a direct result, there is a need for new control solutions and strategies to integrate these different players. Agent-Based Models (ABM) have been increasingly used to model complex systems since they are especially suited to model systems influenced by social interactions between flexible, autonomous, and proactive agents. This paper provides a review of the literature regarding ABM in power systems followed by an analysis in more detail regarding specific applications that are becoming relevant in this new paradigm.

Author Keywords. Agent-Based Model, Power Systems, Electricity Market, Smart Grids, Energy Communities, Storage.

Type: Review Article

1. Introduction

The transition of power systems from vertically integrated structures to deregulated markets and the implementation of new rules and business models originated the need for new operation and modeling strategy techniques. There are also under development new processes, mechanisms and equipment, such as demand response (DR), smart grids, storage systems, electrical vehicles (EV), energy communities, among others, which have been termed by some authors as the "democratization of energy" (Reis, Lopes, and Antunes 2018).

With these new concepts, citizens can become producers and consumers (prosumers), so that various technical, social, economic, and environmental challenges should now be addressed. The complexity of incorporating new actors into the operation of power systems implies greater coordination among all stakeholders and leads to a new operational paradigm that requires innovative or adaptive methods to provide adequate decision support. This process should start with the decomposition of each player into smaller components, represented by individual agents, to perform actions to meet individual goals but also considering the behavior of the other participants and their impact on the overall system (Macal and North 2010). Thus, considering the operation of power systems with the participation of these new players, rather than just looking at the overall picture, makes the problem-solving in this domain an increasingly complex task. Agent-Based-Models (ABMs) can be considered a suitable tool to address this complexity.

ABM has been proposed by many researchers as a proper modeling approach for complex, socio-technical problems (Bonabeau 2002). Mainly, ABM techniques have been applied to model and study electricity systems and markets and gained an increasing recognition (Ventosa et al. 2005). According to the development of these applications, this paper presents a literature review on ABM in Power Systems.

The basic principles and a literature review of ABM in Power Systems is detailed in this work. It includes a survey considering scientific research over the last few years. Different applications of ABM in power systems are presented as well as the main conclusions.

2. Basic Principle of Agent-Based Models

As systems are becoming more complex, new tools, simulation, and modeling approaches are needed. An alternative to typical simulation techniques (such as traditional optimization techniques, discrete-event simulation, and differential equations) are ABM. An ABM is a computational model integrating individual and autonomous agents and their collective behavior. An autonomous agent acts on its own without external direction in response to situations the agent encounters during the simulation (Heath, Hill, and Ciarallo 2009).

The following definitions of ABM are provided by Macal and North (2010), Pyka and Grebel (2006), and Gilbert (2008):

- "Agent-based modeling is a way to model the dynamics of complex systems and complex adaptive systems. Such systems often self-organize and create emergent order. ABM also includes models of behavior (human or otherwise) and is used to observe agent behaviors and interactions' collective effects. The development of agent modeling tools, the availability of microdata and advances in computation have made possible a growing number of agent-based applications across a variety of domains and disciplines" (Macal and North 2010).
- "The ABM approach consists of a decentralized collection of agents acting autonomously in various contexts. The massively parallel and local interactions can give rise to path dependencies, dynamic returns, and interaction. In an environment global phenomena such as the development and diffusion of technologies, the emergence of networks, herd-behavior, among others, which cause the transformation of the observed system can be modeled adequately. This modeling approach focuses on depicting the agents, their relationships and the processes governing the transformation" (Pyka and Grebel 2006).
- "Formally, agent-based modeling is a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment" (Gilbert 2008).

ABM focuses on the modeling and simulation of complex systems, at a local level through the definition of their elementary units and, at a higher level, suited to model adaptive heterogeneous actors – agents.

Shalizi (2006) defined an agent as a persistent thing that has some state worth representing and interacts with other agents, mutually modifying each other's states. Another definition of an agent was provided by Wooldridge and Jennings (1995) and indicates that an agent is a computer system situated in some environment, and capable of autonomous action in this environment in order to meet its design objectives.

So, an agent is an entity situated in some environment that can autonomously react to changes in that environment. Besides, the environment is everything external to the agent and must be observable to or alterable by the agent (Wooldridge and Jennings 1995). Each agent chooses its strategy based on its previous experiences with other agents and through interaction with the environment, which helps him improving its decisions by modifying their strategies.

The three basic concepts of ABM are:

1) Agents: can be a computer code, which can perform some tasks autonomously in a particular environment. The main features of an agent could include autonomy, reactivity, social ability, and pro-activity. In power systems, generators, ancillary service providers, protective devices, system operators, consumers, regulators, and retailers could be the agents;

2) Artifacts: are the components of the systems that are passive and are developed, shared, modified, developed, modified and utilized by the agents to carry out their activities competitively or cooperatively. Examples of artifacts in power systems could be transmission and distribution lines;

3) Workspaces: accommodates the agents and artifacts. It helps to define the topology of the environment and the idea of locality.

3. ABM in Power Systems – Literature Review

ABM has been applied in different scientific areas, including marketing (Xiao and Han 2016; Rand and Rust 2011), treatment of diseases (Corti et al. 2019), biology (Athale, Mansury, and Deisboeck 2005), economics (Khan and Yang 2020; Cristelli, Pietronero, and Zaccaria 2012), financial economics (LeBaron 2006), urban planning (Caprioli, Bottero, and Pellegrini 2019), social sciences (Serrano and Satoh 2020), transportation (Hager, Rauh, and Rid 2015), geographical information systems (el Raoui, Oudani, and Alaoui 2018), pandemics (Jalayer, Orsenigo, and Vercellis 2020), among others.

With the transition from vertically integrated utilities to deregulated electricity markets, power systems' complexity is increasing, namely because new rules and players are emerging and being implemented. Distributed generation (smart grid and microgrids) (Farhangi 2010), EVs (Tan, Ramachandaramurthy, and Yong 2016), consumption flexibility and DR processes (Faria, Spínola, and Vale 2016), large penetration of renewable-based generation (Calabria, Saraiva, and Rocha 2016), energy efficiency measures (Zhou et al. 2016), and building energy management (Mittal et al. 2019), among many others, contribute to the increasing management and operation complexity, the transmission and distribution networks and the interactions between traditional and new players. The uncertainties associated with the renewable-based generation, electricity market prices, energy consumption, or EVs are just a few examples of the increased sources of uncertainty and thus of complexity brought to the power and the energy sector.

In the last years, research has been devoted to deal with this complexity and address the challenges brought by this new paradigm. In this scope, we have looked at scientific research reported in the Web of Science database (WoS, n.d.) using different search terms to analyze the publications produced on this area and provide an overview of the recent research. Table 1 shows the overview of research documents produced since 2010 that were analyzed by different search terms. The search terms have been combined with similar variants within the power systems field to observe the results as accurately as possible. We looked for each search term in the abstract, title, and keywords of the papers. Also, we investigate the most cited papers in each search criterion and the most noticeable research authors by the number of articles produced.

Search term	Documents since 2010	3 most cited articles	Reference Citations	Top 3 authors with most articles
"ABM" AND "Agent Based Model*"	1304	Grimm et al. (2010) Müller et al. (2013) Valbuena et al. (2010)	1233 155 137	An, Gary (13) Dragicevic, Suzana (11) Polhill, J. Gareth (9)
"ABM" AND "Agent Based Model*"AND "Power System*"	59	Sornette (2014) Kuznetsova et al. (2014) Richmond et al. (2010)	118 117 76	Saraiva, Joao Tome (4) Calabria, Felipe Alves (3) Kuznetsova, Elizaveta (3)
"ABM" AND "Agent Based Model*"AND "Power System*" AND (market* OR electrical)	19	Kuznetsova et al. (2015) Hansen, Liu, and Morrison (2019) Chaudhari et al. (2019)	55 16 15	Saraiva, Joao Tome (4) Calabria, Felipe Alves (3) Rocha, Ana Paula (3)

Table 1: Research documents produced since 2010 analyzed by search term according to Web of Science

A total of 1304 documents between 2010 and 2020 were found in the Web of Science database by using the search term *"ABM"* AND *"agent based model*"* in the abstract, title, and keywords. The 3 most cited papers aren't related to power systems and electrical engineering. This suggests the coverage of this topic in different fields and the innovative character of applying such a paradigm in power systems. Figure 1 presents the distribution of ABM among different scientific areas.

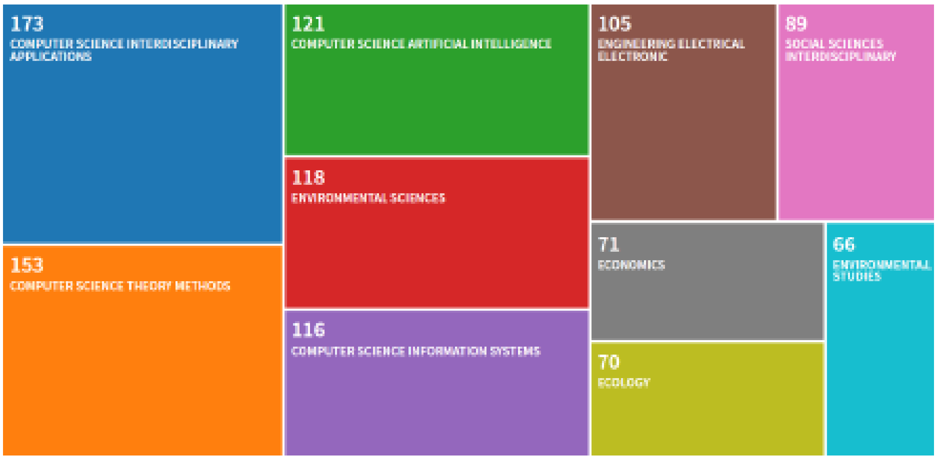

Figure 1: Web of Science applications distribution about results provided from searching words ABM and Agent-Based Models (WoS, n.d.)

The search term *"ABM"* AND *"agent-based model"* AND *Power System** produced only 59 results. This suggests that the marriage between agent-based models and power systems is far from being mature. This was expected given how ABM have been maturing conceptually during the past few years.

The most cited paper (Sornette 2014), with 118 citations, is not directly associated with power systems but with power-law distributions. It presents the different perspectives embraced in theories developed in financial economics compared with physics. However, the second most cited (Kuznetsova et al. 2014), with 117 citations, presents a microgrid energy management framework to optimize the microgrid stakeholder's individual objectives. This framework is exemplified considering a microgrid connected to an external grid via a transformer and includes a middle-size train station with an integrated photovoltaic power production system, a small energy production plant composed of urban wind turbines, and a surrounding district with residences and small businesses. The system is described by an ABM, in which each player is modeled as an individual agent aiming at a particular goal, (i) decreasing its expenses for power purchase or (ii) increasing its revenues from power selling (Kuznetsova et al. 2014).

The author with most papers published in this search field is Saraiva, Joao Tome, with 4 articles (Sousa and Saraiva 2017; Calabria, Saraiva, and Rocha 2015a, 2015b, 2016).

In Sousa and Saraiva (2017), an ABM model is described using Q-learning to provide knowledge for the agents to select their decision. This model is designed to mimic the main features of the common electricity market between Portugal and Spain, the MIBEL. Apart from describing the developed model, this paper also includes preliminary results from its application to the MIBEL case.

Calabria, Saraiva, and Rocha (2016) propose and test a bid based short-term market in order to overcome difficulties identified in the Brazilian electricity market. To simulate the behavior of the hydro units, it was implemented an ABM using the reinforcement Q-Learning algorithm, Simulated Annealing, and linear programming.

A market design based on virtual reservoirs was proposed in Calabria, Saraiva, and Rocha (2015b). This model aims at enhancing the flexibility to enable market participants to comply with their contracts while still ensuring the efficient use of the water and maintaining the current security of supply.

Some of the problems related to the current Brazilian electricity market were analyzed in Calabria, Saraiva, and Rocha (2015a).

This paper proposes a new market design to overcome these issues based on the concept of virtual reservoirs and aims at enhancing the flexibility to enable market participants to comply with their contracts while still ensuring the efficient use of the energy resources and maintaining the current security supply level. ABM simulates the behavior of the market participants in this new framework.

A more refined and focused search, based on search terms *"ABM"* AND *"agent-based model"* AND *Power System** AND *(market* OR electrical)*, produced only 19 results. However, a refined search was done as the first two results weren't directly related with power systems, which is the major topic. So, the search was done excluding the words "physics" and "tourism" providing now 17 results.

The most cited paper in these research areas (Kuznetsova et al. 2015), provides an extended analysis of a microgrid energy management framework based on Robust Optimization (RO). The system is described by an ABM where each stakeholder is modeled as an individual agent. Each of these agents aim at optimizing a specific goal, either in terms of decreasing its expenses from power purchasing or by increasing its revenues coming from selling power.

A systematic review of the potential of ABM to understand energy transactions from a social-scientific perspective is described in Hansen, Liu, and Morrison (2019). Six topic areas were identified, addressing different components of the energy system: Electricity Market, Consumption Dynamics/Consumer Behavior, Policy and Planning, New Technologies/Innovation, Energy System, Transitions.

Chaudhari et al. (2019) present an ABM approach that considers an optimal EV charging infrastructure, taking into account several factors, such as the driver behavior, the location of charging stations, the electricity pricing.

4. Different Applications of ABM in Power Systems

This section reports some relevant publications focusing on operating paradigms with ABM modeling approach in smart grids and markets such as DR, distributed generation, energy community, and their interactions.

4.1. Electricity market simulation

The application of ABM models to power systems and specifically to electricity markets assumes an increased relevance since bottom-up approaches become crucial to understand and model the energy transition. As previously mentioned, ABM can model complex aspects in the electricity markets as they can represent the different system participants' complex behavior.

In this scope, AMES is the acronym for Agent-Based Modeling of Electricity Systems. It is an open-source agent-based computational laboratory for the experimental study of wholesale power markets, developed in 2007 specifically designed to systematically explore strategic trading in restructured wholesale power markets operating AC transmission grids. The wholesale power market includes an independent system operator, load-serving entities, and generation companies, distributed across the transmission grid nodes. Each generation company agent uses stochastic reinforcement learning to update the action choice probabilities currently assigned to the supply offers in its action domain. Besides, AMES facilitates augmenting the empirical input data with simulated input data to allow studying a broader array of scenarios. Downloads, manuals, and tutorial information for all AMES version releases to date are accessible at the AMES homepage (Tesfatsion, n.d.).

The Simulator for Electric Power Industry Agents (SEPIA) was developed in 2002 to improve the efficiency of the North American power network (Amin 2002). It was developed as bottom-up model and simulator which uses autonomous, adaptive agents to represent possible industrial components (e.g., generation units, transmission system and load) and the corporate entities that own these components. According to the survey provided by Zhou, Chan, and Chow (2007), SEPIA and its architecture display good results for electricity market systems. Its distinct features, which consist of its capability to adapt, provided by both Q-learning and genetic classifier learning modules, are highlighted as an advantage. Related to limitations, the survey mention the absence of an independent system operator agent. Also, the adaptation mechanism is restricted to generation companies and focuses on the bidding strategies. It could be extended to other decision making levels.

Electricity Market Complex Adaptive Systems (EMCAS) is a commercial tool developed by the Center for Energy, Environmental and Economic Systems Analysis (CEEESA) at the Argonne National Lab Laboratory (Center for Energy, n.d.). This model includes decentralized agent decision-making features along with learning and adaptation capabilities. It is possible to assess the behavior of the agents after changing market rules. EMCAS agents take decisions based on past experiences and future expectations. Whenever an agent takes a decision, it will consider the results of a similar decision made previously – Look Back. This mechanism can be considered as a short and long-term memory and could consider trades between bid acceptation or rejection, unit utilization, profitability, market versus price bid, and weather versus load. It also considers results based on own unit availability, prices, weather, and loads related to projection results - Look Ahead. When considering its current conditions, such as competing unit availability, own cost structure, and market rules, agents take decisions looking sideways – Look Sideways. Compared with SEPIA, which has a self-learning mechanism for decision rules, the adaptation process in EMCAS is supported by pre-specified decision rules and no adaptation exists. Thus, agents in EMCAS have a lower adaptation capability than those in SEPIA. Moreover, the adaptation in EMCAS is restricted to generation company agents.

Despite several references to ABM applied to power systems, the available models do not adequately consider a number of relevant issues such as the large presence in some systems of hydro stations and its reversal pumping feature and the large share of zero marginal cost intermittent technologies. In Sousa et al. (2013) it is discussed and proposed a conceptual model following the agent paradigm that deals with the inherent complexity of electricity markets such as, the Portuguese/Spanish Electricity Market (MIBEL).

One of the tools that can be used to perform the management of a hydrothermal electric power system at a national level or with cross-border interconnections is VALORAGUA model. This tool establishes the optimal operation strategy for a given power system by using the "value of water" concept, in each power station, for each time interval (i.e. month/week) and each hydrological scenario. The model supplies detailed information on the technical, economic, and environmental behavior of each generation centre and the system. This model also computes thermal-based power generation emissions and optimizes the maintenance schedule of power plants. VALORAGUA is often used to: analyze energy import/export contracts; maximize power generation revenues; manage on the long-term the stored water in reservoirs with regulating capability; define the adequate use of water in multi-purpose units, considering its operation constraints (da Silva 2013).

Multi Agent-based Electricity Market (MASCEM) is a simulator developed at the Polytechnic of Porto, Portugal (Praça et al. 2003) to study competitive electricity markets. The agents in MASCEM include a market facilitator, generators, consumers, market operators, traders, and a network operator. Their strategies are adequate to gain the highest possible advantage from each market context, acting in forward, day-ahead, and balancing markets and considering both simple and complex bids.

4.2. Smart grids

With the increase in the number of EVs and DR customers, ABMs can be a potential framework to challenging model problems in smart grids. Agents decide to buy, sell or store electricity depending on their demand, generation, and storage capacity.

Zhou, Zhao, and Wang (2011) studied the impact of the level of participation of the commercial building in DR programs. It also examined how price-based DR can improve the efficiency and reliability of electricity systems.

A prototype ABM to examine the effects of individual behavior and social learning on electricity use patterns is presented in Snape, Irvine and Rynikiewicz (2011). This paper provides a holistic view on the electricity system considering technical aspects, human interaction, and framework policies. Chassin, Fuller, and Djilali (2014) present a flexible power system modeling tool using an agent-based approach to simulate smart grid paradigms, such as demand response, energy storage, retail markets, electric vehicles, and new automated distribution systems. Dave, Sooriyabandara, and Yearworth (2013) present a business idea where the DR potential of households through aggregators is exploited. These authors detail that peak load reductions can be obtained using this approach.

The potential large-scale introduction of EVs is another relevant aspect of future smart grids. EVs provide an interesting potential to control electricity demand in an intelligent way given the significant load-shifting options. A stochastic model for mobility behavior and ABM simulation tool is presented in Dallinger and Wietschel (2012).

In Foti and Vavalis (2015), a learning approach for strategic consumers in smart electricity markets has been designed. A machine learning approach and its integration with a widely used energy simulation platform was proposed.

Yasir et al. (2015) present an ABM architecture for coordinating locally-connected microgrids, thereby supporting more cost-effective integration into the main power grid. The interconnected microgrids, with renewable energy sources and energy storage devices, employ agents so that each microgrid can choose to save or resell its stored energy in an open market in order to optimize its utility and revenues.

4.3. Energy communities

An agent-based approach to model zero energy communities is described in Mittal et al. (2019). This paper details a conceptual ABM for an urban neighborhood to predict the household level of adopting renewable energy behaviors in the presence of multiple options. Reis et al. (2019) model a community of residential prosumer agents that individually optimize the energy use to minimize energy costs and dissatisfaction. Each residential prosumer is modeled as an individual agent with specific energy needs and preferences.

Reis, Lopes, and Antunes (2018) present a modeling approach to simulate energy trading between two energy community members capable of exchanging information and energy between them.

A community of residential prosumer agents is modelled in Reis et al. (2019). Each residential prosumer is represented by an individual agent with specific energy needs and preferences. The residential agents exchange information with a coordinator agent that provides community resources or power purchased from the grid if needed. At the coordination level several optimization processes are performed to optimize the community resources and at each prosumer level to minimize agents' costs and dissatisfaction.

4.4. Energy storage

Energy storage is a promising technologic development for many contemporary issues in electricity markets and power systems operation. It could be configured in terms of Virtual Power Plants (VPP) and enable energy interaction between multiple PV prosumers under the form of direct sharing and buffered sharing (Liu et al. 2018). Meanwhile, as an intermediary between PV prosumers and the utility grid, VPP coordinates each prosumer's energy consumption behavior by setting internal prices and conducts power transactions with the utility grid. A payment scheme to compensate EVs customers that participate in a VPP is presented in Vasirani et al. (2013). VPPs are considered as coalitions of wind generators and EVs, where wind generators seek to use EVs as a storage devices to deal with the variations of wind generation. The simulation model provided in Praça et al. (2003) introduced VPPs in ABM. Another topic of interest is storage in the form of hydro reservoirs. This aspect is detailed and discussed in Sousa and Saraiva (2015, 2017) in the context of MIBEL. This model is used to define adequate generation/pumping schedules and to assess the impact of these operation strategies in the market prices, therefore, passing from a simple price taker approach to a more complex and realistic price maker model.

5. Conclusions

In recent years, power systems are moving to a more complex operation paradigm with an increasing number of players and more complex and participated processes. In this context, the use of ABM to model and simulate these new problems and agents is becoming increasingly attractive. However, such development is far from being mature due to the innovative character of applying such a paradigm to power systems problems.

This work presents and describes ABM characteristics supported with a literature review addressing how and when ABM should be applied. A survey on the most recent papers associated with ABM is provided, namely an in-depth overview on ABM applied to power systems, where the most cited papers, as well as the most noticeable research authors, are enumerated and presented. Finally, some relevant literature focusing on power system operating paradigms with ABM modeling approach is detailed in this work, specifically smart grids, electricity markets, energy communities, and energy storage systems.

In conclusion, the application of ABM to power systems is far from being mature, meaning that the exploitation of common strategies developed with these tools regarding this new paradigm is a topic to explore in a future research.

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An Agent Based Model to Simulate Local Electricity Markets, LEM, and their Interaction with the Wholesale Market, WSM

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***Abstract*—Local Electricity Markets (LEM) associated with Energy Communities and more specifically with Renewable Energy Communities, REC, are fostering new optimization models to enable the development of strategies regarding the increase of community energy savings and profits. In this scope, this paper presents an Agent-Based Model (ABM) as a decision tool to support energy transactions between the LEM and the Wholesale Market (WSM) on an hourly basis. The developed market environment was modelled as a Markov Decision Process (MDP). In this scope, an Agent Based Model using the Q-Learning mechanism was used to implement it and to simulate the local market model and its interaction with the WSM. The developed model was tested using an energy community that integrates a collective building with 15 apartments and PV generation. The paper describes and discusses the obtained market strategy and the profits that can be obtained by the Energy Community.**

***Index Terms*- Energy Communities, Local Energy Markets, Agent Based Models, Reinforcement Learning**

I. INTRODUCTION

In June 2018, the European Union (EU) agreed on a legal framework that introduces Citizens Energy Communities and Renewable Energy Communities [1, 2]. This framework aims at increasing the renewable-based decentralized generation and empowering consumers as important decision makers in the energy markets. It also allows smaller energy retailers to develop and offer innovative electricity supply packages, making room for new Energy Business Models to emerge. Reis et al. [3] made an overview over different perspectives of this new Energy Business Models. One of these standpoints is the Energy Community business models, where all the members should be considered in the overall arrangement design, implementation and operation. As advocated by the European Directives, Energy Community Business Models 'key activities' include local generation, supply, storage, consumption, trading, aggregation, e-mobility and energy related services, as well as system administration.

One example of this new energy business models is the Local Energy Markets (LEM). Mengelkamp [4] defines the LEM as a social community of residential prosumers and consumers that have access to a joint market platform for trading locally produced electricity among each other. The progressive migration of current centralized market models to this new electricity market design is contributing to the appearance of new agents that should not only interact locally, but also consider the integration with conventional markets. The difficulty of incorporating new actors and to manage the coordination between different stakeholders leads to a new operational paradigm that requires innovative or adaptive approaches to provide adequate decision support in view of the complexity of the problems to handle. In this scope, the use of Agent-Based Modelling (ABM) can help addressing this complexity. A literature review and a survey on the most recent papers associated with ABM are provided in [5].

Considering the appearance of new agents and energy business models, we developed a model that integrates LEMs and the central Wholesale Market (WSM) using an ABM as a decision tool. The developed model considers transactions between both markets, on an hourly-basis, and are done via a Market Community Agent which interacts with the WSM through an Aggregator Agent. In order to simulate the proposed LEM, a collective building which contains 15 apartments and PV generation was considered. Accordingly, and after this introduction, Section II presents a literature review on the topics addressed in this paper, Section III describes the developed ABM, Sections IV and V present the Case Study and the main results and finally Section VI draws the main conclusions.

The main contributions of this paper are:

- Development of an ABM model to simulate energy trading between LEM and WSM;
- Getting insights on the economic viability of this business model.

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II. Literature Review

A. Local Energy Markets

The definition of LEMs consider not only residential and commercial consumers/prosumers but also renewable energy producers that can participate in the trading of the local electricity over LEMs. As stated in [6], LEM provides a market platform to a community and empowers it to strengthen the local economy by reducing electricity costs and keeping profits within the community. LEMs can be seen as trading platforms where electricity is sold and bought [7] within the scope of market matching and pricing mechanisms. [8] refers that LEMs empower electricity end users and small-scale producers by allowing them to directly participate in an electricity market. In this sense, the concept of LEM is well suited to address the Energy Communities main purposes, since it is a mechanism that can induce investments in renewable energy sources, can improve the integration of RES into the energy system, and can contribute to empower local communities and end consumers. It also promotes the participation of local agents as well as the awareness of local consumers to the energy problems.

B. Wholesale Market

The common design of electricity markets involves four different types of frameworks: day-ahead and intra-day markets (by sessions or continuous), bilateral trading markets and balancing markets.

Typically, the day-ahead energy market is organized in terms of a double-sided Uniform Price Auction, where demand agents submit bids to buy energy and supply agents submit bids to sell it. For a particular operation day d, the Day-Ahead Market clears typically at 12 noon of day (d-1). The pricing mechanism is based on the marginal pricing theory, where the prices equal the short-run marginal cost [9]. Under system marginal pricing, generators submit bids to the market (typically involving a price and an energy quantity for every hour of the day of operation). The Market Operator collects the selling bids and sorts them in an ascending order of the price, leading to a supply curve. Buyers submit load purchase offers for every hour, which are also collected by the Market Operator. These bids are ranked by the decreasing order of their prices, building the aggregated demand curve. The intersection of the supply curve with the demand curve defines the market-clearing price for the hour under analysis.

The intraday markets are similar to the Day-Ahead Markets and the main difference is the gate closure. They follow the day-ahead session being usually activated at the end of day d-1 and continuing along day d, the delivery day. In practice, they work as adjustment markets, i.e., closer to the delivery time market agents can adjust their buying or selling positions regarding what was originally cleared in the day-ahead market.

A bilateral market is a platform in which private parties, sellers and buyers, negotiate bilateral agreements for the exchange of electricity under acceptable terms. Each contract has its own price that depends only on the arrangements between the interested parties.

Balancing markets aim at correcting the imbalances associated to the physical trade of energy, in order to maintain the equality between generation and demand, so that power frequency control is ensured. Balancing markets are operated by Transmission System Operators (TSOs), who should be non-commercial organizations and neutral regarding market agents. They use different types of balancing products such as, primary reserve, secondary reserve or automatic frequency restoration reserve, and tertiary reserve or manual frequency restoration reserve to ensure maintaining the system frequency around the specified nominal value [10].

C. Agent Based Models

As systems are becoming more complex, new tools, simulation, and modeling approaches are needed. An alternative to typical simulation techniques (such as traditional optimization techniques, discrete-event simulation, and differential equation-based models) are Agent Based Models (ABM). An ABM is a computational model integrating individual and autonomous agents and their collective behavior. An autonomous agent acts on its own without external direction in response to situations the agent encounters during the simulation [11]. More details and additional definitions on ABM models are provided in [12], [13] and [14].

ABM concepts and models have been applied in different scientific areas, including marketing, treatment of diseases, biology, economics, urban planning, social sciences, pandemics, among others. With the transition from vertically integrated utilities to competitive electricity markets, power systems' complexity is increasing, namely because new rules and players are emerging and being implemented. Distributed generation (namely using renewable primary resources), Electric Vehicles, Demand Flexibility and Demand Response processes, energy efficiency measures, and the development of microgrids and smart grids, among many others, contribute to the increasing management and operation complexity, the transmission and distribution networks and the interactions between traditional and new players. The uncertainties associated with the renewable-based generation, electricity market prices, energy consumption, or EV behavior are just a few examples of the increased sources of uncertainties and thus of the complexity brought to the power sector and to the energy system as a whole. In the last years, research has been devoted to deal with this complexity and to address the challenges brought by this new paradigm. In this scope, Santos and Saraiva [5] provided a literature survey on the most recent publications associate with ABM focusing on the power systems area.

The application of ABM models to power systems and specifically to electricity markets assumes an increased relevance since bottom-up approaches become crucial to understand and model the ongoing energy transition. As previously mentioned, ABM can model complex aspects in the electricity markets as they can represent the complex behavior of different system participants. Some energy management tools using ABM for energy markets are presented in [5, 12].

D. Q Learning

The electricity markets complexity contributes to create dynamic and adaptive systems. In this circumstance, learning and constructing the model of an economic system is a very complex task for market participants, and a model free learning approach can be an appropriate alternative to build a desired bidding strategy. Q learning is a reinforcement learning methodology [15] in which agents can learn a task by interacting with the environment through a trial-and-error search. The Q learning algorithm was initially proposed in [16], and it can be classified as a free model because it doesn't need an explicit knowledge about its environment. Instead, the knowledge about the optimal strategy increases while the historic interaction with the environment is being built by trial and error [16]. Q learning is a useful algorithm to solve Markov decision problems, and this is done by evaluating the payoff for a given state-action pair. When using an ABM, the agent firstly observes the current environment state and then selects an action. Then, the agent receives an immediate reward from the environment, and the environment moves to the next state based on the transition probability. This process is repeated until termination.

The implementation of the Q-learning algorithm typically involves building the Q learning matrix that is composed by cells known as Q values. These Q-values are calculated for each pair of state (s) and action (a), and therefore they can also be described as Q(s, a). As the Q learning focuses on the impacts of rewards (R) on the choices of actions in each state, the Q values are obtained by a function that provides the expected utility of taking a given action in each state. The Q(s, a) function is typically given by (1).

$$Q(s_m, a_n)^{new} = (1 - \lambda) \cdot Q(s_m, a_n) + \lambda \cdot [R(s_m, a_n) + \gamma \cdot maxQ(s_{m+1}, a_n)]. \quad (1)$$

In this expression, λ in (0,1) denotes the learning rate and it reflects the degree to which estimated Q-values are updated by new data and can be different in each episode. If λ equals 0 then the agent does not learn, while if it equals to 1 it induces the agent to consider only the most recent information. ϒ is a discount factor in (0,1) that represents the weight given to future reinforcements. A value of ϒ equal to 0 makes the agent myopic by only considering current rewards, while values closer to 1 turn distant rewards more important [17]. The expression $maxQ(s_{m+1}, a_n)$ represents the best the agent thinks it can do in state s_{m+1}. In an initial phase, the agents will randomly explore state to state until they learn and reach the end of the simulation period. Then, using these Q-values, the agents start their biddings considering the learned experience. Typically, the learning process converges when the Q-values do not change more than a pre-determinate tolerance value regarding the values in the Q-matrix that was built in the previous iteration.

One of the main challenges in Reinforcement Learning is related with the trade-off between exploration and exploitation, which is represented by the greedy policy ε. It means that the agent selects the action that has the maximum Q value with high probability (1− ε) and an arbitrary action from all admissible actions with small probability ε, regardless of the Q values.

III. Developed Agent-Based Model

As mentioned before, this work describes the developed ABM model to simulate the energy trading between LEM and WSM. Section A addresses the overall approach and then Section B described the implementation of the Q-learning.

A. Methodology

The developed structure considers an Energy Community constituted by different types of agents, such as consumers and prosumers. Each of these agents submit their bids to a Market Community Agent which is in charge of maximizing the Energy Community self-energy consumption and the profit in consequence of selling the energy surplus. The energy deficit or surplus in each trading period will be traded between the Market Community Agent and an Aggregator, which operates as a traditional retailer regarding the market clearing mechanism of the WSM. The Aggregator will gather the information about the energy deficit or excess from the Market Community Agent and communicates the buying or selling bids to the WSM as a way to balance supply and demand in the community.

Regarding the coordination mechanism to integrate the Energy Community LEM into the existing WSM, the initial trading is done locally followed by the trading in the WSM. The Aggregator receives the quantities to buy and sell in the WSM and sent back to the Market Community Agent the cleared hourly prices. The obtained values will be considered in the optimization model of the community in an hourly basis. In order to encourage the participation of local agents in the local trading at the LEM, the electricity price of LEM is determined by the energy sold by prosumer agents, the energy bought by all the community members, and the electricity produced by PV panels in the community. It is also defined that PV generation has a Feed in Tariff (FIT) that is set at a lower level than the Aggregator tariff ($C^F < C^{agg}$) to guarantee that LEM favours local transactions rather than buying energy from the grid. In this work, the Aggregator tariff is composed only by the WSM price, that is grid components are not considered.

The above indications mean that when there is energy deficit at the community, the community buys electricity from the grid at the WSM price. When there is surplus of electricity in the community and after considering self-consumption, the LEM has a minimum ensured price that corresponds to the FIT associated to the PV technology. However, in order to increase the revenues from selling this excess, the ABM tries to increase the selling price as close as possible to the WSM price. If the LEM price gets higher than the WSM, that would mean that the selling bid of this excess would not be accepted at the WSM and therefore this amount is sold at the minimum ensured price, that is, at the FIT value.

B. Q-Learning procedure

As mentioned in Section II we introduced in the model the Q-learning procedure, which is a useful algorithm to solve Markov decision based problems. Q-learning, evaluates the payoff that can be obtained for a given state-action pair Q(s,a). The state's definition is in line with the energy communities' perspective, i.e., to enhance the self-supply capacity and to minimize the dependency of the grid. In this application, we considered the following 5 possible states:

- State 1 - the agent has obtained more profit compared to the previous episode, and all its energy that could be dispatched in all the 24 trading hours was cleared in the local market.

- State 2 - the agent has obtained more profit compared to the previous episode, but not all its energy that could be dispatched in all the 24 trading hours was cleared in the local market.
- State 3 - the agent has not obtained any profit or loss, compared with the results of the previous episode.
- State 4 - the agent has gained less profit compared to the previous episode, but not all its energy that could be dispatched in all the 24 trading hours was cleared in the local market.
- State 5 - the agent gained less profit compared to the previous episode, and all its energy that could be dispatched in all the 24 trading hours was cleared in the market.

This structure was based on the state's definition adopted in [18], which on the other hand corresponds to an adaptation from [19]. This strategy is in line with the derivative-following strategy presented in [20]. A derivative follower does incremental increases (or decreases) in price, continuing to move its price in the same direction until the observed profitability level falls. At this point, the direction of the movement is reversed. As illustrated in Figure 1, action a1 corresponds to a maximum bid down, a4 means that neither a bid up nor a bid down is adopted and a7 represents a maximum bid up action.

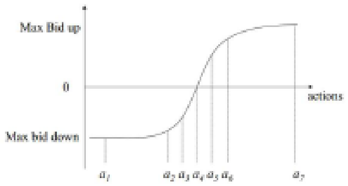

Figure 1. Actions (a1 to a7) used in the Q-Learning procedure.

Actions a2, a3, a5 and a6 represent intermediate values. The reward function corresponds to the profit that each agent obtains in the market if an action a is adopted or selected for a given state s.

In the developed model the utility function corresponds to the increase or decrease in revenues obtained by each action in the day-ahead market. In case of surplus of energy, the revenues will be given by the difference between WSM price and the LEM price. If WSM price is lower than the defined FIT, extra reward will not be paid since FIT is guaranteed. Otherwise, the reward will be higher as lower is the difference between WSM and LEM price (considering a minimum of the defined FIT). This reward will be consequence of the defined bidding strategy of the developed Q-learning methodology. In case of energy deficit, and because we assume that consumers have no elasticity for the price and demand, the bids in the LEM will be equal to the required energy at the market price.

IV. Case Study - Data

We consider a Case Study with a collective building with electricity demand (distributed in common services and 15 apartments) and PV generation. Sample power profiles for demand and PV systems were built using open datasets available at [21] and considering sampling periods of 15 minutes, starting on 1st January 2019 until the 1st January 2020. The Feed In Tariff C^F used in this simulation was set at 50.0 €/MWh. We assumed that the Energy Community is exempted from paying grid tariffs. Regarding the WSM prices we used the 2019 real prices published by the Iberian nominated electricity market operator – OMIE publicly available in [22].

In the proposed model, the LEM and the WSM markets are cleared individually, and their coordination is done as follows:

a) the local energy deficit is bought at the WSM price;

b) the local energy surplus will be firstly self-consumed and then the remaining energy will be traded in the WSM considering the price obtained after the optimization strategy process. If LEM prices are lower than the WSM prices, the community has a profit potential corresponding to the difference between both prices. Otherwise, if WSM prices are lower than the LEM prices, the surplus will be sold at FIT.

As mentioned in Section II, the definition of the Q-Learning procedure is based on a pair state-action Q(s, a). In this Case Study, we used the following 3 actions:

- a1 represents the Action 1 corresponding to a bid down of -1 €/MWh regarding the bid price of the previous iteration;
- a2 represents the Action 2 corresponding to no bid up nor bid down regarding the bid price of last iteration (0 €/MWh);
- a3 represents the Action 3 corresponding to a bid up of +1 €/MWh regarding the bid price of the last iteration.

The learning rate λ was set at 0.8, as well as the discount factor ϒ. The greedy policy parameter ε was set at 0.1, which means that the agent has 90% of probability of choosing the action with higher Q-value (greedy selection).

V. Case Study - Results

As mentioned, the developed ABM model was applied to real data of consumption, PV generation and WSM prices. Table I presents the results for the real WSM annual average price for 2019, and the values obtained without the bidding strategies (which is the FIT value) and considering the LEM strategies. Despite the annual average prices in the WSM are 71.1 €/MWh, these results show that if the LEM strategy is applied, the LEM average market price gets close to the real one. This improvement regarding the initial FIT value is explained because of the use of the ABM model incorporating the Q-Learning approach with bid up/bid-down strategy.

TABLE I – Global results for the annual average selling price

Scenario	**Annual average selling price €/MWh**
Real WSM price data	71.1
Selling price without LEM strategies (FIT)	50.0
Selling price with LEM strategies	65.1

Figure 2 shows the average weekly prices of the WSM and of the LEM after using the bidding strategy, as well as the FIT fixed tariff. As we can see, using the bidding strategy originates that the LEM tries to increase its prices in order to get closer to the WSM prices. However, between weeks 39 and 48, the LEM prices are equal to the FIT value because in this period the optimization process gets values for the LEM prices that are higher than the WSM price. As explained in Section III.A, in these situations, the reward is limited to the FIT value.

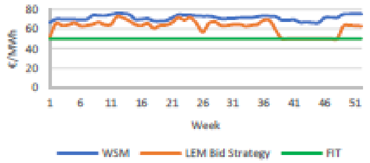

Figure 2. Average weekly results for the WSM and the LEM market prices.

Analyzing now the results with more detail, Figure 3 presents the results for the first month of the simulation. Considering the hourly prices, we can observe that the LEM bid prices have a continuous increase until the end of the month. This reflects the learning capability that the agents have since the start of the process.

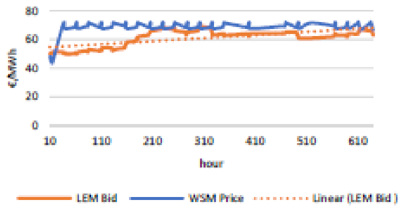

Figure 3. Hourly LEM and WSM prices for the first months

In what concerns the overall supply cost of the community, the use of the learning approach leads to a reduction of 18.7% when compared with the base case in which the energy is bought at the WSM price when there is deficit in the community and it is sold at the fixed FIT in the periods of excess.

VI. Conclusions

This paper presents the results that were obtained with an ABM model as a decision support tool to simulate the energy transactions between the LEM of a Renewable Energy Community and the WSM on an hourly basis. It considers real data for a collective building, with 15 apartments and common services, and PV generation. The simulation used real WSM prices for 2019. The results confirm that the agents have learning capabilities when using the Q-Learning strategy, so that the total supply cost was reduced by 18.7% since the revenues associated to the sold energy are increased.

However, there are some limitations in the proposed framework. Several combinations of the learning parameters should also be evaluated regarding the assessment of their impacts on the average LEM price. The test case used in this simulation assumed that all the energy in excess was sold in the market. Future developments should also consider the installation of storage devices in the community to supply demand when there is no PV generation.

Finally, in this case we assumed that the community members are exempted from paying grid tariffs. In future works, it should be assessed the impact of different levels of exemptions as a way of getting insights on the economic feasibility of the Energy Communities.

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[22] Iberian Market Operator,

Decentralized and Centralized Storage Architectures in Local Energy Markets (LEM) and their interaction with the Wholesale Market (WSM)

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***Abstract*—Energy storage systems, integrated in Renewable Energy Communities (REC), are enabling the development of operation strategies together with Photovoltaic (PV) systems. Additionally, Local Energy Markets (LEM) are emerging mechanisms to enable local energy trading in RECs, the integration of storage systems can increase the community energy savings and profits. In this context, a market environment was modelled as a Markov Decision Process (MDP). In this scope, an Agent Based Model (ABM) using the Q-Learning mechanism was used to implement and to simulate a LEM and its interaction with the Wholesale Market (WSM), also considering an architecture with storage systems. The developed model was tested considering real data regarding energy consumption and PV generation. The paper describes and discusses the obtained market strategy and the profits that can be obtained with this approach.**

Keywords*— *Energy Communities, Local Energy Markets, Storage Systems, Agent Based Models, Reinforcement Learning

I. Introduction

In June 2018, the European Union (EU) agreed on a legal framework that introduces Citizens Energy Communities and Renewable Energy Communities [1, 2]. This framework aims at increasing the renewable-based decentralized generation and empowering consumers as important decision makers in the energy markets. It also designed to allow smaller energy retailers to develop and offer innovative electricity supply packages, making room for new Energy Business Models to emerge. In this scope, [3] presents an overview of different perspectives of this new Energy Business Models. One of these standpoints is the Energy Community business models, where all the members should be considered in the overall arrangement design, implementation, and operation. As advocated by the European Directives, Energy Community Business Models 'key activities' include local generation, supply, storage, consumption, trading, aggregation, e-mobility and energy related services, as well as system administration.

To address some of these challenges, LEM emerges as a new energy business model where consumers have access to a joint market platform to trade locally produced electricity among each other [4]. The progressive migration of current centralized market models to this new electricity market design is contributing to the appearance of new agents that should not only interact locally, but also consider the integration with conventional centralized markets. The difficulty of incorporating new actors and of managing the coordination between different stakeholders leads to a new operational paradigm that requires innovative or adaptive approaches to provide adequate decision support in view of the complexity of the problems to handle. In this scope, the use of ABM can help addressing this complexity. A literature review and a survey on some papers associated with ABM are provided in [5].

Considering the appearance of new agents and energy business models, in [6] it was described a model that integrates LEMs and the central WSM using an ABM as a decision tool. The developed model considers market mechanisms to model the participation of community agents in the LEM and their relationship with the WSM. The proposed market design was implemented considering the day-ahead market on a one-hour basis. The proposed environment considers a LEM, in which participates prosumers with PV systems and consumer agents.

As established by the European Directives, Energy Community business models can include not only local generation trading and aggregation, but also storage. To understand how Energy Storage Systems (ESS) can add value to a LEM, we propose two different architectures regarding the integration of storage systems. The first one is decentralized architecture, where storage, constituted by batteries, is located at the building level, while the second one is centralized within the community. Specifically, the value of battery storage and associated architectures in combination with LEM are examined. To understand the value of local markets and battery flexibility, we compare the outcomes of the two proposed market designs against a reference case that does not incorporate storage systems.

Accordingly, and after this introduction, Section II presents a literature review on the topics addressed in this paper, Section III describes the developed ABM, Sections IV and V present the Case Study and the main results and finally Section VI draws the main conclusions.

The main contributions of this paper are as follows:

- Development of an ABM model to simulate energy trading between LEM and WSM, also considering storage systems;
- Analysis of the communities' self-consumption profile considering different storage system architectures;
- Assess and compare the economic impact of communities' scenarios, with and without storage architectures in LEM;

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II. Literature Review

The definition of LEMs consider not only residential and commercial consumers/prosumers but also renewable energy producers that can participate in the trading of the local electricity over LEMs. As stated in [7], LEM provides a market platform to a community and empowers it to strengthen the local economy by reducing electricity costs and keeping profits within the community. LEMs can be seen as trading platforms where electricity is sold and bought [8] within the scope of market matching and pricing mechanisms. Reference [9] indicates that LEMs empower electricity end users and small-scale producers by allowing them to directly participate in an electricity market. LEMs are fostered by the progress of Information and Communication Technologies enabling consumers and prosumers to trade without intermediaries and they contribute to lower the electricity price since supply fees and grid tariffs are excluded or strongly reduced. The model developed in [10] helps local energy suppliers to obtain optimal contracts and trade the surplus power with an aggregator in a hierarchical electricity trading system. A day-ahead local energy market model is developed in [11] where residential consumers having battery storage systems are the main participants. The results show that the proposed market can also contribute to provide grid services, while increasing the profits of the residential consumers.

Aligned with the growth of the use of distributed energy resources and renewable energy sources, Energy Storage Systems, ESS, namely batteries, have recently experienced a strong increase in interest. They are considered as a complementary set of technologies to distributed generation technologies and renewable energy resources, as they allow increasing the flexibility of power systems in terms of contributing to balance the demand and generation given the rapid increase of variable resources (as wind and PV generation) while contributing to ensure the security of supply and the quality of service [12]. The increase of prosumers has brought new challenges to the established supply-demand dynamics in electricity generation and increased the need for on-site flexibility. Consequently, one can anticipate that storage systems will play an important role on the development of Renewable Energy Communities, RECs, and of Local Electricity Markets, LEMs. A thorough analysis and research on ESS, namely the maturity of the different energy storage systems, capacity, charging and discharging duration and response time is available in [13] and a local electricity market model is developed in [14]. This publication considers that local market approaches can lead to more local use of the distributed resources, reducing or eliminating the need to curtailments and reducing feed-in payments.

The benefits of electricity storage in the presence of peer-to peer trade in local electricity markets with smart grid features is analysed in [15]. Two market designs for a community of prosumers incorporating battery storage systems are proposed. It was investigated the role of battery storage and how it is affected by market design rules. To this end, it was tested a community with prosumers and consumers connected through a local electricity distribution network. Two different local electricity market designs in different setups were proposed. A decentralised market design, in which prosumers and consumers within the community have individually owned batteries. And a centralised storage where only one large storage unit exists which is located centrally and owned by the community as a whole. The results demonstrate a very interesting trade-off between independence of the main grid and utilisation of the two features added – peer-to-peer trade and storage.

III. Modeling Local Electricity Markets considering Storage Systems

A. Market Design

The proposed structure considers an Energy Community constituted by different types of agents, such as consumers and prosumers. Each of these agents, submit their bids to a Market Community Agent which oversees maximizing the Energy Community self-energy consumption and the profit in consequence of selling the energy surplus. This agent is considered as an artifact since it will be utilized to carry out Energy Community Agents' activities in a competitive or cooperative manner. It will receive bids from the Energy Community Agents and perform a set of operations developed according to pre-defined rules in order to obtain a schedule for each trading period. The developed framework considers that the Community energy deficit or surplus in each trading period will be traded between the Market Community Agent and an Aggregator through a bilateral contract. On other hand, the Aggregator operates as a traditional retailer regarding the market clearing mechanism in the Wholesale Market. It will gather the information about the energy deficit or excess from the Market Community Agent and communicates the buying or selling bids to the Wholesale Market as a way to balance supply and demand in the community.

Figures 1a) and 1b) schematically show a community constituted by consumers and prosumers that are connected through a local electricity distribution network. Each prosumer has an energy generation technology in its installation, namely solar PV. The objective of the community is to minimise the electricity consumption cost by prioritising self-sufficiency and to sell any surplus to the WSM through the Market Community Agent. The architecture presented in Figure 1a) shows a community that has a battery storage system located at the building level. The power flow, between batteries and the community doesn't use the public grid because they are located into the building. This will be named as Decentralized Storage System. Figure 1b) illustrates a Centralized Storage architecture in which the storage system is located at a Low Voltage side of the MV/LV substation that feeds a set of buildings. The location of this battery is not inside the community itself, and in this sense, it is termed as a centralized one.

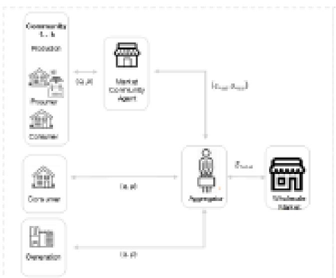

Fig. 1a. Energy Community Market Design using Decentralized ESS

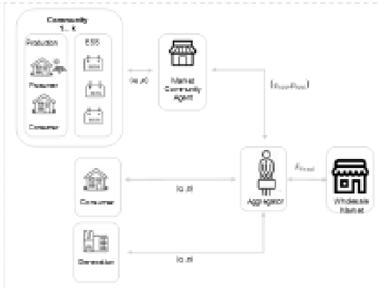

Fig. 1b. Energy Community Market Design using Centralized ESS

B. *Modelling local energy markets and storage systems using an ABM*

As mentioned before, this work will be the developed using an ABM model to simulate the energy trading between the LEM and the WSM. The electricity markets complexity contributes to create dynamic and adaptive systems. In this circumstance, learning and constructing the model of an economic system is a very complex task for market participants, and a model free learning approach can be an appropriate alternative to build a desired bidding strategy. In this way, the Q learning methodology will be used in this work. Q learning is a useful algorithm to solve Markov decision problems, and this is done by evaluating the payoff for a given state-action pair. When using an ABM, the agent firstly observes the current environment state and then selects an action. Then, the agent receives an immediate reward from the environment, and the environment moves to the next state based on the transition probability. This process is repeated until termination.

The implementation of the Q-learning algorithm typically involves building the Q learning matrix that is composed by cells known as Q values. These Q-values are calculated for each pair of state (s) and action (a), and therefore they can also be described as *Q(s, a)*. As the Q learning focuses on the impacts of rewards (R) on the choices of actions in each state, the Q values are obtained by a function that provides the expected utility of taking a given action in each state. This *Q(s, a)* function is typically given by (1).

$$Q(s_m, a_n)^{new} = (1-\lambda)\cdot Q(s_m, a_n) + \\ + \lambda \cdot [R(s_m, a_n) + \gamma \cdot maxQ(s_{m+1}, a_n)] \quad (1)$$

In this expression, λ in (0,1) denotes the learning rate and it reflects the degree to which estimated Q-values are updated by new data and can be different in each episode. If λ equals 0 then the agent does not learn, while if it equals to 1 it induces the agent to consider only the most recent information. ϒ is a discount factor in (0,1) that represents the weight given to future reinforcements. A value of ϒ equal to 0 makes the agent myopic by only considering current rewards, while values closer to 1 turn distant rewards more important [16].

In (1), the expression $maxQ(s_{m+1}, a_n)$ represents the best the agent thinks it can obtain in state s_{m+1}. In an initial phase, the agents will randomly explore state to state until they learn and reach the end of the simulation period. Then, using these Q-values, the agents start their biddings considering the learned experience. Typically, the learning process converges when the Q-values do not change more than a pre-determinate tolerance value regarding the values in the Q-matrix that was built in the previous iteration.

C. *Model of the REC with storage systems*

Regarding the coordination mechanism to integrate the Energy Community LEM into the existing WSM, namely the market mechanisms to model the participation of community agents in the LEM and then its relationship with the WSM, the implemented market design considers the day-ahead market on a one-hour basis. The initial trading is done locally followed by the trading in the WSM of the community energy excess or deficit in each trading period.

The Aggregator receives the quantities to buy and sell in the WSM and sent back to the Market Community Agent the cleared hourly prices. The Market Community Agent receives the quantities and the bids from the community, considering the existing ESS, which performs its strategy based on energy deficit or surplus and taking into account the technical characteristics of the batteries. The batteries will be in the charging mode if there are any surplus of PV power regarding the local demand and in discharging mode if the community demand is higher than local generation. However, and if the stored energy is sufficient to feed the demand, and it also has some surplus, those additional quantities will be considered in the selling bids optimization strategy of the Market Community Agent. So, the social welfare of the community members will increase by reducing the cost of buying electricity from the grid and by increasing the self-consumption level of the community.

Equation (2) presents the overall storage level for the ESS device over time. It is modelled by a simplified linear expression [17] and it assumes that the charging and discharging power rates remain constant during a time slot.

$$W^i_{B,t} = W^i_{B,t-1}\left(1-\sigma^i_{SD,t}\right) + \left(P^i_{BC,t}\eta^i_{BC,t} - \frac{P^i_{BD,t}}{\eta^i_{BD,t}}\right)\Delta t \quad (2)$$

In this expression:

- $W^i_{B,t}$ is the stored energy at time slot *t;*
- $W^i_{B,t-1}$ is the stored energy at time slot *t-1;*
- $\sigma^i_{SD,t}$ is the self-discharge rate (number from 0,0 to 1,0);
- $P^i_{BC,t}$ is the battery charge power;
- $P^i_{BD,t}$ is the battery discharge power;
- $\eta^i_{BC,t}$ is the battery charging efficiency (number from 0,0 to 1,0);
- $\eta^i_{BD,t}$ is the battery discharging efficiency (number from 0,0 to 1,0).

Batteries' charging and discharging rates are limited by α and β respectively originating constraints (3) and (4).

$$0 \le P^i_{BC,t} \le \alpha \quad (3)$$

$$0 \le P^i_{BD,t} \le \beta \quad (4)$$

The State of Charge of the battery (SOC) is given by (5) in which $W^i_{B,N}$ is the nominal capacity of the battery (i.e. the battery size).

$$(SOC)\ v^i_t = \frac{W^i_{B,t}}{W^i_{B,N}} * 100\% \quad (5)$$

As presented in Figures 1a) and 1b), our community is constituted by prosumers, consumers, and ESS (installed in a decentralized or centralized way). To ensure the balance of the electric system, constraint (6) must hold for every time slot. Any power deviation can always be balanced by exchanging power with the grid. In each time slot t the batteries of the ESS can be in the charging mode, in the discharging mode or idle.

$$P_{L,t}^{i} + P_{PV,t}^{i} + P_{C,t}^{i} + P_{Grid,t}^{i} + P_{BC,t}^{i} + P_{BD,t}^{i} = 0 \quad (6)$$

In expression (6):

- $P_{L,t}^{i}$ is the load of the ith prosumer at time slot t;
- $P_{PV,t}^{i}$ is the PV generation of the ith prosumer at time slot t;
- $P_{C,t}^{i}$ is the Consumer Demand at time slot t;
- $P_{Grid,t}^{i}$ is the power exchanged with the grid at time slot t;
- $P_{BC,t}^{i}$ is the battery charge power;
- $P_{BD,t}^{i}$ is the battery discharge power;

Equation (7) represents the net load of the community (prosumer i and consumer i) at time slot t.

$$NP_t^i = (P_{L,t}^i + P_{C,t}^i) - P_{PV,t}^i \quad (7)$$

Batteries are in the charging mode when $\sum_{i=1}^{N} NP_t^i < 0$, and the surplus PV power is used to charge the battery systems, unless the SOC reaches its maximum value. The charging power of a centralized system is calculated by (8).

$$P_{BC,t}^i = \begin{cases} \frac{-\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BC,max}^i} \cdot P_{BC,max}^i & \frac{-\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BC,max}^i} < 1 \ \& \ SOC_t^i < SOC_{max}^i \\ P_{BC,max}^i & \frac{-\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BC,max}^i} \geq 1 \ \& \ SOC_t^i < SOC_{max}^i \\ 0 & SOC_t^i = SOC_{max}^i \end{cases} \quad (8)$$

Batteries will be in discharging mode, when $\sum_{i=1}^{N} NP_t^i \geq 0$. In this case, the residual demand of the community is met by discharging the battery system, unless the SOC reaches its minimum. The discharging power is calculated by (9).

$$P_{BD,t}^i = \begin{cases} \frac{\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BD,max}^i} \cdot P_{BD,max}^i & \frac{\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BD,max}^i} < 1 \ \& \ SOC_t^i > SOC_{min}^i \\ P_{BD,max}^i & \frac{\sum_{i=1}^{N} NP_t^i}{\sum_{i=1}^{NB} P_{BD,max}^i} \geq 1 \ \& \ SOC_t^i > SOC_{min}^i \\ 0 & SOC_t^i = SOC_{min}^i \end{cases} \quad (9)$$

D. Implementation of the Q-Learning approach

Having the quantities to buy or to sell between the LEM and the WSM, the reinforcement learning starts regarding the strategy to be performed. The state's definition is in line with the energy communities' perspective, i.e., to enhance the self-supply capacity and to minimize the dependency of the grid. In this application, we considered the following 5 possible states:

- State 1 - the agent has increased its profit compared to the previous episode, and all its energy that could be dispatched in all the 24 trading hours was cleared in the local market.
- State 2 - the agent has increased its profit compared to the previous episode, but not all its energy that could be dispatched in all the 24 trading hours was cleared in the local market.
- State 3 - the agent hasn't obtained any profit or loss, compared with the results of the previous episode.
- State 4 - the agent has reduced its profit compared to the previous episode, but not all its energy that could be dispatched in all the 24 trading hours was cleared in the local market.
- State 5 - the agent reduced its profit compared to the previous episode, and all its energy that could be dispatched in all the 24 trading hours was cleared in the market.

This structure was based on the state's definition adopted in [18], which on the other hand corresponds to an adaptation the one used in [19]. This strategy is in line with the derivative-following strategy presented in [20]. A derivative follower does incremental increases (or decreases) in price, continuing to move its price in the same direction until the observed profitability level falls. At this point, the direction of the movement is reversed. As illustrated in Figure 2, action a1 corresponds to a maximum bid down (in which the bid price is decreased as much as possible), a4 means that neither a bid up nor a bid down is adopted and a7 represents a maximum bid up action (in which the bid price is increased as much as possible).

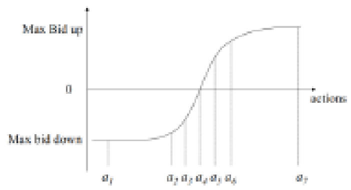

Fig. 2. Actions used in the Q-Learning procedure

Actions a2, a3, a5 and a6 represent intermediate possible values of the bid prices. The reward function corresponds to the profit that each agent obtains in the market if an action a is adopted or selected for a given state s.

In the developed model the utility function corresponds to the increase or decrease of revenues obtained by each action in the day-ahead market. The LEM framework considers that the Market Community Agent has access to a bilateral contract with a Feed-in-Tariff (FIT), in case of surplus of energy. In this case, the revenues will be given by the difference between WSM price and the LEM price. If WSM price is lower than the defined FIT, extra reward will not be paid since FIT is guaranteed. Otherwise, the reward will be higher as lower is the difference between WSM and LEM price (considering a minimum of the defined FIT). This reward will be consequence of the defined bidding strategy of the developed Q-learning methodology. In case of energy deficit, and because we assume that consumers have no elasticity for the price and demand, the bids in the LEM will be equal to the required energy at the market price.

IV. CASE STUDY - DATA

As a reference case, designated as Ref-Case, we considered a Portuguese collective building with electricity demand distributed by the common services and by 15 flats. All the apartments are organized as an energy community considering a collective self-consumption scheme. It has a renewable generation unit constituted by PV systems with overall 45 kWp and 73.2 MWh of annual generation. The sample power profiles for the demand and the PV systems were built using open datasets available at [21] and with sampling periods of 15 minutes, starting on 1st January 2019 until the 1st January 2020. For a global energy demand of 145,4 MWh, 66% (95,6 MWh) is provided by the electrical supplier which means that the remaining 34% (49,8 MWh) is produced by PV system and self-consumed. In this reference situation, the surplus energy generated by the PV regarding the demand is paid at a Feed-in Tariff, FIT, set at 50.0 €/MWh and the energy supplied by the public network is paid at the market price. Regarding the market prices, we used real data obtained for 2019 from the Iberian Electricity Market [22], that exists in common between Portugal and Spain since 2007.

Then, based on the previous Ref-Case in which no storage equipment exists, we simulated the operation of the LEM using the Q-Learning approach. This second situation is designated as Case-PV. Regarding the introduction of storage, we built two more case studies. The decentralized storage architecture, established at the building level, has three interconnected modules of 15 kWh each of Li-ion batteries, given that this is one of the most widely used battery technologies [23]. On the other hand, the centralized structure has a 300 kWh of storage, located at the nearest MV/LV substation. In this case, the dataset is replicated to a combination of 3 collective buildings, with the same sample profile demand and PV production of the reference case. This means it has a demand three times the one of the reference case, and three times its PV generation with the same profiles. These two cases using storage equipment are designated as Case-ST45 and Case-ST300. In addition, we assumed that the Energy Community is exempted from paying grid tariffs.

V. CASE STUDY – RESULTS

As mentioned, the developed ABM model was applied to real data of consumption, PV generation and 2019 WSM prices of the Iberian Electricity Market. The demand data considers 16 consumers for each collective building (15 apartments and common services), the generation of the PV systems, and storage (decentralized with 45 kWh and centralized with 300 kWh capacities).

Table I presents the global energy demand, the demand supplied by the public grid, the demand supplied by the self-consumption and the electricity injected back to the grid for the three analysed cases using the Q-Learning approach, that is for the Case-PV, the Case-ST45 and for Case-ST300.

The results show that when compared with the PV case the ST45 case has a lower amount of energy injected back into the grid. This is line with the fact that the demand supplied by the public grid decreases and the demand supplied by self-consumption increases in case ST45. These results show that the operation strategy is successful in terms of maximizing the energy community self-energy consumption. Case ST300 is also designed to prioritize self-consumption in such a way that the demand supplied by self-consumption is higher than the one supplied by the public grid.

Figure 3 presents the distribution of the energy demand for these 3 cases. It is possible to observe that in cases ST45 and ST300 there is an increase of the demand that is fed by self-consumption. This distribution is a consequence of the maximization of the self-consumed energy by the optimization of the use of the energy storage (through the adequate selection of its charging and discharging periods).

TABLE I. ANNUAL ENERGY COMMUNITY BALANCE

Energy (MWh)	Case Studies		
	Case-PV	*Case-ST45*	*Case-ST300*
Global energy demand	145.4	145.4	436.2
Demand supplied by public grid	95.6	78.6	212.1
Demand supplied by self-consumption	49.8	66.8	224.1
Electricity injected back into the grid	23.4	13.9	4.9

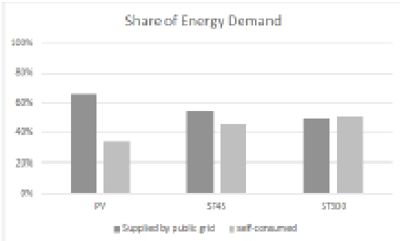

Fig. 3. Share of Community Energy Demand

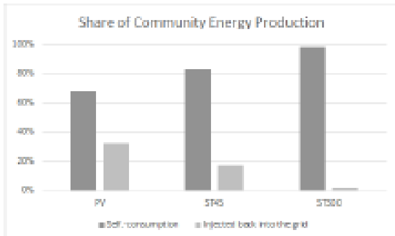

Fig. 4. Share of Community Energy Production

However, and if the stored energy is sufficient to feed the demand, and there is still some surplus, these additional quantities will be injected back into the grid and will be used in the selling bids strategy of the Market Community Agent. In Figure 4 we can observe the increase of the rate of self-consumption in cases ST45 and ST300, when compared with the Case-PV in which there is no storage systems. Notwithstanding, the energy surplus injected back into the grid decreases when going from ST45 to ST300. When comparing ST45 with ST300, the share of energy injected into the grid decreases almost to zero in ST300. This is related with the capacity of the storage system in this case which has more than 6 times the one that was used in case ST45. This allows storing a larger volume of energy coming from the PV panels in the periods in which the demand is more reduced than the PV generation. These excesses can now be stored in ST300 rather than being injected back in the grid as it occurred more frequently in ST45.

Table II presents the results for the real WSM annual average price for 2019, the values obtained without using the bidding strategy, that is the FIT value, and the values using the LEM strategies (Case-PV, Case-ST45 and Case-ST300). Despite the annual average price in the WSM is 71.1 €/MWh, these results show that if the LEM strategy is applied, the LEM average market price gets closer to the WSM price. This improvement regarding the initial FIT value is explained because of the use of the ABM model incorporating the Q-Learning approach with bid up/bid-down strategy.

TABLE II. RESULTS FOR THE ANNUAL AVERAGE SELLING PRICE

Scenario	Annual average selling bid price €/MWh
Real WSM price	71.1
Selling price without LEM strategies (FIT)	50.0
Selling price with LEM PV strategies	62.0
Selling price with LEM ST45 strategies	59.2
Selling price with LEM ST300 strategies	59.4

Figure 5 shows the average weekly prices of the WSM and of the LEM after using the bidding strategy, as well as the FIT fixed tariff. As we can see, using the bidding strategy, independently of the simulated case, originates that the LEM tries to increase its prices in order to get closer to the WSM prices. This reflects the learning capability that the agents have since the start of the process.

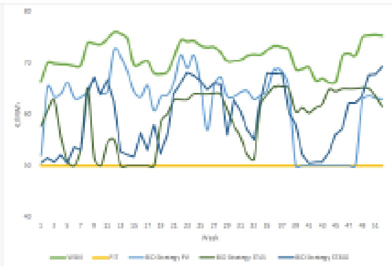

Fig. 5. Average weekly prices for the WSM and the LEM markets

In what concerns to the overall supply cost of the community, the use of the learning approach leads to reductions of 25%, 28% and 22%, respectively in the Case-PV, in the Case-ST45 and in Case-ST300 compared with the results in the Case-Ref. Recall that in the Case-Ref there is PV generation, there is no storage equipment and the excess of generated PV electricity regarding the demand is paid at the FIT price and the deficit of electricity (when the demand is larger than the PV generation) is paid at the WSM price. The reduction of the above percentage when going from ST45 to ST300 is explained because the adopted operation strategy gives priority to the increase of self-consumption. As explained before, the self-consumption level is maximum in ST300 and conversely the amount of energy surplus to trade in the market is much smaller. This ultimately means that the revenue obtained from selling energy in the market is smaller which explains that the cost reduction is also smaller.

VI. Conclusions

This paper presents the results that were obtained with an ABM model as a decision support tool to simulate the energy transactions between the LEM of a Renewable Energy Community and the WSM on an hourly basis. It is simulated an energy community with PV generation and storage systems. The results confirm that the agents have learning capabilities when using the Q-Learning strategy, namely to follow the strategy adopted regarding self-consumption and storage interaction, and the reduction of the total supply cost since the revenues coming from selling energy increase. In what concerns future deployments, it will be developed an economic assessment to evaluate the feasibility of investing in storage systems. The impact of different levels of exemptions of grid tariffs, should also be assessed as a way of getting insights on the economics of Energy Communities.

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Simulation of the Operation of Renewable Energy Communities Considering Storage Units and Different Levels of Access Tariffs Exemptions

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***Abstract*— Power systems are evolving very rapidly namely in what concerns the technologies used to generate electricity, the diversification of commercial relationships involving different agents and more specifically the empowerment of consumers. In this scope, several countries passed new legislation to induce the installation of Renewable Energy Communities, RECs, to induce new investments at a local level, to empower end consumers and to increase their self-sufficiency. However, the way Local Energy Markets, LEMs, will be integrated into Wholesale Markets, WSM, is not yet fully established. To this end, this paper proposes a design and an optimization model to increase the mentioned self-sufficiency level, to better manage the energy produced locally, also admitting the installation of battery storage units, and to profit as much as possible of them. LEM interaction with WSM, is based on an Agent Based Model architecture equipped with a Q-learning strategy. An economic assessment is also included, in order to get insights if some level of exemption, for instance associated with some components of the Access Tariffs, have to be considered in order to induce the massification of RECs.**

***Keywords*— Agent Based Models, Local Energy Markets, Reinforcement Learning, Renewable Energy Communities, Storage Systems.**

I. Introduction

In May 2019, European Union (EU) institutions concluded the final legislative files for the Clean Energy for All Europeans Legislative Package (CEP) [1]. This is a legal framework that defines the European climate and energy policies and sets the EU ambitions on this topic for the 2030 horizon. The CEP for Europe introduces three new concepts that are designed to help consumers and the public to participate in the development of a new energy paradigm - Collective Self-Consumption (CSC), the RECs and the Energy Communities (EC) of Citizens. The objective of the package is to ensure that the transition to a decarbonized and decentralized energy system is carried out in an unbiased manner. This new energy paradigm, called by some authors as the democratization of energy, aims to provide a more decentralized and open energy market. This new approach also paves the way for the establishment of new electricity markets, namely Local Energy Markets. In this way, LEMs associated with ECs and more specifically with RECs, are fostering new optimization models to enable the development of strategies regarding the increase of communities' energy savings and profits. The evolution of this approach, regarding new electricity markets designs, has resulted in the emergence of new agents that should not only interact locally, but also consider the integration with the conventional centralized markets. Due to the complexity of this new structure, the need for effective decision support has become more prevalent. Therefore, it is important that the various involved stakeholders can adopt new strategies and adaptive approaches to provide adequate decision support in view of the complexity of the problems to handle. In this scope, the use of Agent-Based Modelling (ABM) can help addressing this complexity. A literature review and a survey on the most recent papers associated with ABM are provided in [2].

The model developed in this work considers a framework that allows community agents (consumers and prosumers with PV systems) to participate in the LEM and interact with the WSM by a Market Community Agent. The rapid emergence and evolution of prosumers also has created new challenges to the established supply-demand dynamics in the electricity generation, which include the need for more flexible and on-site generation. Because of this, storage systems are expected to play a significant role in the development of RECs and LEMs. In this sense, and to improve RECs self-sufficiency and to better manage the energy produced locally, the developed model also considers storage systems as participants in the trading between LEM and WSM.

Besides the implemented legal framework and the incentives for the deployment of RECs, the economic viability of the investments (namely in storage systems) and operation of RECs, specifically considering different tariff and charge exemption designs, should be studied in order to get conclusions on the breakeven of the investments.

Accordingly, and after this introduction, Section II presents a literature review on the topics addressed in this paper, Section III describes the developed ABM, Section IV present the Case Study and the main results and finally Section V draws the main conclusions.

The main contributions of this paper are as follows:

- Development of an ABM model to simulate energy trading between LEM and WSM, considering storage systems;

- Getting insights related with the payment of grid tariffs and in particular with the component applied to self-consumption namely by comparing different levels of exemptions;

II. Literature Review

A. Local Energy Markets

The LEM concept is ideal for the development of energy communities as it allows end users and producers to participate in the electricity trading system. It can also help improving the integration of renewable energy into the energy system. The objective of these markets is to provide a platform for the local economy and reduce electricity costs since supply fees and grid tariffs are excluded or strongly reduced [3].

In this context, the model developed in [4] helps local energy suppliers to obtain optimal contracts and trade the surplus power with an aggregator in a hierarchical electricity trading system. Considering the appearance of these new agents and energy business models, in [5] it is developed a model that integrates LEMs and the WSM using an ABM as a decision tool. The developed model considers transactions between both markets, on an hourly-basis, and are done via a Market Community Agent which interacts with the WSM through an Aggregator Agent. A day-ahead local energy market model is developed in [6] where residential consumers having battery storage systems are the main participants. The results show that the proposed market can also contribute to provide grid services, while increasing the revenues of the residential consumers. In [7], the advantages of electricity storage are analyzed in the presence of smart grid features in the electricity markets. Two market designs for prosumers with integrated battery storage systems were presented. This research investigated the effects of market design rules on the operation of the community and the role of storage systems. A comprehensive analysis of the various aspects of Energy Storage Systems (ESS) is also available in [8] also providing a framework for developing a LEM. According to [9], the emergence and evolution of local market models can help improving the efficiency of the electricity system and reducing the need for feed-in payments and curtailments.

B. Agent Based Models

The concept of an ABM allows agents to take their decisions based on their past experiences with other agents and through the interaction with the environment. The agents usually have local and imperfect information which, combined with their past experiences, help them improving their decisions by modifying their strategies. This type of model allows the market participants to develop their own strategies and preferences as adaptive agents. They can then learn from their past experiences to improve their performance. This learning and adaptation process can be performed either within one single agent or based on the cooperation between two or more agents. In a competitive market environment, agents naturally learn isolated and use the learned knowledge for their own advantage. This modelling process corresponds to an explicit learning procedure. As previously mentioned, ABM can model complex aspects in power systems and in the electricity markets, as they can represent and implicitly model the complex behavior of different system participants. The uncertainties associated with the renewable-based generation, the electricity market prices, the energy consumption, or smart grids behaviours, are just a few examples of the increased sources of uncertainties and thus of the complexity brought to the power sector and to the energy systems. Some energy management tools using ABM applied and used for energy markets are detailed in [5, 10-14].

C. Q-Learning

The complexity of the electricity markets makes it very challenging for market participants to develop a model based on a traditional economic framework. Therefore, a free learning approach can be an appropriate alternative to build a desired bidding strategy. Reinforcement Learning (RL) is a machine learning approach that requires agents to interact with their environment to learn the best path to take based on the given scenario. Unlike other methods, this approach does not provide agents with advice. Instead, it allows them to explore the environment in order to maximize their potential rewards [15].

Q-learning (QL) is one of the most well-known RL algorithms. It was originally proposed in [16] and it is fully detailed in [15]. It is a useful algorithm to solve Markov decision problems (MDP). A MDP can be defined as a framework under which an agent observes the environment characterized by a state s, selects an action among the ones available at that state and then the process responds at the next time step by moving the system to a new state and by allocating the agent with the corresponding reward. This leads to the QL matrix that is composed by cells known as Q-values. Thus, Q-values are calculated for each pair of state *(s)* and action *(a)*, and therefore they can also be described as *q(s,a)*. As the QL focuses on the impacts of rewards *(r)* and on the choices of actions in each state, the Q-values are obtained by a function that provides the utility of taking a given action in a given state. This *Q(s, a)* function is typically given by (1).

$$Q(s_m, a_n)^{new} = (1-\lambda)\cdot Q(s_m, a_n) + \\ + \lambda \cdot [R(s_m, a_n) + \gamma \cdot maxQ(s_{m+1}, a_n)] \quad (1)$$

In this expression, λ in (0,1) denotes the learning rate and it reflects the degree to which estimated Q-values are updated by new data and can be different in each episode. If λ equals 0 then the agent does not learn, while if it is equal to 1 it induces the agent to consider only the most recent information. ϒ is a discount factor in (0,1) that represents the weight given to future reinforcements. A value of ϒ equal to 0 makes the agent myopic by only considering current rewards, while values closer to 1 turn distant rewards more important [17].

In (1), the expression $maxQ(s_{m+1}, a_n)$ represents the best the agent thinks it can obtain in state s_{m+1}. In an initial phase, the agents will randomly explore state to state until they learn and reach the end of the simulation period. Then, using these Q-values, the agents start their biddings considering the learned experience. Typically, the learning process converges when the Q-values do not change more than a pre-specified tolerance value regarding the values in the Q-matrix that was built in the previous iteration.

D. Regulatory Context

The mentioned EU CEP aims to place consumers at the centre of the energy transition by allowing the definition of new models and rules for citizens [18]. The definitions of Self-Consumption. CSC and Energy Communities are based on the legal framework set by CEP. Their legal concepts and main regulatory characteristics are defined in a report provided from the Council of the European Energy Regulators [19]. For CSC, the national approaches refer in general to multi-family houses and/or Small and Medium-sized Enterprises, SME. Storage is also an important element to maximize the self-consumption rate of locally produced electricity and in several cases it is specifically considered in the legislation e.g., through incentive schemes. In some countries, CSC is currently allowed only in a limited way (e.g., via private grids) or tolerated within a regulatory grey zone. In most regulatory frameworks, a CSC structure, includes prosumers that are geographically close and that join to produce energy and share the surplus with the other CSC members. The mentioned geographically close criterium depends on how the EU directive is transposed to each EU member state and it is clearly an important aspect that may turn into a barrier regarding the development of CSCs and RECs.

In Portugal, DL 162/2019 [20] stated that CSC and REC should receive a remuneration for the surplus energy injected back into the grid and which can be commercialized by an independent aggregator or utility company. It is also stated that the charges associated with CIEG (Costs of General Economic Interest), a component of the grid tariffs paid by end consumers, could be totally or partially deducted from the grid access tariffs. In 19th June 2020, the government dispatch, n.° 6453/2020 [21], stated that CSC and REC projects, starting operation till the end of the calendar year 2021, benefit from an exemption regarding the payment of the CIEG component of the access network tariffs for seven years. More recently, it was passed the DL 15/2022 of January 14 corresponding to new Portuguese electricity law. This new legislation incorporated the concepts and provisions already included in the DL of 2019 and clarified the proximity criterium mentioned in the previous paragraph.

III. Modeling Local Electricity Markets considering Storage systems

A. Market Design

The proposed structure considers an EC constituted by different types of agents, such as consumers and prosumers. Each of these agents submit their bids to a Market Community Agent which oversees maximizing the EC self-energy consumption and the profit in consequence of selling the energy surplus. This agent is considered as an artifact since it will be utilized to carry out Energy Community Agents' activities in a competitive or cooperative manner. It will receive bids from the Energy Community Agents and perform a set of operations developed according to pre-defined rules in order to obtain a schedule for each trading period. The developed framework considers that the EC deficit or surplus in each trading period will be traded between the Market Community Agent and an Aggregator through a bilateral contract. On other hand, the Aggregator operates as a traditional retailer regarding the market clearing mechanism in the WSM. It will gather the information about the energy deficit or excess from the Market Community Agent and communicates the buying or selling bids to the WSM to balance supply and demand in the community.

Figure 1 schematically shows a community constituted by consumers and prosumers that are connected through a local electricity distribution network. Each prosumer has an energy generation unit in its installation, namely PV. The community itself has an ESS and its objective is to minimise the electricity taken from the grid by prioritising self-sufficiency and to sell surplus to the WSM through the Market Community Agent. The storage system is located at the Low Voltage side of the MV/LV substation that feeds a set of buildings.

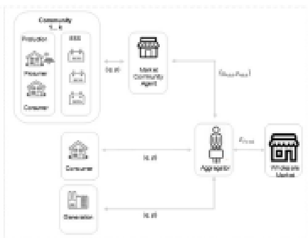

Fig. 1. Energy Community Market Design

B. Modelling local energy markets and storage systems

As mentioned before, this work is developed using an ABM model to simulate the energy trading between the LEM and the WSM. In this model, the initial trading is done locally followed by the interaction/trading in the WSM. The Aggregator receives the quantities to buy and sell in the WSM and sends back to the Market Community Agent the cleared hourly prices. The Market Community Agent receives the quantities and the bids from the community, considering the existing ESS, which performs its strategy based on the energy deficit or surplus of the community and its technical characteristics. If there is a surplus of PV power, the batteries will either be charging or discharging depending on the community's demand. However, if the energy is sufficient to meet the community needs, the additional surplus will be considered in the selling bids optimization strategy of the Market Community Agent. So, the community's Social Welfare will be enhanced by lowering the cost of electricity purchased from the grid and increasing the level of self-consumption.

Equation (2) presents the overall storage level for the ESS device over time. It is modelled by a simplified linear expression [22] and it assumes that the charging and discharging power rates remain constant during a time slot.

$$W_{B,t}^{i} = W_{B,t-1}^{i}\left(1-\sigma_{SD,t}^{i}\right) + \left(P_{BC,t}^{i}\eta_{BC,t}^{i} - \frac{P_{BD,t}^{i}}{\eta_{BD,t}^{i}}\right)\Delta t \quad (2)$$

In this expression:

– $W_{B,t}^{i}$ is the stored energy at time slot *t;*
– $W_{B,t-1}^{i}$ is the stored energy at time slot *t-1;*
– $\sigma_{SD,t}^{i}$ is the self-discharge rate (number from 0,0 to 1,0);
– $P_{BC,t}^{i}$ is the battery charge power;
– $P_{BD,t}^{i}$ is the battery discharge power;
– $\eta_{BC,t}^{i}$ is the battery charging efficiency (from 0,0 to 1,0);
– $\eta_{BD,t}^{i}$ is the battery discharging efficiency (from 0,0 to 1,0).

Batteries' charging and discharging rates are limited by α and β respectively originating constraints (3) and (4).

$$0 \leq P_{BC,t}^{i} \leq \alpha \quad (3)$$

$$0 \leq P_{BD,t}^{i} \leq \beta \quad (4)$$

The State of Charge (SOC) of the battery is given by (5) in which $W_{B,N}^{i}$ is the nominal capacity of the battery (i.e., the battery size).

$$(SOC)_{t}^{i} = \frac{W_{B,t}^{i}}{W_{B,N}^{i}} * 100\% \quad (5)$$

To ensure the balance of the community system, constraint (6) must hold for every time slot. Any power deviation can always be balanced by exchanging power with the grid. During each time slot, the batteries can be charged or discharged.

$$\left(P_{PV,t}^{i} + P_{BD,t}^{i} + P_{Grid,t}^{i}\right) - \left(P_{L,t}^{i} + P_{C,t}^{i} + P_{BC,t}^{i}\right) = 0 \quad (6)$$

In expression (6):

- in case the agent i is a prosumer, $P_{L,t}^{i}$ and $P_{PV,t}^{i}$ are its demand and PV generation at time slot *t*;
- in case the agent *i* is a consumer, $P_{C,t}^{i}$ represents its demand at time slot *t*;
- $P_{Grid,t}^{i}$ is the power exchanged with the grid at time slot *t*;
- $P_{BC,t}^{i}$ is the battery charging power;
- $P_{BD,t}^{i}$ is the battery discharging power;

Equation (7) represents the net load of the community agent *i* either being a prosumer or a consumer at time slot *t*.

$$NP_{t}^{i} = \left(P_{L,t}^{i} + P_{C,t}^{i}\right) - P_{PV,t}^{i} \quad (7)$$

Batteries are in the charging mode when $\sum_{i=1}^{N} NP_{t}^{i} < 0$, and the surplus PV power is used to charge the battery system, unless the SOC reaches its maximum value. Batteries will be in discharging mode when $\sum_{i=1}^{N} NP_{t}^{i} \geq 0$. In this case, the residual demand of the community is met by discharging the battery system, unless the SOC reaches its minimum.

The ESS operation strategy follows the iterative procedure illustrated in Figure 2. It considers a battery discharging mode operation (until the pre-defined SOC minimum limit of 20% is reached) if the demand is higher than the community production (as detailed in Equation 7). If the PV production is higher than the demand, the surplus will charge the batteries (until the predefined maximum level of SOC is reached, which was set at 80% is in this work). If there is still surplus, this energy will be traded between the LEM and WSM following the optimization model that will be detailed in the followed section. If the energy stored is insufficient to feed the demand, then the market community agent must buy the energy in deficit at the WSM.

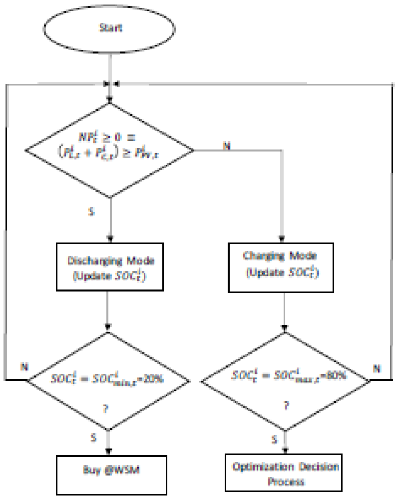

Fig. 2. Iterative procedure included in the operation strategy of the ESS

C. Implementation of the Q-Learning approach

The learning process begins with the quantity to be sold or bought between the WSM and the LEM. The state's definition is in line with energy communities' perspective, which is to enhance the self-sufficiency and reduce the grid's dependence. In this work, we considered the following 5 possible states:

- State 1 - the agent has increased its profit compared to the previous episode, and all its energy that could be dispatched in the 24 trading hours was cleared in the local market.
- State 2 - the agent has increased its profit compared to the previous episode, but not all its energy that could be dispatched in the 24 trading hours was cleared in the local market.
- State 3 - the agent hasn't obtained any profit or loss, compared with the results of the previous episode.
- State 4 - the agent has reduced its profit compared to the previous episode, but not all its energy that could be dispatched in the 24 trading hours was cleared in the local market.
- State 5 - the agent reduced its profit compared to the previous episode, and all its energy that could be dispatched in all the 24 trading hours was cleared in the market.

This structure was based on the state's definition adopted in [11], which on the other hand corresponds to an adaptation the one used in [23]. This strategy is in line with the derivative-following strategy presented in [24]. A derivative follower does incremental increases (or decreases) in the price, continuing to move its price in the same direction until the observed profitability level falls. At this point, the direction of the movement is reversed.

If there is any surplus, the players in the LEM will put bids (C^{Bid}) with a minimum guaranteed price defined according to a bilateral contract (that has a price paid to the renewable PV generation C^{PV}).

After defining the Bid Price (C^{Bid}), the Market Community Agent calculates the Utility Function, that consists of the ratio between C^{Bid} and C^{PV}. The higher this ratio is, the higher will be the community profits by applying the optimization model. If the WSM price (aggregator tariff C^{agg}) is lower than C^{PV}, the Market Community Agent will receive the guaranteed reward defined by the bilateral contract, that is C^{PV}. Otherwise, and if the C^{Bid} is lower than the C^{agg} and higher than C^{PV}, the reward will be equal to the difference between C^{Bid} and C^{PV}. The process follows with the calculation of the Utility Function, and considering the states defined in the optimization model. The Q-values are then calculated by selecting actions that are pre-defined and shown in Figure 3. After submitting a new C^{Bid}, the iterative process continues, and the new Utility Function ratio is calculated. This formulation between two consecutive periods is related with the state's definition of the MDP and with the Q-Learning procedure and after defined a new action.

In case of energy deficit, and because we assume that consumers have no elasticity regarding the price, the bids in the LEM will be equal to the required energy at the market price.

As illustrated in Figure 3, action a_1 corresponds to a maximum bid down (in which the bid price is decreased as much as possible), a_4 means that neither a bid up nor a bid down is adopted and a_7 represents a maximum bid up action (in which the bid price is increased as much as possible). Actions a_2, a_3, a_5 and a_6 represent intermediate possible values of the bid prices.

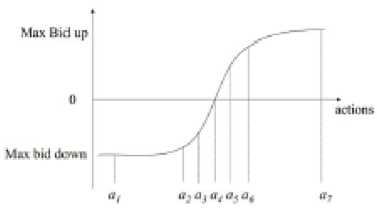

Fig. 3. Actions used in the Q-Learning procedure

IV. Case Study - Data and Results

As mentioned, the developed ABM model was applied to real data for consumption, PV generation and WSM prices. Regarding the electricity demand, we considered a Portuguese collective building with 45 flats plus common services. All the apartments are organized as an EC considering a CSC scheme. The building has a renewable generation unit constituted by 3 PV systems with overall 27 kWp. A 300 kWh storage system was considered in this simulation with SOC limits ranging from 20 to 80% of the nominal capacity. The sample power profiles for the demand and the PV systems were built using open datasets available at [25] and with sampling periods of 15 minutes, starting on 1st January 2019 until the 1st January 2020. Regarding the market prices, we used real data obtained for 2019 from the Iberian Electricity Market [26], that exists in common between Portugal and Spain since 2007.

The annual EC balance is presented in Table I. These results show that the operation strategy is successful in terms of maximizing the EC self-energy consumption, which represents almost 51% of the global energy demand. In a complementary way, the amount of energy injected back to the grid is only 4,9 MWh, which represents about 1% of the global electricity demand through the year.

TABLE I. ANNUAL ENERGY COMMUNITY BALANCE

Energy	MWh
Global energy demand	436,2
Demand supplied by public grid	212,1
Demand supplied by self-consumption	224,1
Electricity injected back into the grid	4,9

Figure 4 shows the average weekly prices of the WSM and of the LEM after using the bidding strategy, as well as the bilateral contract fixed price C^{PV}. As we can see, the use the developed bidding strategy originates that the market community agent tries to increase its prices, followed by the bid optimization strategy, in order to get closer to the WSM prices and thus increase the revenues.

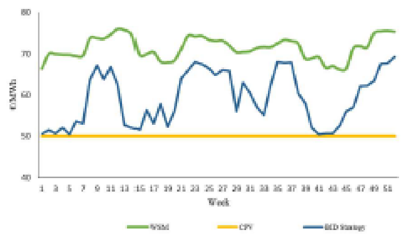

Fig. 4. Average weekly results for the WSM and the LEM market prices

Table II presents the results for the real WSM annual average price for 2019, the selling value of the PV generation excess without using the bidding strategy, that is the C^{PV} value, and the values using the LEM strategies. Despite the annual average price in the WSM is 71,1 €/MWh, these results show that if the LEM strategy is applied, the LEM average market price (59,35 €/MWh) gets closer to the WSM price.

TABLE II. RESULTS FOR THE ANNUAL AVERAGE SELLING PRICE

Scenario	€/MWh
Real WSM price	71,10
Selling price without LEM strategies (C^{PV})	50,00
Selling price with LEM strategies	59,35

This improvement regarding the initial C^{PV} value (50,00 €/MWh) is explained because of the use of the ABM model incorporating the Q-learning approach with bid up/bid-down strategy.

Analyzing now the impact of the CIEG exemptions, Figure 5 presents the evolution of the Net Present Value (NPV) for the PV and ESS, for a 20-year cash flow analysis. It is possible to observe that as the exemption level increases, from a scenario without exemption till a scenario with 100% exemption, the NPV evolves in the positive direction, meaning that it gets less negative and so the consumers obtain important savings. The results that were obtained indicate that a 50% of exemption increases the NPV by 10% while a scenario with total exemption increases it by 20%, when compared with a scenario without CIEG exemptions.

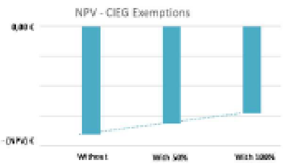

Fig. 5. Impact of the CIEG exemptions on overall investment costs

V. Conclusions

This paper presented the results obtained using an ABM model as a decision support tool to simulate the energy transactions between the LEM of a REC and the WSM, considering a community having PV units and an ESS. The results confirm that agents have learning capabilities when using the Q-Learning strategy, namely, to follow the strategy adopted regarding self-consumption and storage interaction, and the reduction of the total supply cost since the revenues coming from selling energy back to the grid increase. It was also possible to observe the impact that different levels of exemptions of the CIEG component included in the Portuguese grid tariffs have in the total costs, namely in systems with ESS. These results reveal that such exemptions could be a promoter for the massification of RECs.

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Annex B

Annex B1: Access and Energy Tariffs

TARIFA DE ACESSO ÀS REDES EM BTE			PREÇOS	
Potência			**(EUR/kW.mês)**	**(EUR/kW.dia) ***
		Horas de ponta	12,875	0,4221
		Contratada	1,305	0,0428
Energia activa			**(EUR/kWh)**	
	Períodos I, IV	Horas de ponta	0,0846	
		Horas cheias	0,0550	
		Horas de vazio normal	0,0209	
		Horas de super vazio	0,0186	
	Períodos II, III	Horas de ponta	0,0838	
		Horas cheias	0,0546	
		Horas de vazio normal	0,0204	
		Horas de super vazio	0,0187	
Energia reactiva			**(EUR/kvarh)**	
		Fornecida	0,0300	
		Recebida	0,0228	

* RRC art. 119.º, n.º 6

Annex B2.1 Self-consumption network tariffs -Without CIEG exemption (2020)

TARIFA DE ACESSO ÀS REDES DO AUTOCONSUMO ATRAVÉS DA RESP EM MT			PREÇOS	
Potência			(EUR/kW.mês)	(EUR/kW.dia) *
		Horas de ponta	2,011	0,0660
Energia activa			(EUR/kWh)	
	Períodos I, IV	Horas de ponta	0,0548	
		Horas cheias	0,039	
		Horas de vazio normal	0,0134	
		Horas de super vazio	0,013	
	Períodos II, III	Horas de ponta	0,0546	
		Horas cheias	0,0389	
		Horas de vazio normal	0,0133	
		Horas de super vazio	0,013	

* RRC art. 119.º, n.º 6

TARIFA DE ACESSO ÀS REDES DO AUTOCONSUMO ATRAVÉS DA RESP EM BTE			PREÇOS	
Potência			(EUR/kW.mês)	(EUR/kW.dia) *
		Horas de ponta	6,613	0,2168
Energia activa			(EUR/kWh)	
	Períodos I, IV	Horas de ponta	0,0797	
		Horas cheias	0,051	
		Horas de vazio normal	0,018	
		Horas de super vazio	0,0165	
	Períodos II, III	Horas de ponta	0,0793	
		Horas cheias	0,0507	
		Horas de vazio normal	0,0178	
		Horas de super vazio	0,0165	

Annex B2.2 Self-consumption network tariffs -With 50% CIEG exemption (2020)

TARIFA DE ACESSO ÀS REDES DO AUTOCONSUMO ATRAVÉS DA RESP EM MT			PREÇOS	
Potência			(EUR/kW.mês)	(EUR/kW.dia) *
		Horas de ponta	2,011	0,0660
Energia activa			(EUR/kWh)	
	Períodos I, IV	Horas de ponta	0,0303	
		Horas cheias	0,0222	
		Horas de vazio normal	0,009	
		Horas de super vazio	0,0086	
	Períodos II, III	Horas de ponta	0,0301	
		Horas cheias	0,0221	
		Horas de vazio normal	0,0089	
		Horas de super vazio	0,0086	

* RRC art. 119.º, n.º 6

TARIFA DE ACESSO ÀS REDES DO AUTOCONSUMO ATRAVÉS DA RESP EM BTE			PREÇOS	
Potência			(EUR/kW.mês)	(EUR/kW.dia) *
		Horas de ponta	6,613	0,2168
Energia activa			(EUR/kWh)	
	Períodos I, IV	Horas de ponta	0,0443	
		Horas cheias	0,0295	
		Horas de vazio normal	0,0123	
		Horas de super vazio	0,0108	
	Períodos II, III	Horas de ponta	0,0439	
		Horas cheias	0,0292	
		Horas de vazio normal	0,0121	
		Horas de super vazio	0,0108	

Annex B2.3 Self-consumption network tariffs -With 100% CIEG exemption (2020)

TARIFA DE ACESSO ÀS REDES DO AUTOCONSUMO ATRAVÉS DA RESP EM MT			PREÇOS	
Potência			(EUR/kW.mês)	(EUR/kW.dia) *
		Horas de ponta	2,011	0,0660
Energia activa			(EUR/kWh)	
	Períodos I, IV	Horas de ponta	0,0058	
		Horas cheias	0,0054	
		Horas de vazio normal	0,0046	
		Horas de super vazio	0,0042	
	Períodos II, III	Horas de ponta	0,0056	
		Horas cheias	0,0053	
		Horas de vazio normal	0,0045	
		Horas de super vazio	0,0042	

* RRC art. 119.º, n.º 6

TARIFA DE ACESSO ÀS REDES DO AUTOCONSUMO ATRAVÉS DA RESP EM BTE			PREÇOS	
Potência			(EUR/kW.mês)	(EUR/kW.dia) *
		Horas de ponta	6,613	0,2168
Energia activa			(EUR/kWh)	
	Períodos I, IV	Horas de ponta	0,0089	
		Horas cheias	0,0079	
		Horas de vazio normal	0,0065	
		Horas de super vazio	0,005	
	Períodos II, III	Horas de ponta	0,0085	
		Horas cheias	0,0076	
		Horas de vazio normal	0,0063	
		Horas de super vazio	0,005	