PhD Thesis
Automation, Electronics and
Telecommunications Engineering

An Integrated Framework for Modelling and Control of eP2P Interactions based on Model Predictive Control

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Tesis Doctoral:	An Integrated Framework for Modelling and Control of eP2P Interactions based on Model Predictive Control

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A todos los que no soy yo y me han ayudado a llegar hasta aquí, mi agradecimiento.
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Resumen

El paradigma energético está experimentando cambios sustanciales en los últimos años. En cuanto a la producción, se observa cómo la generación distribuida, con un aporte cada vez mayor de fuentes renovables, está desplazando a las grandes plantas de generación concentrada. Pero el cambio fundamental no consiste tanto en el suministro de energía como en la dilución de la clasificación tradicional entre productores y consumidores para dar paso al concepto de prosumidores. Es decir, en lugar de ser simplemente consumidores de energía, los hogares y las industrias también se convierten en productores. En principio, el objetivo de esta producción, que es intrínsecamente distribuida, es el autoconsumo. Sin embargo, cuando hay un excedente de producción, los prosumidores pueden elegir entre almacenar el excedente, si tienen un sistema de almacenamiento de energía, o vender la fracción no utilizada de la energía.

Un tipo obvio de prosumidores son aquellas industrias que cuentan con instalaciones de generación renovable y que, como consecuencia de su proceso de producción, generan subproductos que pueden ser utilizados para la cogeneración. En este caso, un problema obvio para la empresa es seleccionar en todo momento las fuentes de energía que minimizan el coste de producción, lo que se conoce como Optimal Power Dispatch (OPD). Si, además, se conoce el perfil temporal de consumo de energía asociado al proceso de fabricación (por unidad de materia prima introducida), también es posible realizar un programa de producción óptimo para minimizar el coste de la energía, lo cual se denomina Optimal Power Scheduling (OPS). El capítulo 3 presenta un Controlador Predictivo Económico basado en Modelo (EMPC) que realiza simultáneamente OPD y OPS utilizando como caso de estudio una almazara olivarera.

La aparición de la figura de los prosumidores energéticos hace necesario ampliar, mejorar o sustituir los mecanismos tradicionales de intercambio energético. Esta tesis incluye enfoques novedosos para modelar el comportamiento de los prosumidores. También propone nuevas estructuras para facilitar el comercio de energía, siempre desde la perspectiva de la *peerificación* del paradigma energético. Así, otra línea de investigación estudia el establecimiento de mercados *peer-to-peer* (P2P) para el intercambio de energía entre prosumidores heterogéneos (viviendas, vehículos, edificios inteligentes, etc.). Se compara la eficiencia de los mercados basados tanto en subastas dobles discretas (Discrete Double Auction - DDA) como en subastas dobles continuas (Continuous Double Auctions - CDA). También se introduce un Sistema de Gestión Energética (Energy Management System - EMS) que incluye un software de agente de mercado que permite que las tareas necesarias para la participación en las subastas (determinación de la valoración privada, selección de roles y adaptación de precios) se lleven a cabo automáticamente. Los capítulos 4, 5 y 6 presentan algunos ejemplos de estos mercados de intercambio establecidos entre diferentes tipos de prosumidores: i) mercado de energía para vehículos eléctricos que coinciden aparcados en un gran lugar de trabajo, ii) mercado de energía para hogares dentro de un mismo barrio y iii) mercados integrados de energía y electricidad para entidades energéticas heterogéneas.

La evolución de los mecanismos mencionados y la aparición de nuevos modelos de mercado deben ir acompañados del desarrollo de técnicas de control que optimicen y automaticen todos los procesos relacionados con el ahorro y la comercialización de la energía, por parte de un conjunto de prosumidores cada vez más heterogéneos. Esta tesis trata de cómo las diferentes variantes de los controladores predictivos pueden contribuir a este último aspecto. Para las industrias con capacidad de cogeneración, el EMPC contribuye a la programación óptima de la producción para maximizar el rendimiento de la reutilización de la energía, ya sea a través del autoconsumo o de la comercialización de excedentes. Por otro lado, se propone el uso del control predictivo estocástico para maximizar el rendimiento esperado de la participación de los prosumidores, cualquiera que sea su tipo, en mercados P2P donde el precio de la energía está sujeto a incertidumbres.

Abstract

The energy paradigm is undergoing substantial changes in recent years. In terms of production, it is observable how distributed generation, with an ever-increasing contribution from renewable sources, is displacing large concentrated generation plants. But the fundamental change is not so much about energy supply as about diluting the historical roles of producers and consumers to give way to the concept of prosumers. That is, instead of just being energy consumers, households and industries also become producers. In principle, the purpose of this production, which is inherently distributed, is self-consumption. However, when there is a surplus of production, prosumers can choose between storing the excess, if they have an energy storage system, or sell the unused fraction of energy.

An obvious type of prosumers are those industries that have renewable generation facilities and which, as a consequence of their production process, generate by-products that can be used for cogeneration. In this case an obvious problem for the company is to select at all times the power sources that minimize the cost of production, which is known as Optimal Power Dispatch (OPD). If, in addition, the energy consumption time profile of the manufacturing process (per unit of raw material introduced) is known, it is also possible to make an optimal production schedule to minimize energy cost, which is called Optimal Power Scheduling (OPS). Chapter 3 presents an Economic Model Predictive Controller (EMPC) that simultaneously performs OPD and OPS using an olive mill as an example.

The emergence of the role of energy prosumers makes it necessary to extend, improve or replace the traditional mechanisms of energy exchange. This thesis includes novel approaches for modelling the behaviour of prosumers. It also proposes new structures to facilitate energy trading, always from the perspective of the peerification of the energy paradigm. Thus, another line of research studies the establishment of peer-to-peer (P2P) markets for the exchange of energy between heterogeneous prosumers (homes, vehicles, intelligent buildings, etc.). The efficiency of markets based on both discrete double auctions (DDAs) and continuous double auctions (CDAs) is compared. An Energy Management System (EMS) is also introduced including market agent software that allows the necessary tasks for participation in the auctions to be carried out automatically (determination of private valuation, role selection and price adaptation). Chapter 4, Chapter 5 and Chapter 6 present some examples of such exchange markets stablished between different types of prosumers: i) energy market for electric vehicles that coincide parked in a large workplace, ii) power market for households within the same neighbourhood and iii) integrated energy and power markets for heterogeneous energy entities.

The evolution of aforementioned mechanisms and the appearance of new market models must be accompanied by the development of control techniques that optimise and automate all the processes related to energy saving and trading, by a group of increasingly heterogeneous prosumers. This thesis deals with how different variants of predictive controllers can contribute to this last aspect. For industries with cogeneration capacity, the EMPC contributes to the optimal scheduling of production to maximise the return from energy reuse, either through self-consumption or through the trading of surpluses. The use of stochastic predictive control is proposed in order to maximise the expected return on the participation of prosumers, whatever their type, in continuous markets where the price of energy may undergo stochastic variations.

Contents

Acronyms

B2G Business to Grid.

CDA Continuous Double Auction.

DA Double Auction.

DDA Discrete Double Auction.

DNO Distribution Network Operator.

DRG Distributed Renewable Generation.

DSIC Dominant Strategy Incentive Compatible.

DSM Demand Side Management.

EE Economy Efficient.

EMPC Economic Model Predictive Control.

EMS Energy Management System.

EP Energy Package.

ESS Energy Storage Systems.

EV Electric Vehicle.

FPI Training of Research Staff (FPI in its Spanish acronym).

H2V Home to Vehicle.

IMB Intra-Marginal Buyer.

IMS Intra-Marginal Seller.

IR Individual Rationality.

LP Limit Price.

LTI Linear Time Invariant.

MG Microgrig.

MIMO Multiple-input multiple-output.

MPC Model Predictive Control.

MS-SMPC Multiple Scenarios Stochastic Model Predictive Control.

NPSS Net Purchase and Sale System (Compensation Scheme).

OOP Object-Oriented Programming.

OPD Optimal Power Dispatch.

OPS Optimal Power Scheduling.

P2P Peer-to-Peer (alt. Prosumer-to-Prosumer).

PhV PhotoVoltaic.

PQ Power Quota.

PV Private Value.

QP Quadratic Programming.

RES Renewable Energy Sources.

RG Renewable Generation.

S-D Supply and Demand.

SA Strategy Advisor.

SBB Strong Budget Balance.

SISO Single-input single-output.

SMPC Stochastic Model Predictive Control.

SOC State Of Charge.

SS-MPC State-Space Model Predictive Control.

TA Trading Agent (Software).

V2G Vehicle to Grid.

V2H Vehicle to Home.

V2V Vehicle to Vehicle.

XMB Extra-Marginal Buyer.

XMS Extra-Marginal Seller.

Notation

$f(t)$	Continuous function
$f[k]$	Discrete function
$\lceil\cdot\rceil^+$	$max(0,\cdot)$
$\lfloor\cdot\rfloor_-$	$min(0,\cdot)$
$\mid a \mid$	Absolute value of a
$\mathbb{E}(\cdot)$	Mathematical expectation operator
$\odot$	Hadamard Product: element-wise multiplication operator between two arrays
$\|.\|^2$	Euclidean norm
$\mathcal{T}$	Set of traders within a market
$\mathcal{S}$	Set of suppliers
$\mathcal{D}$	Set of demanders
λ	Private Value (PV)
λ^S	A vector containing the private values of the suppliers.
λ^D	A vector containing the private values of the demanders
$\mathbf{\Lambda}^S$	The set of all possible suppliers' valuation profiles
$\mathbf{\Lambda}^D$	The set of all possible demanders' valuation profiles
a	Ask
b	Bid
$\underline{\mu}$	Minimum relative gain
$\overline{\mu}$	Maximum relative gain
l_a	Lowest ask value (at minimum relative gain)
h_a	Highest ask value (at maximum relative gain)
l_b	Lowest bid value (at maximum relative gain)
h_b	Highest bid value (at minimum relative gain)
$\mathcal{R}_{bid}$	Range of possible bid prices
$\mathcal{R}_{ask}$	Range of possible ask prices
$\mathcal{I}_b$	Set of intramarginal bids
$\mathcal{I}_a$	Set of intramarginal asks

p	Price
q	Quantity
$S(p)$	Supply prices.
$D(p)$	Demand prices.
q^*	SD equilibrium quantity
$[p_L^*, p_H^*]$	Interval of equilibrium prices.
ω	Offer
φ	Offering quantity
ϑ	Offering price
Ω	The set of all possible offers
$\mathcal{O}$	A finite set of offers
$t(\omega)$	The trader who shouts an offer (ω).
$\lambda(\varphi)$	The private valuation (per energy unit) of the trader for a certain offered quantity (φ).
$\mathbb{M}_{\mathbf{a},\mathbf{b}}$	Market mechanism that makes the allocation between a and b
$\Phi(\mathbf{a},\mathbf{b})$	Quantity allocation. Output of $\mathbb{M}$.
$\Pi(\mathbf{a},\mathbf{b})$	Price allocation. Output of $\mathbb{M}$
u^D	Utility of a demander.
u^S	Utility of a supplier.
$\mathcal{Q}$	The set of feasible allocations of quantities to the suppliers and demanders
$\mathcal{Z}$	The set of all energy transactions occurred during certain market session
$\mathcal{B}$	Set of traded bids
$\mathcal{A}$	Set of traded asks
$\mathbf{SW}$	Social Welfare
$\overline{\boldsymbol{SW}}$	Expected Social Welfare
$\mathbf{SW}^*$	Optimal Social Welfare
η_π	Profit allocative efficiency
π_{CDA}	Total profits actually realized during a CDA
π_{DDA}	Total profits actually realized during a DDA
$\mathcal{L}$	Relative Liquidity
N_p	Prediction horizon.
N_c	Control horizon
$\hat{x}$	Future value of x that would result from the application of an optimized input trajectory
$\tilde{x}$	Predicted value of x
$\eta_{c1\rightarrow c2}^{CONV}$	Conversion efficiency from carrier $c1$ to carrier $c2$ at converter $CONV$
$e_{c1}^{ch/dis}$	Charging/Discharging efficiency of carrier $c1$ storage
$\phi_{m1\rightarrow c2}$	Energy equivalence of product $m1$ when transformed into $c2$
T_{con}^{i}	Connection time of trader i
$T_{acc}^{i,j}$	Access time of trader i in period j
$T_{neg}^{i,j}$	Negotiation time of trader i in period j

$T^{i,j}_{trade}$	Trade time of trader i
T^{i}_{eff}	Effective transfer time of trader i
P_{load}	Load power
P_{gen}	Generated power
P_{sto}	Power injected/drained from storage
P_{util}	Power purchased from the utility
P_{P2P}	Power purchased from P2P market
P_{sc}	Self consumed power
$\mathcal{H}$	Set of houses
P_{pv}	Installed photovoltaic power
B_{max}	Maximum storage capacity

Part I

Preface

1 Introduction

A man must drive his energy, not be driven by it.

ECONOMY AND TECHNIQUE OF LEARNING, 1932
WILLIAM FREDERICK BOOK

THIS *brief introductory chapter aims to explain to the reader the motivation of this doctoral work within the current energy paradigm. To this end, Section 1.1 presents the present-day context of energy technology development, justifying the need for this work. Section 1.2 contextualizes the thesis within the research projects to which it has been associated. Section 1.3 sets the objectives of the thesis. Contributions made during the doctoral process are listed in Section 1.4. Section 1.5 establishes the methodology used. Finally, the structure of the rest of the thesis is presented in Section 1.6.*

1.1 Research Context

Energy harnessing is undoubtedly the factor that has most defined the development of mankind since the appearance of the first rational human beings. The process is always the same [1]: first, we find a new source of energy, which we are not even able to use; later we discover the way to take advantage of this energy source to turn it into work; eventually, we are able to manage it to produce, approximately, only the quantity we need to complete a certain productive task. This was the case with the discovery of fire around 250000 years ago, but also with the first water-driven prime movers (waterwheels, Roman Empire, first century BCE) and with the first wind-driven machines (windmills, Persian Empire, around the 10th century CE).

As for fossil fuels, charcoaling made it possible to increase the calorific yield in metal smelting processes, but the real revolution came with the nearly simultaneous appearance of coke-based smelting and the steam engine (British Empire, 18th century). The steam engine patented by James Watt (1769), although very inefficient (5%), averaged powers around 20 kW, quintupling the capacity of the contemporary waterwheels, tripling that of the windmills of the time and being 25 times higher than the performance of a good horse.

During the 19th century, parallel to the improvement in the efficiency of steam engines (which reached ≈1 MW in the 1870s), water turbines (Fourneyron, Francis, Pelton) were developed, and with them the first electric hydrogeneration plants. The first steam turbine to produce electricity was also patented in the 19th century (Charles Parsons, 1884). The phenomenal creative impulse of the fathers of commercial electricity (Thomas A. Edison, George Westinghouse, William Stanley, Nikola Tesla, etc.), made it possible to establish the basis of a commercially viable system of electricity generation, transmission, and use in a matter of three decades.

Although the structure of the electrical system was already standardised around 1900, the challenge since then has been to maintain the enlargement of the units that compose it. Since then, the maximum size of turbogenerators has been multiplied by around 200 (≈2 GW), and the degree of efficiency of thermal generation has been multiplied by 12 (to reach efficiencies greater than 60% with cogeneration). Inexpensive and reliable electricity has completely transformed the human lifestyle: lighting houses and streets, powering time-saving appliances and gadgets that expand our communication and leisure possibilities, and powering ever faster and cleaner means of transport. The twentieth century also saw the emergence of new fuels (nuclear) and the generalisation of others (hydrocarbons). The latter accounted for more than 60% of world energy production in 2000. However, since the middle of the century, environmental awareness of problems such as global warming, as well as the development of new technologies for harnessing Renewable Energy Sources (RES), have driven the deployment of Renewable Generation (RG) worldwide.

With the turn of the century, this trend has only increased. Paradoxically, the race to larger and larger generators has slowed and even reversed, with more and more emphasis on installing small and medium-sized generators connected to the grid at distribution level or directly to the consumer. When this kind of generation comes from renewable sources, we speak of Distributed Renewable Generation (DRG). Of course, renewable sources still have the problem of their stochasticity, the impossibility of controlling the magnitude of solar, hydraulic or wind power available at any given time to be converted into electrical or thermal energy. For this reason, the deployment of DRG cannot be explained without the parallel development of increasingly efficient and cheap Energy Storage Systems (ESS).

Although storage systems can store energy, there is a whole field of research dedicated to optimising the use of these reserves. As long as there are shiftable loads, i.e. loads whose utilisation can be anticipated or delayed over time, the use of storage and different consumption equipment can be optimised together towards different objectives (flattest possible demand curve, minimisation of economic cost, etc.). Such optimisation techniques are known as Demand Side Management (DSM). Initially, the primary objective of end users when installing a DRG system in their homes, businesses or industries is to use the produced energy to meet their own electricity and/or heat needs, which is known as self-consumption. However, as the efficiency of the consumption equipment and the productivity of the generators improve, a surplus of energy appears. Initially, this surplus energy can be stored in an ESS, if available, to be consumed later during periods when there is no production or it is lower than consumption. However, if the excess production is too large, it may even exceed storage capacity. Once the ESS is full, any energy production above the instantaneous consumption must be discarded and becomes lost energy. During the first years of the DRG deployment, such a situation would clearly indicate a wrong dimensioning of the system, either by the installation of over-sized generators or by the selection of an under-sized ESS. Today this is not the case precisely because states have implemented legislative mechanisms to encourage renewable sources to account for an ever-increasing proportion of the national annual electricity generation.

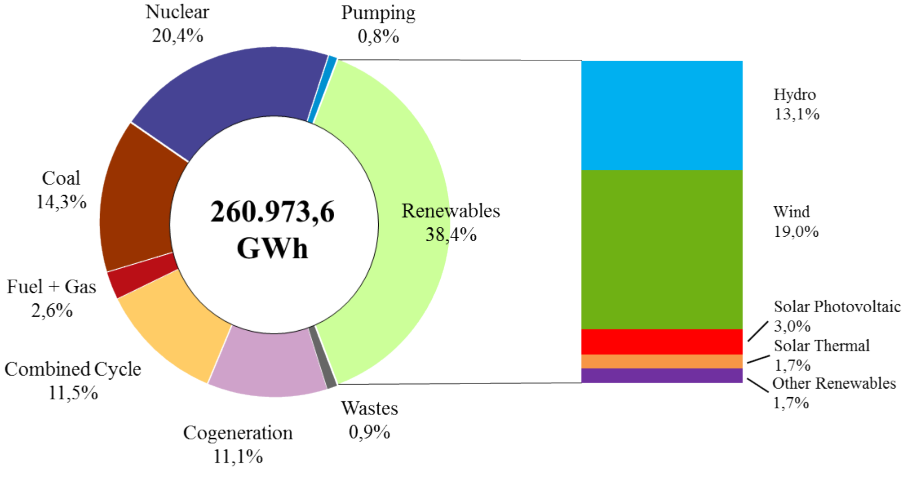

Figure 1.1 Spanish Electricity Mix in 2018 [2].

The first of these mechanisms, related to power pool, is the possibility of obtaining subsidies for the installation of DRG systems. The second is to compel traditional Distribution Network Operators (DNO) to absorb excess renewable production, and to compensate the end user for this surplus. To have DNO as the only alternative to which to sell the excess production poses a problem, since it leaves to its total discretion (possibly forced also by the legislator) the determination of the main parameters of the trade: amount of power/energy, price per unit and form of economic compensation. This is particularly odd considering the distribution of ownership of installed capacity with renewable generation capacity. As far as we know, these data are not available for Spain, but they are available for Germany, which is a country with a much more developed renewable sector than Spain. In Germany, in 2016, more than 55% of renewable energy capacity belonged to individual owners, while only ≈15% was owned by standard power providers (see Figure 1.2).

We are also living in a global context in which the emergence of the concept of a shared economy has revolutionised other sectors such as passenger transport or tourist accommodation. It would therefore seem logical to think of a future in which energy, understood as one more commodity, could be exchanged directly between heterogeneous end users, who can alternate between various roles (pure consumer, pure producer or prosumer) according to their production and consumption profiles []. The second part of this thesis has been dedicated to studying this type of energy interactions, analyzing the different commercialisation possibilities, proposing new market structures and implementing control techniques for the optimisation, at individual level, of the economic energy performance of the different entities participating in the market.

1.2 Thesis Context

This thesis is part of a scholarship for the Training of Research Staff (FPI in its Spanish acronym), associated in turn with the COOPERA Project (Model Predictive Control of Distributed Energy Systems with Renewable Sources and Stationary and Mobile Storage) [3], which was selected in the Call for R+D+i Projects "Research Challenges" 2013 of the Ministry of Economy of the Kingdom of Spain. The general objective of the project consisted in the development of methodologies for the modelling and control of systems formed by microgrids[1] with production based on renewable energies, where storage is of special interest. This storage was planned to be carried out both with electrochemical systems (batteries, supercondensers, etc.) and by means of hydrogen. In addition, both types of storage were carried out either statically or by means of electric or hybrid hydrogen-based vehicles, giving rise to Vehicle-to-Grid (V2G) systems.

[1] According to IEEE Standard 2030.7-2017 [4] a microgrid is "a group of interconnected loads and distributed energy resources with clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid and can connect and disconnect from the grid to enable it to operate in both grid-connected or island modes".

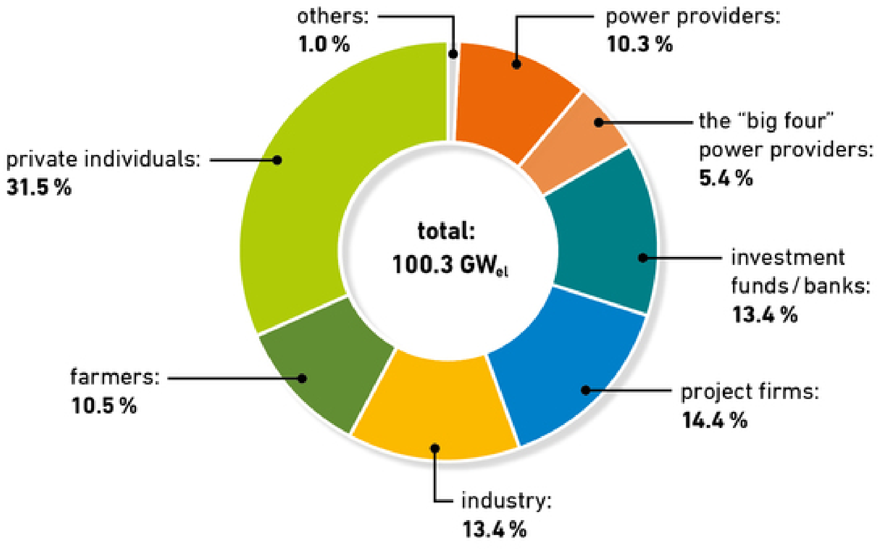

Figure 1.2 Ownership distribution of installed RES capacity for power production in Germany in 2016.
Source: German Renewable Energies Agency. Reprinted with permission.

1.3 Thesis Goals

The main objectives of the doctoral thesis, as defined in the original Research Plan, were:

- Development of modelling methodologies for the control of V2G systems and their integration into microgrids. The calculation of reduced models that are suitable for the analysis and design of controllers is especially relevant.
- Design and development of control algorithms based on distributed and hierarchical Model Predictive Control (MPC) for microgrids with hydrogen storage considering V2G systems.
- Implementation of control algorithms in experimental facilities, both at laboratory and real plant level.

The secondary objective was the validation and technical-economic evaluation of results in order to make recommendations for technological development and implementation, define performance indicators and draw conclusions for optimisation.

However, some internal project circumstances and some external constraints have made these objectives change slightly over time. These modifications are summarised below, as well as some of the limitations that this thesis lacks.

During the years of execution of the project there was a certain deflation of the expectations placed on the hydrogen economy, i.e. the proposed use of hydrogen as a primary fuel for means of transport and as a storage mechanism. In addition, we realised that it might be much more interesting not to limit the study only to V2G interactions, but to generalize it to any kind of interaction between end producers/consumers. Hence, the acronym P2P has been included in the definitive title of the thesis, which besides its original meaning of *peer-to-peer*, also has for us the interpretation of *prosumer-to-prosumer*.

The definitive approach of the thesis has focused on the study of the structures needed to execute purchase-sale energy interactions from a higher economic level. With this abstraction it is possible to broaden the framework, so that any energy entity (industry, building, single-family house, electric vehicle, or even the DNO itself) can be assimilated to a peer and therefore included within the analysis. As already mentioned, the concept of V2G was replaced by that of P2P, extending the scope of application of models and control techniques. With the change of denomination, all kinds of interactions between any type of entity comparable to a peer can be covered: Vehicle to Home (V2H), Home to Vehicle (H2V), Vehicle to Vehicle (V2V), Business to Grid (B2G), etc. The disadvantage of this decision is that we have not gone down to the control level of the physical medium over which the exchange is established, but simply assume that the aforementioned interactions are physically feasible and technically controllable. However, this issue is discussed in the Future Research Directions section of the Final Remarks chapter.

Regarding implementation, the main difficulty lies in the multi-agent nature of the problem. As a result of this, several programmable electronic generators and/or loads, with their corresponding converters, are required to simulate energy purchase-sale interactions. During the stay at the University of Aalborg, whose Department of Energy Technology has such equipment, it was possible to perform tests in an experimental laboratory set-up. The rest of the experiments were carried out using an ad-hoc simulation platform built on Matlab using Object-Oriented Programming (OOP).

Considering all these factors, the definitive formulation of the objectives of the thesis could be summarised as follows:

Thesis Objectives

1. Development of modelling and control techniques that improve the optimisation of the energy operation of multicarrier systems.
2. Development of modelling and control techniques that improve the optimisation of peer to peer energy purchase-sale interactions between end users.
3. Proposals for novel market architectures for energy trading between end-users. Analysis of the standard indicators used to measure the performance of this type of markets and improvement suggestions.
4. Validation of new stochastic control techniques that take uncertainties into account for managing the participation of the agents in the new market architectures

1.4 Summary of Contributions

The following contributions have been identified:

Thesis Contributions

1. As for the development of methodologies for modelling P2P systems control (Objective 2) the fundamental contribution has been the definition of prosumers as economic agents that can participate simultaneously in discrete markets in which energy packages are traded, and that are based on discrete double auctions (DDAs), as well as in continuous markets in which power quotas are traded, and that are based on double continuous auctions (CDAs). This definition incorporates mechanisms for the valuation of each mode of energy marketing, the selection of roles within the market, as buyer or seller, the automatic adaptation of prices and the control of the power flows that determine the use of the storage system of the prosumers, if they have it.
2. Given the stochastic nature of the type of agents and markets involved, a strategic advisor based on stochastic MPC (inherently distributed because it resides in different entities that can collaborate or compete with each other) has been implemented (Objective 2). This 'strategizer' defines a market behaviour profile (market entry/exit points and quantities to be negotiated) that maximizes the mathematical expectation of obtained profits.
3. As for the implementation of these control algorithms in experimental facilities (Objective 3), during the stay in Denmark, some of these concepts were tested in a real experimental setup. For the rest of the tests an ad-hoc simulation platform was built, using Matlab's Object Oriented Programming, which allows the multi-agent simulation of the energy interactions under study.
4. As a consequence of the model definition, new performance indicators have been proposed for CDAs (Secondary Objective).
5. A technique was designed for industrial prosumers (whose application to residential ones is straighforward) that allows the joint realisation of Optimal Power Scheduling (OPS), by managing shiftable loads, and Optimal Power Dispatch (OPD), by choosing among different available power sources. This approach makes it possible to optimize the use of the energy-economic operation and can be used to synchronize the periods of availability of tradeable energy stock with the hourly periods in which the price in the different energy markets are more profitable.

1.5 Research Methodology

The methodology followed during the doctoral process involved the following phases:

1. **Revision** of the state of the art: first of all, the state of the art of existing technologies was analysed, analysing the most innovative solutions applied to microgrids. This allowed the main actions to be carried out to be outlined more clearly.
2. Development of modelling and control techniques: at this stage the different strategies and structures proposed in the thesis were developed. First generically and then applied to specific problems.
3. Implementation of the techniques: The implementation of the proposed methods was carried out, building the necessary simulation tools and making use of the laboratory set-ups that were available.
4. Experimental validation: it was necessary to validate the developed methods by implementing the agents and their controllers and analyzing the results obtained.
5. Redesign and corrective actions: based on the evaluation of the validation of the proposals, the necessary actions were carried out to redesign the solutions provided in the project.
6. Dissemination of Results: throughout the whole process, the relevant scientific results were published.

1.6 Structure of this Dissertation

This thesis is structured in three sections, each composed of a series of chapters.

The first section is a preface, and in addition to the present introductory chapter, it incorporates a brief chapter of preliminaries in which some concepts, structures and basic terminology are presented before being subsequently used in the thesis.

The second section is the central part of the thesis, and consists of four chapters, one for each of the contributions made.

The third and final section, consisting of a single chapter, presents the conclusions of the work and proposes lines of future research.

2 Preliminaries

If you have built castles in the air, your work need not be lost; that is where they should be. Now put the foundations under them.

WALDEN, 1854
HENRY DAVID THOREAU

THIS *chapter briefly presents some basic theoretical concepts and structures on which the contributions of this thesis are based. To this end, Section 2.1 introduces the structures used to model energy trading, including the different types of double auctions and the performance indicators that have been used so far to compare them. Section 2.2 presents the fundamentals of Model Predictive Control (MPC), the advanced control technique used to build all the controllers included in this thesis.*

2.1 Markets

2.1.1 Supply and Demand

An economic market is defined as an actual or nominal place where forces of demand and supply operate, and where traders (suppliers and demanders) interact (directly or through intermediaries) to exchange goods, services, contracts or instruments, for money or barter. A *market institution* defines how this exchange takes place by laying down mechanisms or rules for i) determining price of the traded item, ii) communicating the price information, iii) facilitating deals and transactions, and iv) effecting distribution.

Each market participant should have a mechanism to valuate his own goods. This valuation defines his *private value* (λ), abbreviated PV onward, which is generally internal and not advertised. To determine his market price range, each trader can establish a minimum relative gain, $\underline{\mu}$, on its private value, giving rise to its *minimum-gain limit prices* l_a –the value below which it is not willing to sell– and h_b –the value above which it is not willing to buy. Although normally any trader would like its relative gain to be as large as possible, it might also establish a maximum value, $\overline{\mu}$, giving rise to its respective *maximum-gain limit prices* h_a and l_b. Finally, its price ranges in the market (i.e. the ranges of its possible bids and asks[1]) are:

$$\begin{aligned} \mathcal{R}_{bid} &= \left[l_b, h_b\right] = \left[\lambda(1-\overline{\mu}), \lambda(1-\underline{\mu})\right] \\ \mathcal{R}_{ask} &= \left[l_a, h_a\right] = \left[\lambda(1+\underline{\mu}), \lambda(1+\overline{\mu})\right] \end{aligned} \tag{2.1}$$

Note that if the minimum required relative gain equals zero, meaning that any positive gain is acceptable, private value and limit price (abbreviated LP onward) are the same, and selling/buying intervals are left/right-open. Analogously, selling/buying intervals are right/left-open if the maximum relative gain is not defined (ideally infinite). Specifically, the buying interval might be lower bounded by zero if negative relative gains and/or valuations of the good made no sense. As the name implies, private valuations are not publicly known in most practical scenarios. The relative minimum gains required by each trader are also secret and, in the most general case, vary from trader to trader. Limit prices are therefore not publicly known values either. What is known instead are the prices that self-interested traders make away from their private values (always beyond their limit prices) in order to make at least a minimum profit. These actually offered prices and quantities also make a set of supply and demand curves, called the *apparent* supply and demand curves, in contrast to the *underlying* supply and demand based on traders' private values or limit prices.

A typical representation of trading forces within a market is realised through the supply and demand (S-D) staircases. In this kind of representation, demand quantities are plotted ordered from higher to lower monetary amounts, while supply quantities are plotted ordered from lower to higher monetary amounts. It must be pointed out that

[1] A bid is an offer to buy, while an ask is an offer to sell

these monetary amounts can correspond either to private valuations, to limit prices or to the prices actually offered by the different traders, giving rise to 3 different S-D graphs (see Figure 2.1). In any case, when both corresponding curves intersect, supply equals demand at a point that determines a unique equilibrium quantity $q^* \geq 0$ and, in general, an interval of equilibrium monetary amounts $[p_L^*, p_H^*]$. Those units of the good located to the left(right) of the equilibrium quantity, which would yield a positive(negative) payoff if traded at an equilibrium price are called *intramarginal(extramarginal)*, and its owners are called intramarginal(extramarginal) buyers (IMBs/XMBs) and intramarginal(extramarginal) sellers (IMSs/XMSs) respectively [5].

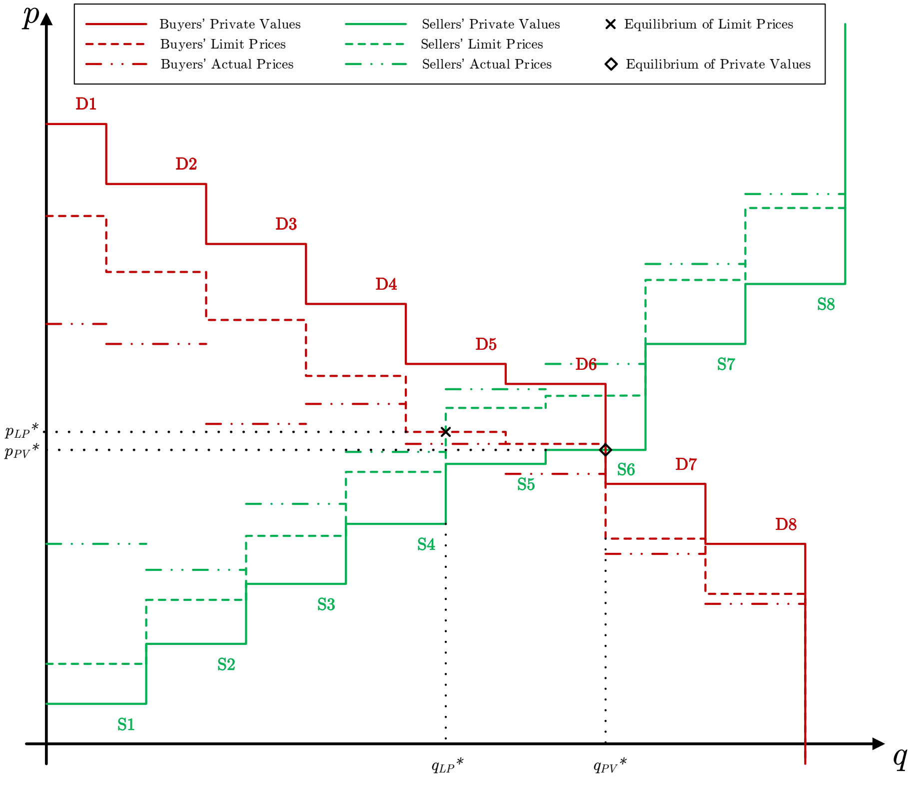

Figure 2.1 The three different Supply and Demand staircases formed respectively by Private Values, Limit Prices and Actual Prices, for a set of 8 Suppliers and 8 Demanders.

2.1.2 Double Auction based Markets

An auction is an unified market mechanism in which traders' message (called a *bid* for an offer to buy and an *ask* for an offer to sell) includes an offered quantity at an offered price, and which give higher priority in transactions to better offers (higher bids and lower asks) [6]. If both buyers and sellers are allowed to make offers, the auction is said to be *two-sided* or *double* (DA). If traders are only allowed to bid or ask for individual items at a time, the market is said to be *single unit*, while it is called a *multi-unit* market if agents can trade more than one unit of goods. If the negotiated good is *indivisible*, the agents can only negotiate on a non-negative integer amount of goods. On the other hand, if the negotiated good is *divisible*, agents can negotiate any continuous value of goods. The rules of the market institution can also impose conditions on successive bids and asks (for example, subsequent offers are valid only if they improve previous ones, in terms of price, until a transaction occurs[2]). If every trader knows what other traders bid and ask the auction is said to be *open*, otherwise it is *closed* or sealed. Finally, another distinction can be made regarding what happens to unmatched offers: either they are left open until they are filled or the auction closes, giving a *persistent shout* auction, or they are cleared.

Let $\mathcal{T} = \mathcal{S} \cup \mathcal{D}$ be a set of traders, where $\mathcal{S}$ is the set of suppliers, $\mathcal{D}$ is the set of demanders, and $\mathcal{S} \cap \mathcal{D} = \emptyset$. Let $\boldsymbol{\lambda}^S = \{\lambda^{S_1},\ldots,\lambda^{S_x}\}$, where $x = |S|$, be a vector containing the private values of the x suppliers, and $\boldsymbol{\lambda}^D = \{\lambda^{D_1},\ldots,\lambda^{D_y}\}$, where $y = |D|$, be the corresponding vector for demanders's private values. Further, let $\boldsymbol{\Lambda}^S$ be the set of all possible suppliers' valuation profiles, and $\boldsymbol{\Lambda}^D$ be the set of all possible demanders' valuation profiles.

Definition 2.1.1 An *offer* $\omega = (\varphi,\vartheta)$ is a message that a trader $t \in \mathcal{T}$ sends to the double auction market for either buying or selling certain quantity (φ) of the commodity with a specified price (ϑ).

Let Ω be the set of all possible offers. For each offer $\omega \in \Omega$, $t(\omega)$ denotes the trader who *shouts* ω and $\lambda(\varphi))$ denotes the private valuation (per unit) of the trader for a certain offered quantity φ [3].

Definition 2.1.2 An ask is a selling offer $a = (\varphi^a,\vartheta^a) \in \Omega$ such that $t(a) \in \mathcal{S}$. A bid is a buying offer $b = (\varphi^b,\vartheta^b) \in \Omega$ such that $t(b) \in \mathcal{D}$. For any finite set $O \subset \Omega$, we let $\mathbf{a} = \{a_1,\ldots,a_n\} = \{(\varphi^a_1,\vartheta^a_1),\ldots,(\varphi^a_n,\vartheta^a_n)\}$, where $n = |\mathbf{a}|$, be the set of currently active asks and $\mathbf{b} = \{b_1,\ldots,b_m\} = \{(\varphi^b_1,\vartheta^b_1),\ldots,(\varphi^b_m,\vartheta^b_m)\}$, where $m = |\mathbf{b}|$, be the set of currently active bids.

Values n and m depend respectively on the number of suppliers (x) and demanders (y) present in the market at any given time, as well as on the number of offers that each trader can make (i.e. depending on whether the auction is single unit or multi-unit). It should be noted that in the most general case of multi-unit auctions, each supplier (resp. demander) can perform more than one ask (resp. bid). Let's denote the asks corresponding to a certain supplier S_i as $\mathbf{a}^{S_i} = \{\forall a \in \mathbf{a} : t(a) = S_i\} \subset \mathbf{a}$, and the bids corresponding to a certain demander D_j as $\mathbf{b}^{D_j} = \{\forall b \in \mathbf{b} : t(b) = D_j\} \subset \mathbf{b}$.

[2] New York Stock Exchange (NYSE) rule.

[3] It is assumed that each trader gives the same private value to all of its offered quantity, thought different prices for different portions of that total offered quantity could be actually offered

Definition 2.1.3 Given a set of asks, $\mathbf{a}$, and a set of bids, $\mathbf{b}$, a *matching mechanism* between $\mathbf{a}$ and $\mathbf{b}$, denoted as $\mathbb{M}_{\mathbf{a},\mathbf{b}} = \{\Phi(\mathbf{a},\mathbf{b}),\Pi(\mathbf{a},\mathbf{b})\}$, is a mechanism that receives as inputs the asks made by suppliers, and the bids made by demanders, and outputs an *allocation* $\{\mathbf{q}^a,\mathbf{q}^b\} = \Phi(\mathbf{a},\mathbf{b})$ together with a *specification* of the prices to be paid by suppliers and demanders $\{\mathbf{p}^a,\mathbf{p}^b\} = \Pi(\mathbf{a},\mathbf{b})$.

Vectors $\mathbf{q}^a = \{q_1^a,\ldots,q_n^a\}$, where $q_k^a \in [0,\varphi_k^a]$, and $\mathbf{q}^b = \{q_1^b,\ldots,q_m^b\}$, where $q_k^b \in [0,\varphi_k^b]$, contain the quantities that the mechanism determine to be traded. Obviously, sold and bought quantities must coincide, so $\sum_{k=1}^n q_k^a = \sum_{k=1}^m q_k^b$. Once the matching mechanism is run on the reported offers $\{\mathbf{a},\mathbf{b}\}$, each supplier and demander experiences a certain utility.

The utility of a demander $D_k \in \mathcal{D}$ is a function of her true valuation λ^{D_j}, the output allocation $\mathbf{q}^{D_j} = \{\forall q_k^b \in \mathbf{q} : t(b_k) = D_j\}$ granted to each of her bids, and the output prices $\mathbf{p}^{D_j} = \{\forall p_k^b \in \mathbf{p} : t(b_k) = D_j\}$ for each of those bids. This utility is then given by $u^{D_j}(\lambda^{D_j},\mathbf{q}^{D_j}(\mathbf{a},\mathbf{b}),\mathbf{p}^{D_j}(\mathbf{a},\mathbf{b})) = \sum \mathbf{q}^{D_j}(\mathbf{a},\mathbf{b}) \odot (\lambda_j \cdot \mathbf{1} - \mathbf{p}^{D_j}(\mathbf{a},\mathbf{b}))$ and the utility of a supplier $i \in \mathcal{S}$ is defined similarly as $u^{S_i}(\lambda^{S_i},\mathbf{q}^{S_i}(\mathbf{a},\mathbf{b}),\mathbf{p}^{S_i}(\mathbf{a},\mathbf{b})) = \sum \mathbf{q}^{S_i}(\mathbf{a},\mathbf{b}) \odot (\mathbf{p}^{S_i}(\mathbf{a},\mathbf{b}) - \lambda_j \cdot \mathbf{1})$, where the symbol $\odot$ represents the component-wise multiplication between two vectors of the same dimensions. Sellers and buyers act strategically so as to maximise their utility.

2.1.3 Desirable Properties of Matching Mechanisms for Double Auctions

There are a set of desirable properties that a double-sided matching mechanism $\mathbb{M}$ should ideally satisfy:

- Individual Rationality (IR): A mechanism is individually rational only if all traders with positive allocation perceive a positive utility as well. Or, on the contrary, no trader experiences in any case a negative utility for participating in the mechanism. So, for all $S_i \in \mathcal{S}$ and $D_j \in \mathcal{D}$ and for all offer profiles $\{\mathbf{a},\mathbf{b}\}$, it holds that $u^{S_i}(\lambda^{S_i},\mathbf{q}^{S_i}(\mathbf{a},\mathbf{b}),\mathbf{p}^{S_i}(\mathbf{a},\mathbf{b})) \geq 0$ and $u^{D_j}(\lambda^{D_j},\mathbf{q}^{D_j}(\mathbf{a},\mathbf{b}),\mathbf{p}^{D_j}(\mathbf{a},\mathbf{b})) \geq 0$.
- Dominant Strategy Incentive Compatibility (DSIC): A mechanism is said to be incentive compatible if all of the participants maximise their utilities when they truthfully reveal any private information asked for by the mechanism. This property is also known as truthfulness and truth-telling. Formally, for every reported offer profile $\{\mathbf{a},\mathbf{b}\}$, for every supplier S_i, it must hold that

$$u^{S_i}(\lambda^{S_i},\mathbf{q}^{S_i}(\{\mathbf{a}_\lambda^{S_i},\mathbf{a}^{-S_i}\},\mathbf{b}),\mathbf{p}^{S_i}(\{\mathbf{a}_\lambda^{S_i},\mathbf{a}^{-S_i}\},\mathbf{b})) \geq u^{S_i}(\lambda^{S_i},\mathbf{q}^{S_i}(\mathbf{a},\mathbf{b}),\mathbf{p}^{S_i}(\mathbf{a},\mathbf{b}))$$

  where $\{\mathbf{a}_\lambda^{S_i},\mathbf{a}^{-S_i}\}$ is the vector obtained from $\mathbf{a}$ by replacing ϑ_i with λ^{S_i} in all the asks of $\mathbf{a}^{S_i}$. The demanders' formulation is symmetric.
- Strong Budget Balance (SBB): If suppliers receive only and exclusively the entire monetary amount paid by the demanders, the mechanism is said to be strongly budget balanced (i.e. the auctioneer does not receive any remuneration but neither has to subsidise the market). Formally, for every offer profile $\{\mathbf{a},\mathbf{b}\}$

it must hold that $\sum \mathbf{q}^b(\mathbf{a},\mathbf{b}) \odot \mathbf{p}^b(\mathbf{a},\mathbf{b}) - \sum \mathbf{q}^a(\mathbf{a},\mathbf{b}) \odot \mathbf{p}^a(\mathbf{a},\mathbf{b}) = 0$. If the suppliers receive only and exclusively the monetary amount paid by the demanders, but not its totality, the mechanism is said to be weakly budget balanced (the auctioneer takes a portion of the monetary amount). Formally, it must hold that $\sum \mathbf{q}^b(\mathbf{a},\mathbf{b}) \odot \mathbf{p}^b(\mathbf{a},\mathbf{b}) - \sum \mathbf{q}^a(\mathbf{a},\mathbf{b}) \odot \mathbf{p}^a(\mathbf{a},\mathbf{b}) > 0$.

- Economic Efficiency (EE): A mechanism is said to be efficient if the sum of the utilities granted for all players (i.e. the social welfare) is the best possible. In particular, this means that, after all trading has completed, the items should be in the hands of those that value them the most. Let Q be the set of feasible allocations of quantities to the suppliers and demanders. For an allocation $\mathbf{q} = \{\mathbf{q}^a, \mathbf{q}^b\} \in Q$ the social welfare of $\{\mathbf{q}^a, \mathbf{q}^b\}$, for offer profile $\{\mathbf{a},\mathbf{b}\}$, is denoted as $\mathbf{SW}(\mathbf{a},\mathbf{b},\mathbf{q}) = \sum_{k=1}^{|\mathbf{b}|} q_k^b \lambda(q_k^b) - \sum_{k=1}^{|\mathbf{a}|} q_k^a \lambda(q_k^a)$. Then, recalling that $\lambda(\mathbf{q}^a)$ and $\lambda(\mathbf{q}^b)$ are random vectors in $\mathbf{\Lambda}^S$ and $\mathbf{\Lambda}^D$ respectively, it is possible to define the expected social welfare of mechanism $\mathbb{M}$ as $\overline{\boldsymbol{SW}} = \mathbb{E}[\mathbf{SW}(\mathbf{a},\mathbf{b},\mathbf{q}(\mathbf{a},\mathbf{b}))]$, where the expectation operator averages the randomness of the traders' valuations and the randomness of the mechanism itself. For a profile of offers $\{\mathbf{a},\mathbf{b}\}$, the *optimal allocation* is defined as the allocation $\mathbf{q}^*(\mathbf{a},\mathbf{b}) \in Q$ that maximises $\mathbf{SW}(\mathbf{a},\mathbf{b},\cdot)$. The expected optimal social welfare is then given by $\mathbf{SW}^* = \mathbb{E}[\mathbf{a},\mathbf{b},\mathbf{q}^*(\mathbf{a},\mathbf{b})]$.
- Revenue Maximisation: When there is an auctioneer who can determine matches in which the price paid by the buyer is higher than the price received by the seller, the auctioneer makes a profit equal to the difference between the two prices. In these cases one of the objectives when (the auctioneer itself) designs the mechanism is to maximise the revenue (sum of profits) derived from the matching process.
- Liquidity: In certain cases, it may be interesting to maximise a) the total traded volume (e.g. because the auctioneer receives a commission depending on the total amount of traded goods) and/or b) the number of transactions (e.g. because the auctioneer receives a individual commission for each of them).

2.1.4 Mechanism Design

Unfortunately, Myerson and Satterhwhite demonstrated in their famous theorem [7] that it is impossible to design a mechanism that simultaneously fulfills the 4 main properties (IR, DSIC, SBB and EE). To avoid the need to subsidise the market, there are two alternatives, either relaxing efficiency or giving up incentive compatibility.

The most common matching mechanism is the one that clears the market at the price where the supply equals the demand. This is called equilibrium matching (ME). In a ME auction, shouts are matched when the market is cleared if and only if they are intra-marginal. If we denote the supply and the demand at price p as S(p) and D(p), the trading volume with ME is:

$$q_{me} = \max_p \min[S(p), D(p)] \tag{2.2}$$

and if all transactions are made at the price at which q_{me} is achieved, what is called *uniform pricing*, the transaction price can be defined as

$$p_{me} = \arg\max_{p} \min[S(p), D(p)] \tag{2.3}$$

In a *discrete-time* double auction (DDA), the change in allocation of goods or *market clearing* occurs at one or more fixed time instants between the start of the auction and the end of the trading period. Traders must place their bids and asks before each clearing instant, and both set of offers are used to determine the supply and demand staircases for commodities.

The equilibrium point sets the (*uniform*) trading price, and thus the surpluses, for all the trades within that trading period. In a *continuous* double auction (CDA), in contrast, buyers and sellers can individually choose to accept a bid or ask at any particular price (*discriminatory price*) at any point in time, and then update their allocation immediately.

2.1.5 Performance Indicators used for Continuous Double Auctions

There are a number of indicators that have been used in the literature to study the differences in performance between CDAs and DDAs. Some of these indicators, such as *profit dispersion* [8] or *price volatility* [9], are used to analyse the time evolution of the convergence of a CDA towards the theoretical equilibrium of the equivalent DDA. Others, such as *relative concentration* and *relative capacity* [10], study the imbalances between supply and demand and how these asymmetries affect the temporal evolution of convergence mentioned above.

However, the most commonly used indicator to define the performance of an CDA is that of *allocative efficiency* [6].

Definition 2.1.4 (Allocative Efficiency) (η_π) measures how the total surplus actually realised during a CDA (π_{CDA}) compares to the maximum surplus that theoretically could be made, were the auction discrete (π_{DDA}). In this latter case, all transactions are cleared at the equilibrium price p^*. Let $\mathcal{B}$ and $\mathcal{A}$ be, respectively, the set of bids and asks that managed to trade during certain trading period of the CDA, and $\mathcal{I}_b$ and $\mathcal{I}_a$ the set of intramarginal bids and asks that would have traded in the equivalent DDA.

$$\eta_\pi = \frac{\pi_{CDA}}{\pi_{DDA}} = \frac{\left(\sum_{b\in\mathcal{B}} q^b(\lambda^b - p^b)\right) + \left(\sum_{a\in\mathcal{A}} q^a(p^a - \lambda^a)\right)}{\left(\sum_{i\in\mathcal{I}_b} q^i(\lambda^i - p^*)\right) + \left(\sum_{j\in\mathcal{I}_a} q^j(p^* - \lambda^j)\right)} \tag{2.4}$$

Allocative efficiency therefore captures the profit-extraction capacity of a certain continuous auction protocol, together with the underlying price adaptation strategies of its component agents. However, it does not take into account the performance of the auction in terms of the volume of assets traded. Maximizing the volume of traded goods (or alternatively, the number of transactions) may be desirable for example when dealing with perishable goods [11] (which are depreciated or destroyed over time) or in cases where a flat fee is charged per transaction. In fact, there are references in the literature that propose maximal matching mechanisms, in which maximizing the volume of trade is prioritised over maximisation of profits [12, 13]. Regarding continuous double energy auctions, references [14] and [15] compute the relationship between tradeable energy and actual traded one. However, the former defines this relationship as allocative efficiency (rather than the ratio of profits), while the latter defines it as Percentage of Traded Energy (PTE). Here, the term liquidity is used, according to its economic definition [4], and the adjective 'relative' is added to indicate that the comparison is made with respect to the equivalent DDA.

Definition 2.1.5 (Relative Liquidity) ($\mathcal{L}$) compares the total quantity of goods traded within a CDA session with the total quantity that would have been traded if the DA were discrete. Let $\mathcal{Z} \equiv (z_1, \ldots, z_k)$ be the set of all transactions closed during certain trading period of the CDA. Then,

$$\mathcal{L} = \frac{q_{CDA}}{q_{DDA}} = \frac{\sum_{z \in \mathcal{Z}} q_z}{q^*} \tag{2.5}$$

2.2 Model Predictive Control

2.2.1 The Model Predictive Control Paradigm

The MPC paradigm is based on the choice of the best amongst all feasible input sequences over a future horizon according to some criteria. Using the concept of receding horizon, the first input of this sequence is applied to the system and the scheme is repeated at the next sampling time, as new state information is available. This way, MPC solves a constrained dynamic optimal control problem by means of a repeated on-line optimisation of the open-loop problem instead of a difficult off-line computation of a control law.

The methodology of all the controllers belonging to the MPC family is characterised by the following strategy [16], represented in Figure 2.2:

1. The future outputs for a determined horizon N_p, called the prediction horizon, are predicted at each sampling instant t using the dynamic model of the system. These predicted outputs $y(t+k \mid t)$[5] for $k = 1 \ldots N_p$ depend on the known values up to instant t (past inputs and outputs and current state) and on the future control signals $u(t+k \mid t)$, $k = 0 \ldots N_p - 1$, which are those to be computed and sent to the system.

2. The sequence of future control signals is calculated by optimizing a determined criterion which, in general, will try to keep the output as close as possible to the reference trajectory $w(t+k)$ (which can be the setpoint itself or a close

[4] "The degree to which an asset or security can be quickly bought or sold in the market without affecting the asset's price." - Investopedia

[5] The notation indicates the value of the variable at the instant $t+k$ calculated at the current instant t.

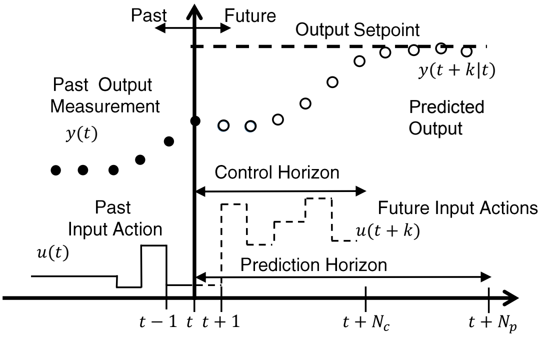

Figure 2.2 MPC Strategy [17]. Reprinted with permission..

approximation to it). This criterion usually takes the form of a quadratic function of the errors between the predicted output signal and the predicted reference trajectory and it can include the necessary control effort. Although the Euclidian norm is the most used, also the first or the infinity norms can be considered in the cost function.

3. The control signal $u(t \mid t)$ is sent to the process while the next control signals calculated are discarded, because at the next sampling instant $y(t+1)$ is already known (feedback action). Step 1 is repeated with this new value and all the sequences are brought up to date. Thus, the signal $u(t+1 \mid t+1)$ is calculated (which may be different from $u(t+1 \mid t)$ because of the new information available) using the receding horizon concept.

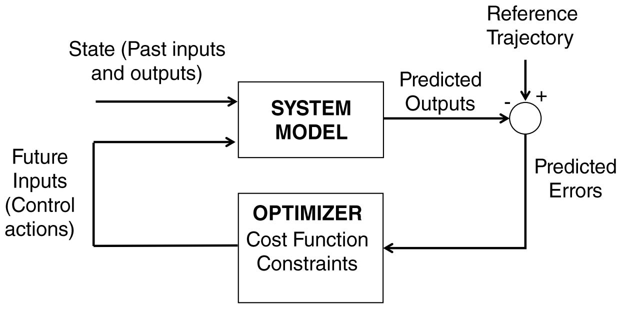

Figure 2.3 Basic structure of MPC [17]. Reprinted with permission..

This strategy is implemented using the basic structure shown in Figure 2.3. A dynamical model is used to predict the future system output, based on past and current values and on the proposed optimal future control actions. These actions are calculated by the optimiser taking into account the cost function as well as the constraints.

2.2.2 Model Predictive Control and Microgrids

Several features of MPC makes it a suitable methodology to be used in microgrids and in general multi-carrier energy systems. Besides its intuitive formulation, the method is easy to understand and it can include constraints and nonlinearities and manage multivariable as well as distributed cases. However, since an optimisation problem is solved at each sampling instant, the computational cost is high compared to traditional control schemes. The following are some of the microgrid related issues that can be addressed by MPC:

- The coordinated operation of different RESs and ESSs in the microgrid is a difficult task. The multivariable nature of MPC provides an optimal control solution that can manage the operation of the microgrid units in a coordinated way in order to achieve the objectives.
- The intermittence and variability of renewable generation, as well as demand, can be included in the optimisation problem by considering stochastic variables, leading to a control action that can cope with randomness.
- MPC can be used when binary/logical variables must be considered in the optimisation. This is the case of the connection/disconnection of units (storage devices, electric vehicles, loads, etc.) or the consideration of changing situations, as is the case of different price of energy for purchasing or selling.
- When sudden changes in the microgrid appear, such as the disconnection or malfunctioning of a certain unit, MPC can adapt to this new situation by changing its structure and therefore allow a normal operation of the microgrid, provided that there are degrees of freedom available.
- In case that several agents participate in the problem, as is the case of a network of microgrids or microgrids that are geographically distributed, the problem can be solved in a distributed way. MPC can provide a distributed solution, so that complex problems can be addressed.

2.2.3 Methodology

MPC is a family of methods that differ amongst themselves in the type of model, the cost function and the solving method. Different formulations of MPC can be used for microgrid control. Since storage is an important component of microgrids, the dynamic models of microgrids are generally formulated as state-space equations where the state variable $x(t)$ coincides with the state of charge of the energy storage units. Therefore, state-space MPC is a good candidate to control microgrids and thus state-space models can be used to formulate the predictive control problem. Besides, this formulation can easily deal with multivariable systems, which is the common case in microgrids. The following equations are used in the linear case to capture system dynamics:

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned} \tag{2.6}$$

The state vector is $x(t)$, $y(t)$ and $u(t)$ are scalars in the single-input single-output (SISO) case, but in multiple-input multiple-output (MIMO) systems the input vectors $u(t)$ is of dimension m and $y(t)$ of dimension n. In microgrids usually the output $y(t)$ coincides with the state $x(t)$, so the process is MIMO and matrix C equals identity.

Once a dynamic model is available, it can be included in the cost function and proceed to its minimisation. The various MPC algorithms use different cost functions for computing the control law. Typically, the main goal is that the future output $y(t)$ tracks a certain reference signal $w(t)$ along the horizon while penalizing the control effort $u(t)$ necessary for doing so. In the most general case of MIMO processes, inputs and outputs are vectors and therefore the costs are computed using quadratic functions, where R and P are positive definite weighting matrices which are usually diagonal:

$$J(N_p,N_c) = \sum_{j=1}^{N_p} \|\hat{y}(t+j \mid t) - w(t+j)\|_R^2 + \sum_{j=1}^{N_c} \|u(t+j-1)\|_P^2 \tag{2.7}$$

being $\|.\|_R^2$ the 2-norm[6]. N_p is the prediction horizon and $N_c \leqslant N_p$ is the control horizon, which do not necessarily have to take the same value. The value N_p sets the limit of the time instants in which it is desirable for the output to track the reference. The control horizon concept (N_c) consists of considering that after a certain interval $N_c < N_p$ the proposed control signals will be kept constant, that is, $u(t+j)$ does not change after $j = N_c$:

This can significantly reduce the number of decision variables and, therefore, the complexity of the problem. The coefficients $\delta(j)$ and $\lambda(j)$ are sequences that consider the relative weight of error and control effort along the horizon; usually constant values or exponential sequences are considered.

Notice that $x(t)$ must be calculated using and observer in case the state vector is not accessible. Then, the predictions along the horizon are given by [18]:

$$\begin{aligned}
\mathbf{y} &= \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{N_p} \end{bmatrix} x(t) + \begin{bmatrix} CB \\ CA^2B \\ \vdots \\ \sum_{i=0}^{N_p-1} CA^iB \end{bmatrix} u(t-1) \\
&+ \begin{bmatrix} B & \dots & 0 \\ C(AB+B) & \dots & 0 \\ \vdots & \ddots & \vdots \\ \sum_{i=0}^{N_p-1} CA^iB & \dots & \sum_{i=0}^{N_p-N_c} CA^iB \end{bmatrix} \mathbf{u}
\end{aligned}$$

[6] Defined as $\|x\|_R^2 = x^T Rx$.

where boldface lower letters are used to indicate vectors composed of elements along the horizon and boldface upper case letters denote matrices composed of other matrices and vectors. Then, the last equation can be written in vector form as:

$$\mathbf{y} = \mathbf{F_1} x(t) + \mathbf{F_2} u(t-1) + \mathbf{H_1}\mathbf{u} \tag{2.8}$$

Then, the control action is calculated as

$$\mathbf{u} = (\mathbf{H_1}^T \mathbf{H_1} + \lambda I)^{-1} \mathbf{H_1}^T (\mathbf{w} - \mathbf{F_1} x(t) - \mathbf{F_2} u(t-1)) \tag{2.9}$$

Notice that the prediction (2.8) has of three terms: the first is the free response of the system $\mathbf{f} = \mathbf{F_1} x(t)$, which depends on the current state and therefore is known at instant t. The second term, that depends on $u(t-1)$, does not depend on the decision variable $\mathbf{u}$ and therefore does not affect the optimisation since. The third term does depend on the future control sequence $\mathbf{u}$, which is calculated minimizing the objective function (2.7), that (in the case of $\delta(j) = 1$ and $\lambda(j) = \lambda$) can be written as:

$$J = (\mathbf{H_1}\mathbf{u} + \mathbf{F_1} x(t) + \mathbf{F_2} u(t-1) - \mathbf{w})^T R(\mathbf{H_1}\mathbf{u} + \mathbf{F_1} x(t) + \mathbf{F_2} u(t-1) - \mathbf{w}) + \lambda \mathbf{u}^T P \mathbf{u}$$

If there are no constraints, the analytical solution that provides the optimum can be calculated by imposing that the derivative of J must equal 0, giving:

$$\mathbf{u} = (\mathbf{H_1}^T \mathbf{H_1} + \lambda I)^{-1} \mathbf{H_1}^T (\mathbf{w} - \mathbf{F_1} x(t) - \mathbf{F_2} u(t-1))$$

As stated in the previous section, the receding horizon implies that only the first element of the control sequence, $u(t)$, is used and all the computation is repeated at the next sampling time.

The control law is always a static state feedback law. In the constrained case the solution is obtained solving a Quadratic Programming (QP) algorithm.

Part II

Contributions

3 Simultaneous Optimal Power Dispatch and Optimal Power Scheduling through Economic Model Predictive Control

Observe due measure, for right timing is in all things the most important factor.

WORK AND DAYS, C. 700 BC
HESIOD

THIS *chapter proposes a strategy that tackles Optimal Power Scheduling and Optimal Power Dispatch together through the use of Economic Model Predictive Control. The modelling of energy entities as energy hub and the modelling of loads are described in Section 3.2. In Section 3.3, the EMPC strategy is presented. Section 3.4 describes a case study based on an olive mill with a waste valorisation line where four different operating scenarios are simulated. Finally, Section 3.5 concludes the chapter.*

3.1 Introduction

Until the emergence of distributed generation systems and the extension of small-scale renewable production equipment, end-users have been pure consumers of local electricity distribution companies. For decades, the only way for these end-users to save on their electricity bills has been to use the most energy-intensive equipment during lower energy price periods. Logically, this is cumbersome for humans, since it requires someone to be aware of the prices to decide on activation and physically present to switch on different household appliances (in the case of households) or productive equipment (in the case of businesses), which is not always possible. The use of timers is also an option, but these must also be programmed by someone. The appearance of smart appliances in recent years has led to the appearance of new lines of automation such as domotics, and the intensification of automation in factories, with concepts such as industry 4.0. The deployment of devices that can not only be tele-operated but are also capable of communicating with each other through the Internet of Things greatly facilitates saving strategies, since it relieves people of the role of implementers. On the other hand, one or more machines are in charge of optimizing the energy operation of the house or factory. These elements are called Energy Management Systems (EMS), and usually consist of a hardware device interposed between the network connection point and the various equipment of the installation, and a software program that executes the tasks of smart metering, optimisation and control of such equipment.

The use of EMSs allows the implementation of a range of demand optimisation strategies that fall within the concept of Demand Side Management (DSM). Several of these techniques have been widely discussed in the literature, such as Load Shaping, which literally consists of artificially moulding the profile of the load in pursuit of different objectives: economic savings, network decongestion, etc. The set of operations that allow optimal load shaping is known as Optimal Power Scheduling (OPS).

In recent decades, distributed renewable generation facilities have appeared and become widespread. Techniques and equipment that enable the energy recovery of operational wastes, especially in industry, are also increasingly common. Nowadays, the improvement and cheapening of energy storage systems results in more and more homeowners and companies including these systems in their energy installation, especially to broaden the profitability potential of their renewable generation.

All this makes it increasingly common that both homes and industries dispose of several energy vectors (electricity from the utility, electricity from RG, district heating, biomass...) to satisfy several types of loads (electricity consumption, heat consumption, cold consumption, etc.). These are known as multi-carrier energy systems or microgrids, although this term is usually reserved for all-electrical systems. The EMSs of this type of installations, in addition to choosing the optimal periods for the use of the different loads, must also select the most profitable sources to satisfy the demand generated by these loads. This task is known as Optimal Power Dispatch (OPD).

Finally, the possibility of selling part of the surplus renewable production represents an additional degree of freedom to consider when optimizing energy planning. This chapter proposes a strategy that tackles both OPS and OPD together through the use of Economic Model Predictive Control (EMPC).

3.2 Modelling

3.2.1 Modelling of Energy Entities as Energy Hub

To model the energy entities (either homes, companies or industries) in terms of energy, the Energy Hub concept is used, with the modifications adopted in [19] to contemplate renewable energy consumption and production, leading to a complete Energy Hub equation given by:

$$(\mathbf{L}+\mathbf{T}) = \mathbf{C}\cdot(\mathbf{P}+\mathbf{R}) - \mathbf{S}\cdot\mathbf{E} = \begin{bmatrix} \mathbf{C} & -\mathbf{S} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{P}+\mathbf{R} \\ \mathbf{E} \end{bmatrix} \tag{3.1}$$

which means that the sum of loads **(L)** plus remaining energy sold to the grid **(T)** must be equal to the aggregation of purchased energy **(P)** and energy obtained from renewable sources **(R)** multiplied by the conversion matrix **(C)**, plus the stored energy (**E**) multiplied by the storage matrix **(S)** . The elements of matrix **C** are the conversion efficiencies of the different energy converters the entity has at its disposal. The **S** matrix includes the charging and discharging efficiencies of the different storage elements that may exist for the different energy carriers.

The energy hub concept is generalised here to model the energy entities from a mass-energy perspective, which allows to handle energy flows (electricity, heat, etc.) and mass flows (raw goods, subproducts, wastes, biomass) simultaneously in a single modelling interface.

3.2.2 Modelling of Loads

The operation of any energy entity is possible through the succession of a series of energy operations. The activation of any of these operations implies the satisfaction of different types of energy loads not only at the present time but also in the immediate future. In a domestic environment, an operation might be the individual utilisation of devices or appliances whose requirements are known a priori (e.g. using a dishwasher in a fixed-time program). For industries, an operation might be the triggering of the manufacturing process of a certain quantity of raw material. In any case, the activation of such operations generates certain multicarrier energy loads.

Let $\boldsymbol{O} = \{\mathrm{o}_1,\ldots,\mathrm{o}_{N_\mathrm{o}}\}$ be the set of possible energy operations, where $N_o = |\boldsymbol{O}|$. Let $\boldsymbol{C} = \{c_1,\ldots,c_{N_c}\}$ be the set of possible energy carriers, where $N_c = |\boldsymbol{C}|$. Let τ_p^i be the time duration of operation $o_i, i \in \{1,\ldots,N_o\}$ and let $\boldsymbol{\ell}_i = \left[\ell_i^j(k)\right]^\top$, $j \in \{1,\ldots,N_c\}$, $k \in \{1,\ldots,\tau_p^i\}$ be the time multicarrier unitary (per single use of appliance or per unit of raw material) demand profiles. Let $\mathbf{u}^{\mathrm{o}}(k) = [u_i(k)]$ be the vector that contains the activation commands for the N_o possible energy-requiring operations at instant k.

The global multicarrier load profile can be calculated by means of the convolution operation. The length of the convolution of two sequences of length M and N respectively is equal to $M+N-1$. Therefore, taking a certain instant τ_0 as a reference, for an operation profile of length $\Delta\tau$ hours, the global load profiles can be computed as:

$$\mathbf{L}(k)\Big|_{k=\tau_0}^{k=\tau_0+\Delta\tau+\max_i(\tau_p^i)-1} = \sum_{\forall i\in O} \boldsymbol{\ell}_i * \mathbf{u}^o(k)\Big|_{k=\tau_0-\max_i(\tau_p^i)}^{k=\tau_0-\max_i(\tau_p^i)+\Delta\tau} \tag{3.2}$$

where $\mathbf{L} = \left[\mathbf{L}^j\right]^\top$ contains the resulting temporal multicarrier *global* load vectors, result of adding the individual multicarrier loads associated to the N_o possible simultaneous operations.

The convolution operation is used to predict future load demands, based on current and previous quantities of goods introduced in the productive process. For this approach to be applicable, it is necessary that unitary energy demand profiles can be determined.

3.3 Optimisation

3.3.1 Dynamics of the Energy Hub

State-space-based Model Predictive Control (SS-MPC) is used to perform Optimal Power Scheduling and Optimal multi-carrier Power Dispatch for the energy entity. Model Predictive Control is adequate to control multi-carrier energy systems as it allows to consider properly the dynamics of storage elements, the characteristics of gas and electricity distribution networks and to include constraints in a systematic way [20].

The dynamic of the energy hub that represents the entity is defined by the following discrete-time LTI model in state space:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{x}(k) + \boldsymbol{\Lambda}(k)\cdot\mathbf{u}(k) \\ \mathbf{y}(k) &= \boldsymbol{\Gamma}(k)\cdot\mathbf{u}(k) \end{aligned} \tag{3.3}$$

Let $\mathcal{S} = \{s_1,\ldots,s_m\}$ be the set of available energy storage, where $m = |\mathcal{S}|$. The state vector $\mathbf{x}(k) = [E_1,\ldots,E_m]$ represents the levels of the different multi-carrier storage systems available to the energy entity. The input vector $\mathbf{u}(k) = \left[\mathbf{u}^L(k),\mathbf{u}^E(k),\mathbf{u}^o(k)\right]^\top$ contains all the exterior and interior inputs to all the converters and storage elements, along with the command sequence operation activations. The storage is modelled as follows:

$$\begin{bmatrix} E_1(k+1) \\ \vdots \\ E_m(k+1) \end{bmatrix} = \begin{bmatrix} E_1(k) \\ \vdots \\ E_m(k) \end{bmatrix} + \underbrace{\begin{bmatrix} e_1^{ch} & \cdots & 0 & -\frac{1}{e_1^{dis}} & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & e_m^{ch} & 0 & \cdots & -\frac{1}{e_m^{dis}} \end{bmatrix}}_{\boldsymbol{\Lambda}^E} \cdot \underbrace{\begin{bmatrix} Q_1^{ch}(k) \\ \vdots \\ Q_m^{ch}(k) \\ Q_1^{dis}(k) \\ \vdots \\ Q_m^{dis}(k) \end{bmatrix}}_{\mathbf{u}^E(k)} \tag{3.4}$$

where the charge and discharge flows of each tank are modelled as semidefinite positive separate variables.

Vector $\mathbf{y}(k) = \left[\mathbf{L}^j, \mathbf{T}^j\right]^\top$, which contains all the outputs of the hub, can be expressed in terms of the coupling conversion and coupling storage matrices as follows:

$$\mathbf{y}(k) = \mathbf{\Gamma}^L(k) \cdot \mathbf{u}^L(k)^\top + \mathbf{\Gamma}^E(k) \cdot \mathbf{u}^E(k)^\top \tag{3.5}$$

which is equivalent to (3.1) with $\mathbf{\Gamma}^L(k) = \mathbf{C}$ and $\mathbf{\Gamma}^E(k) = \mathbf{e} \odot \mathbf{S}$, where $\odot$ means the Hadamard product of the $\mathbf{e}$ matrix containing the efficiencies of each storage interface and the $\mathbf{S}$ matrix that relates the different stored elements with its possible outputs. Obviously, to be consistent with the formulation presented in (3.3) the following definitions are assumed:

$$\mathbf{\Lambda}(k) = \left[\mathbf{0} | \mathbf{\Lambda}^E(k)\right] \tag{3.6a}$$

$$\mathbf{\Gamma}(k) = \left[\mathbf{\Gamma}^L(k) | \mathbf{\Gamma}^E(k)\right] \tag{3.6b}$$

Using this operative, a generic energy hub can be described by a set of matrices $H = \{\mathbf{\Lambda}(k), \mathbf{\Gamma}(k)\}$, which is one of the advantages of the formulation proposed in [21], which provides a simple method to model this kind of theoretical structures.

3.3.2 Formulation of the Control Problem

Manipulated variables $\mathbf{u}(k)$ are divided into three groups: those that control the mass flow/power input to the different energy converters available in the installation, $\mathbf{u}^L(k)$; those that control the mass/flow (dis)charging power of the storage facilities, $\mathbf{u}^E(k)$, and those that trigger the different energy operations, $\mathbf{u}^o(k)$. The EMPC receives the state of the storage systems as feedback ($\mathbf{x}(\mathbf{k})$).

EMPC is solved in a receding horizon fashion. At a sampling instance τ_k, the EMPC receives a state measurement of the current process state which is used to initialise the EMPC. An optimal piecewise input trajectory is computed over the prediction horizon corresponding to the time $t \in [\tau_k, \tau_{k+N})$ in real-time. The optimal input trajectory computed at a given sampling instance is denoted as $\mathbf{u}^*(t|\tau_k)$. The first control action, denoted as $\mathbf{u}^*(0|\tau_k)$ is sent to the control actuators to be implemented over the sampling period from τ_k to τ_{k+1}. At the next sampling period, the EMPC is re-solved.

For each optimisation instant τ_k, the EMPC problem consists on finding the:

$$\mathbf{u}^*(t|\tau_k) = \arg\min_{\mathbf{u}} \mathcal{J}(\mathbf{x}(\tau_k), \mathbf{u}) = \sum_{l=\tau_k}^{\tau_{k+N_p-1}} \boldsymbol{\rho}(l) \cdot \mathbf{u}(l) - \boldsymbol{\upsilon}(l) \cdot \hat{\mathbf{y}}(l) \tag{3.7}$$

subject to the dynamics of (3.3) and to the following generic constraints:

$$\underline{\mathbf{x}} \leq \hat{\mathbf{x}}(l+1) \leq \overline{\mathbf{x}} \tag{3.8a}$$
$$\underline{\mathbf{u}} \leq \mathbf{u}(l) \leq \overline{\mathbf{u}} \tag{3.8b}$$
$$\underline{\mathbf{y}} \leq \hat{\mathbf{y}}(l) \leq \overline{\mathbf{y}} \tag{3.8c}$$
$$\underline{\zeta_n} \leq \sum_{\forall i} u_{n_j}(l) \leq \overline{\zeta_n} \tag{3.8d}$$

where N_p is the prediction horizon. Vector $\boldsymbol{\rho}(l)$ contains the prices of the purchasable input energy carriers during time period l, $\boldsymbol{\upsilon}(l)$ contains the prices at which the grid purchases the different energy types during time period l, ζ_n is the operating input capacity of the n^{th} energy converter/storage element within the hub, and $u_{n_j}(l)$ is the j^{th} input to the n^{th} converter/storage during hour l. Underlined symbols represent minimum allowable values, while overlined ones stand for maximum ones. The hat indicates future values of states and outputs that would result from the application of the optimised input trajectory.

Since a storage cannot be charged and discharged at the same time, two binary variables δ_s^{ch} and δ_s^{dis}, with $s \in \{1,...,m\}$, are introduced for each one of the m available storage devices. The following additional constraints

$$0 \leq Q_s^{ch}(l) \leq \delta_s^{ch}(l) \cdot \overline{Q_s^{ch}} \tag{3.9a}$$
$$0 \leq Q_s^{dis}(l) \leq \delta_s^{dis}(l) \cdot \overline{Q_s^{dis}} \tag{3.9b}$$
$$0 \leq \delta_s^{ch}(l) + \delta_s^{dis}(l) \leq 1 \tag{3.9c}$$

for $l = \tau_k, \ldots, \tau_{k+N-1}$, are imposed to $\mathbf{u}^E(l)$ in order to force only one of each two variables $Q_s^{ch}(l)$ and $Q_s^{dis}(l)$ to be greater than zero at the same time.

Load satisfaction is one of the model's constraints through (3.3). These loads are linearly dependent on the values of the manipulated variable $\mathbf{u}^o(k)$. Therefore, this formulation allows the OPS to be performed inherently by shaping the loads according to equation (3.2). Of course, the range of shiftability both in the use of different household appliances or air conditioning equipment (in domestic environments) and in the production profile (in industrial environments) is restricted by a series of constraints that are particular to each particular house or specific industry.

$$F(\mathbf{u}^o) \leq 0 \tag{3.10}$$

where $F(\circ)$ is a set of arbitrary functions.

Finally, there is an additional constraint due to domestic legislation in Spain. Produced renewable energy must be self-consumed, and if and only if there is a surplus of renewable energy, this excess can be pumped into the grid. Oppositely, if renewable production is not enough to cover the load demand for a certain time slot, and thus non-renewable energy might be purchased, no energy can be sold to the grid during that same time slot:

$$\mathbf{P} > 0 \implies \mathbf{T} = 0 \tag{3.11}$$

To sum up, the control problem is completely defined by the objective function (3.7), subject to the model constraints (3.3), the output constraints (3.2), and the input constraints (3.8) (a-d), (3.9) (a-c), (3.10) (a-c) and (3.11).

3.4 Case Study: An Olive Mill with a Waste Valorisation Line

3.4.1 Problem Description

To test the previous controller, it was implemented in an industrial case study: the virgin olive oil extraction process in an olive mill [22]. VOOEP is a thermomechanical process that requires heat energy to warm the crushed olive paste and electrical energy to supply the different extraction and centrifugation equipment. Figure 3.1 shows the time profiles of electro-thermal consumption per 8 t of processed olives, from its introduction into the process to the storage of the corresponding volume of oil after τ_p hours.

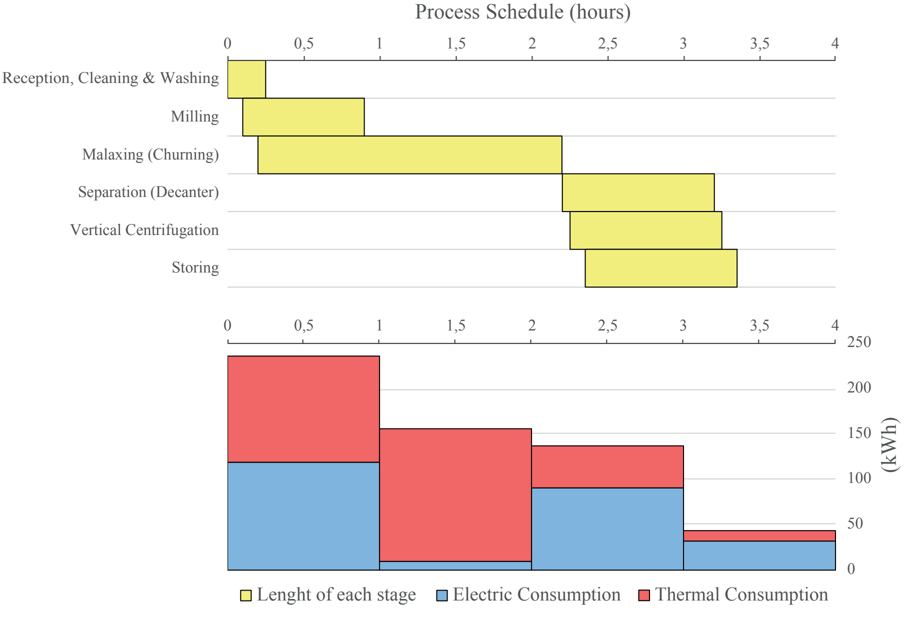

Figure 3.1 Combined graph. Bars show the Gantt Chart for the oil extraction process; Columns show the hourly based aggregated electric and thermal loads associated to the process. Calculations have been made for 8000 kg of olives introduced in an hour, which fill the decanter.

During the extraction process, a series of by-products and residues are generated that can be reused to produce energy or sold in secondary markets. Figure 3.2 shows the mass balance per processed ton of olives.

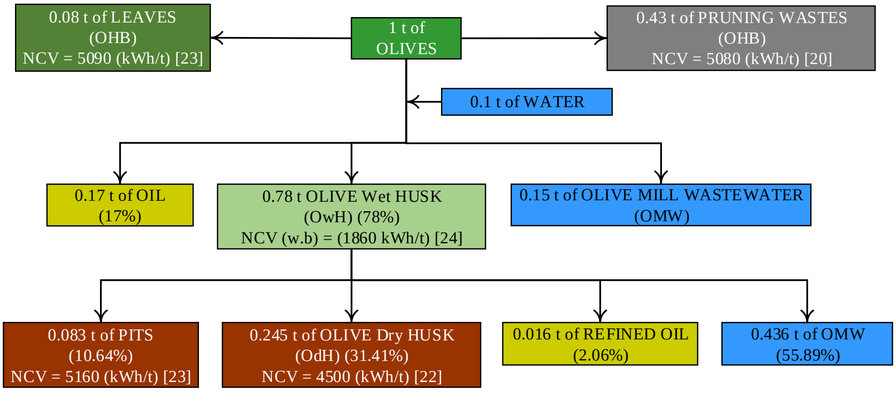

Figure 3.2 Mass & Energy Balance for the two phase olive oil extraction process. Modified from [23] with data from [24, 25, 26, 27, 28].

The *Biogas to Proton Exchange Membrane Fuell Cell* (Biogas2PEM-FC [1]) project was an European FP7 project that aimed to valorise subproducts and wastes from olive oil production process, determining whether energy generation through common disposal of stone-free Olive Wet Husk (OWH) and Olive Mill Wastewater (OMW), which together form so-called Solid-Liquid Olive Mill Wastes (SLOMW), can be economically beneficial when compared to current habitual disposal procedures, namely the selling of the OwH and the elimination of OMW through natural evaporation. Project partners proposed a treatment strategy which combines the solution to the environmental problem with the energetic valorisation of aforementioned residues, by means of the sequential realisation of the following processes: (i) Common anaerobic digestion of solid and liquid wastes to produce biogas; (ii) Reformation of biogas to obtain a hydrogen-rich gas stream, including a post-treatment stage to remove as much damaging impurities for the Fuel Cell (FC) as possible, and (iii) Generation of electricity by means of a proton exchange membrane fuel cell. A semi-pilot scale prototype plant was deployed at SCA San Isidro, in Loja (Granada, Spain), and real operating tests were conducted with good results.

The integration of the waste reuse line in the oil mill's energy installation results in an energy hub model as shown in Figure 3.3. Within this layout, $\mathbf{x}(k) = \left[E_{bg}(k), E_{rg}(k), E_{ohb}(k)\right]^\top$ represents the state of the biogas, reformed gas and olive harvesting biomass tanks, respectively. The inputs vector $\mathbf{u}(k) = \left[\mathbf{u}^L(k), \mathbf{u}^E(k), o_i(k)\right]^\top$,

[1] Biogas2PEM-FC web page: www.biogas2pemfc.eu

where:

$$\mathbf{u}^L(k) = \left[P_{el}(k), P_{ng_1}(k), P_{ng_2}(k), R_{ohb}(k), R_{slomw}(k), R_{el}^L(k), R_{el}^T(k), P_{bg_1}(k), \ldots P_{bg_2}(k), P_{bg_3}^L(k), P_{bg_3}^T(k), P_{rg}^L(k), P_{rg}^T(k)\right]$$

$$\mathbf{u}^E(k) = \left[Q_{bg}^{ch}(k), Q_{bg}^{dis}(k), Q_{rg}^{ch}(k), Q_{rg}^{dis}(k), Q_{ohb}^{ch}(k), Q_{ohb}^{dis}(k)\right]$$

contains all the exterior and interior inputs to all the converters and storage elements. The vector of outputs is $\mathbf{y}(k) = \left[L_{el}, T_{el}, L_{he}, T_{ohb}, T_{slomw}, T_{fert}\right]^T$, which must comply with equation (3.5).

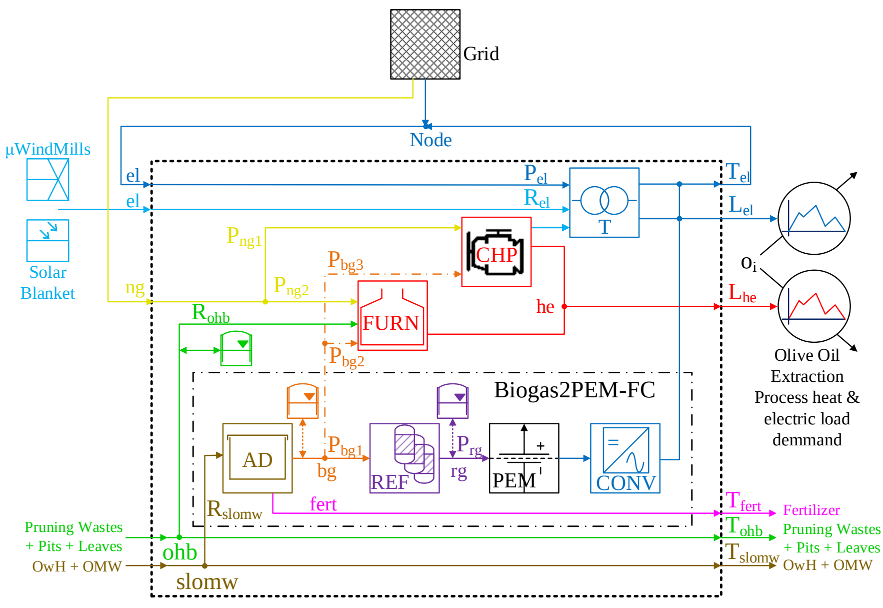

Figure 3.3 Layout of the mass-energy hub model of a generic olive mill. Solid lines in the figure represent actual installation of the mill, while discontinuous lines represent extra elements of the Biogas2PEM-FC treatment line, which are considered only for some simulation scenarios.

The elements of matrices **C** and **S** are built using the energy conversion efficiencies from Table 3.1. The efficiencies of energy converters within the Biogas2PEM-FC line come from real tests performed during the project. The energetic equivalence of resulting OHB and SLOMW per tonne of introduced olives is calculated using the data on Figure 3.2. The remaining efficiencies are set according to reasonable engineering values.

The proposed control structure is depicted in Figure 3.4. The mill is splitted into two different levels (dotted red line). On one hand the manufacturing side, whose low-level regulation is already implemented. The EMPC is applied over the energy

Table 3.1 Energy conversion efficiencies used for simulations.

Efficiencies			
Concept	Value	Concept	Value
$\eta^{T}_{el\to el}$	0.98	$\eta^{CHP}_{ng\to el}$	0.4
$\eta^{CHP}_{ng\to he}$	0.45	$\eta^{CHP}_{bg\to el}$	0.37
$\eta^{CHP}_{bg\to he}$	0.4	$\eta^{AD}_{slomw\to bg}$	0.00592
$\eta^{FURN}_{ng\to he}$	0.9	$\eta^{FURN}_{ohb\to he}$	0.8
$\eta^{FURN}_{bg\to he}$	0.85	$\eta^{REF}_{bg\to rg}$	0.58
$\eta^{PEM}_{rg\to el}$	0.46	$\eta^{CONV}_{elDC\to elAC}$	0.95
e^{ch}_{bg}	0.8	e^{dis}_{bg}	1
e^{ch}_{rg}	0.8	e^{dis}_{rg}	1
$\phi_{ol\to ohb}$	3020[a] (kWh/$\mathrm{t_{ol}}$)	$\phi_{ol\to slomw}$	1022[b] (kWh/$\mathrm{t_{ol}}$)

[a] Equivalent to 0.083 tonnes of pits + 0.08 tonnes of leaves + 0.43 tonnes of pruning wastes

[b] Equivalent to 0.78 tonnes of pit-free OwH (see Figure 3.2)

level of the mill, but it also determines the rate at which olives are introduced, thus affecting the manufacturing side. The manipulated variables are divided into: activation commands for energy operations, control signals for the energy converters and control signals for the storage systems. In this case, the only energy operation contemplated is manufacturing. The manipulated variable is the number of tons of olives introduced into the process per hour, i.e. $\mathbf{u}^o(k) = o_i(k)$, being $o_i(k)$ the amount of introduced olives (in $\mathrm{t\,h^{-1}}$). Lower level controllers of the manufacturing side use (o_i) as a reference to rule the production machinery to extract the corresponding amount of VOO. For its part, u^L and u^E drive the generation of the electricity and heat needed by the production equipment ($\mathbf{L}$) and the exceeding energy that is sold, either in electricity or biomass form ($\mathbf{T}$). The translation of $\mathbf{u}$ into low-level control actions is beyond the scope of this paper. The EMPC receives the state of the storage systems as feedback (x).

Working ranges of converters and storage are displayed in Table 3.2). These values particularise the operational constraints (3.8) and (3.9).

The difference between the amount of olives that the mill expects to receive in future control instants and the actual amount received is considered as a source of uncertainty for the system. On one hand, at each optimisation instant τ_k, the optimiser knows exactly the amount of received olives, $o_r(t)$, as well as the portion of this arrived olives that has been already introduced in the process, $o_i(t)$, for $t \in \{\tau_0,\dots,\tau_{k-1}\}$. On the other hand, based on reception data from previous campaigns, it has an estimation of the amount of olives that the mill expects to receive in the future $N-1$ hours, $\tilde{o}_r(k)$. With these inputs the optimiser calculates an optimal profile of olive introduction,$o_i^*(t|\tau_k)$, in order to minimise the operative energy costs, which actually shapes the load demanded

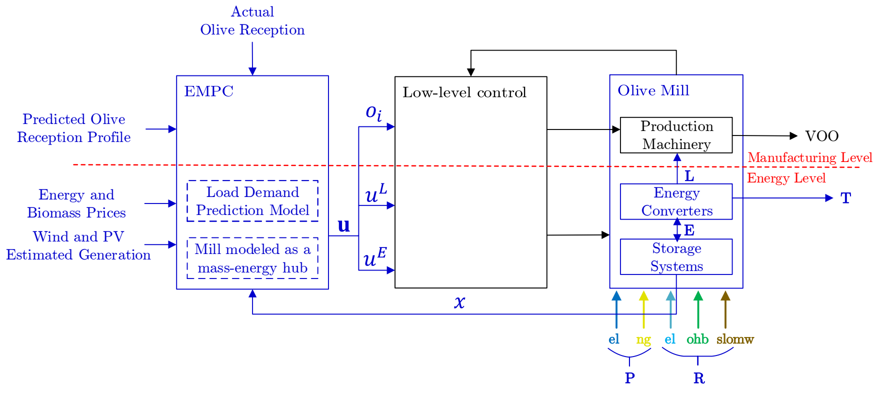

Figure 3.4 Control Scheme. Blue colour indicates those parts of the system which are covered in this work. Adapted from Figure 8 in [29].

Table 3.2 Working Ranges of converters and storage used for simulation.

Working Ranges			
Element	Min	Max	Units
Electric energy consumable from the grid	0	2500	kWh
Natural Gas consumable from the grid	0	2000	kWh
CHP	0	250000	kWh
Furnace	0	350000	kWh
Anaerobic Digester	0	150400 [a]	kWh
Reformer	0	150000	kWh
PEM	0	100000	kWh
Olive Harvesting Biomass Deposit	0	38400 [b]	MWh
Biogas Deposit	0	10000 [c]	kWh
Reformate Gas Deposit	0	10000 [d]	kWh

[a] Equivalent to 80 tonnes of SLOMW.
[b] Equivalent to 768 tonnes of OHB.
[c] Equivalent to 1666 Nm^3 of biogas ($NCV_{bg} = 6$ kWh/m^3)
[d] Equivalent to 1058 Nm^3 of reformed gas ($NCV_{rg} = 9.45$ kWh/m^3)

by the mill.

$$\begin{bmatrix} L_{el}(l)\Big|_{l=\tau_k}^{l=\tau_{k+N-1}+\tau_p} \\ \\ L_{he}(l)\Big|_{l=\tau_k}^{l=\tau_{k+N-1}+\tau_p} \end{bmatrix} = \begin{bmatrix} \ell_{el}^u * o_i(l)\Big|_{l=\tau_k-\tau_p+1}^{l=\tau_{k+N}} \\ \\ \ell_{he}^u * o_i(l)\Big|_{l=\tau_k-\tau_p+1}^{l=\tau_{k+N}} \end{bmatrix} \tag{3.12}$$

The generic operating constraints of the equation (3.10) are translated here into three specific constraints. On the one hand, the controller is forced to ensure that all olives received (or expected to be received) during the day are brought into production during the same day. On the other hand, in order to ensure sustainability in the use of gas storage, their content must be identical at the beginning and at the end of the day. On the other hand, waste is not stored between days, so the waste storage must be empty at the end of each day.

$$\sum_{h=\tau_0}^{\tau_k} o_r(h) + \sum_{l=\tau_{k+1}}^{24} \tilde{o}_r(l) = \sum_{h=\tau_0}^{\tau_{k-1}} o_i(h) + \sum_{l=\tau_k}^{24} o_i(l) \tag{3.13a}$$

$$E_{bg}(\tau_0) - E_{bg}(\tau_{24-k}) = 0 \qquad E_{rg}(\tau_0) - E_{rg}(\tau_{24-k}) = 0 \qquad E_{ohb}(\tau_{24}) = 0 \tag{3.13b-d}$$

Finally, regulatory constraint of equation (3.11) translates in the following particular constraint:

$$(P_{el}(l) > 0) \vee (P_{ng_1}(l) > 0) \implies (R^T_{el}(l) = 0) \wedge (P^T_{bg_3}(l) = 0) \wedge (P^T_{rg}(l) = 0) \tag{3.14}$$

3.4.2 Tests and Results

Four different scenarios have been tested, which include all or some of the elements shown in Figure 3.3.

Scenario I: Current Operation This case represents the current way in which olives are processed, that is, at the start of the morning shift, the olives received during the previous day are introduced at maximum rate until all of them are processed. The rationale behind this is to avoid the need for extra shifts and thus its associated overruns, but this does not even take the energy pricing profile into account.

Scenario II: Load Shaping If the olives were not stored till next day but its time of introduction could be selected, the associated loads could be shaped according to (3.12). This leads to a dispersion with regard to processing times, which might force the mill to add working shifts. However, the operation during time slots with lower energy prices also results in a saving of around 1250 €/day in energy costs, as can be seen in Figure 3.8.

Scenario III: Biogas2PEM-FC line with Load Shaping This scenario introduces the Biogas2PEM-FC processing line (dotted dashed box in Figure 3.3, excluding the biogas and reformed gas deposits). This offers the mill another way to valorise its wastes and subproducts other than selling them at relatively fixed stable prices. Instead, they are able to produce renewable electricity whose excess is injectable to the grid. The price of this electricity equals the hourly price of purchased electricity, being this amount discounted from future consumptions at an equivalently priced hourly period (*net metering* schema).

Scenario IV: Biogas2PEM-FC, Gas Storage and Load Shaping Finally, the gas storage elements are added to the simulation to analyse its effect on energy costs.

For all of them the actual hourly olives reception profile is randomly generated from normal distributions, whose mean value and standard deviation parameters are established according to reception data from the same days during previous harvesting campaigns. The mill offers two reception periods to its associates, either in the morning or evening (see Table 3.3).

Table 3.3 Parameters of normal distributions used to model hourly reception of olives.

Reception Period	Time	μ (t/h)	σ (t/h)
Morning	9:00 - 14:00	38	8
Evening	17:00 - 21:00	144	20

Each scenario has been tested for a single day of operation. The resulting optimisation problem is a MILP which has been implemented using YALMIP Toolbox [30] and solved using IBM® ILOG ® CPLEX Optimiser [31], both over MATLAB.

The daily olives introduction profiles generated by the EMPC-based optimiser for the four scenarios are depicted in Figure 3.5, where the difference between expected olives and actually received can also be seen. The optimiser performs OPS by arranging these introduction instants to minimise the cost of purchased energy and/or maximise the revenue obtained from energy sold (Figure 3.6).

The timing of olives introduction directly determines the resulting load profiles (Figure 3.7). The EMPC also provides the OPD through the matrix of energetic sources needed to satisfy the demand (Figure 3.9). Figure 3.8 shows that even without considering the Biogas2PEM-FC processing line, a sensible increase in revenue (+4.75%) can be obtained only by arranging the olives introduction instants to time slots where the energy is cheaper. Reduction in energy cost in this case is much greater than the foreseeable increment in labour costs due to adding extra working shifts. Waste revaluation strategies such as the one proposed by the Biogas2PEM-FC project increase the production alternatives of the energy hub. Thanks to this, the EMPC can obtain a greater benefit by carrying out the OPD (around +8.5% when compared to current operation).

3.5 Conclusions

In this chapter, EMPC is used to jointly perform the OPS and OPD of an energy entity. This entity can be a house, a business, a factory or, more generally, a microgrid, as long as they have energy operations whose realisation can be displaced in time. Whatever the type, the energy level of the entity is modelled using the Energy Hub

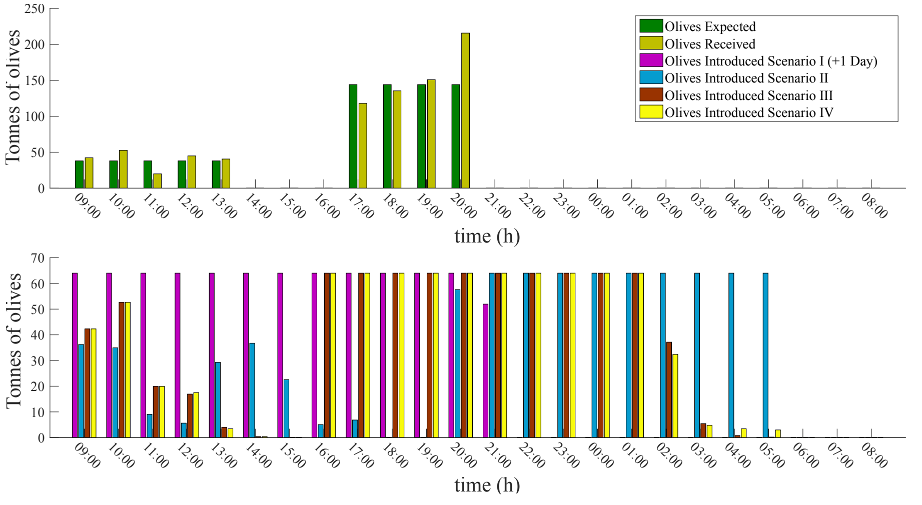

Figure 3.5 Olives expected vs. actually received profiles (top) and resulting olives introduction profiles for each scenario (bottom).

concept. The optimal selection of the timing of the operations shapes the demand. This demand is equal to the convolution of the activation instants with the multi-carrier unitary demand profiles of each operation.

The proposed controller is applied to the Real-Time Energy Management of an olive mill. The results show that improvements are obtained in the economic performance derived from the energy operation of the plant (excluding the profits obtained from the sale of the product itself). The greater the number of energy conversion alternatives for the plant, the greater the improvements.

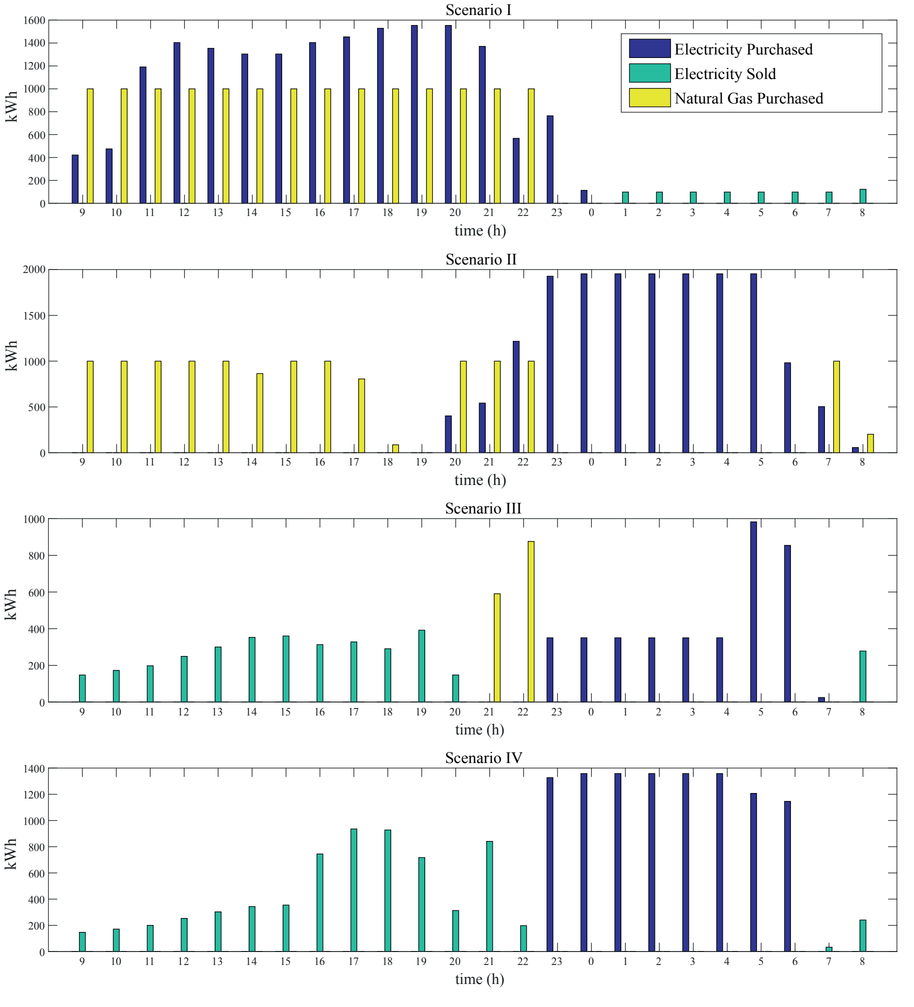

Figure 3.6 Disaggregation of purchased and sold energy, for each scenario. Note that values for Scenario 1 actually represent the following day.

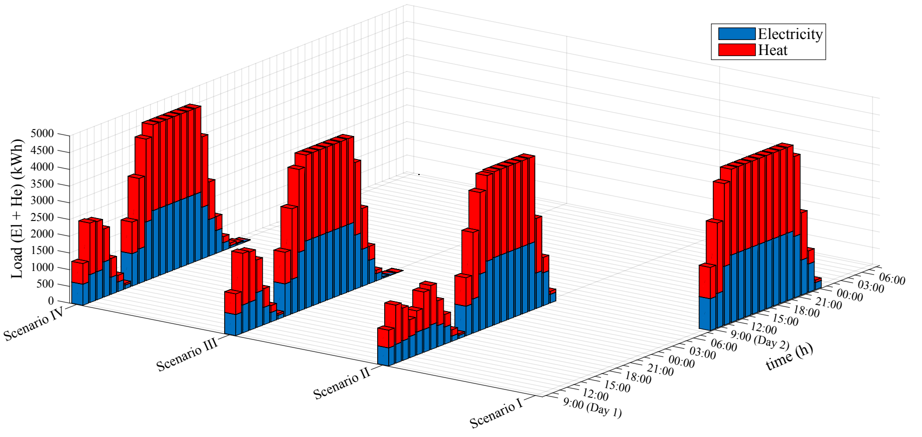

Figure 3.7 Comparative of resulting aggregated load (Electricity + Heat) for each scenario.

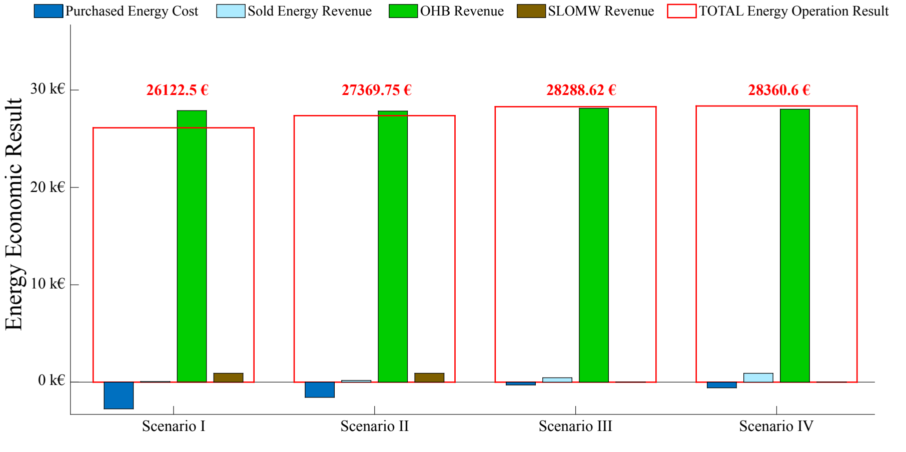

Figure 3.8 Comparative of Energetic Economic Result for each scenario.

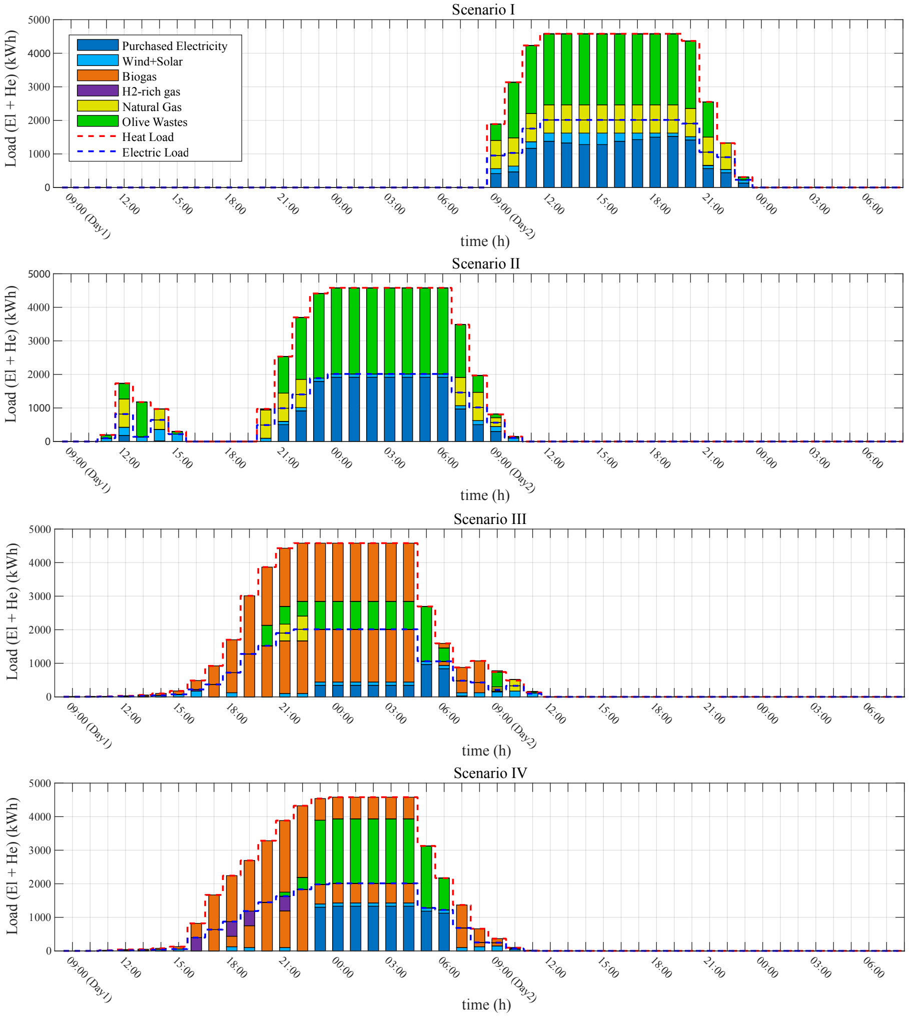

Figure 3.9 Disaggregation of total loads by energy source, for each scenario. Note that aggregated electricity and heat load from Figure 3.7 have been depicted in dashed lines.

4 Influence of Time in the Efficiency Comparison between CDAs and DDAs for Energy P2P Trading

Energy is time, and time is everything.

OUR KNOWLEDGE OF THE EXTERNAL WORLD, 1914
BERTRAND RUSELL

In *this chapter, a comparative analysis of different market structures based on auctions is carried out in order to subsequently propose a solution that fits different P2P energy exchange scenarios. Section 4.2 sets out the particularities of energy that condition its trading as a market good. It also discusses the literature regarding the use of double auctions in eP2P markets. Section 4.3 discusses the performance of various types of DAs in a particular static market case where a minimum relative profit level is required. Section 4.4 and Section 4.5 introduce the issues related to time use and dynamic market variability. Section 4.6 presents an empirical analysis of the performance of different types of DAs in the case of dynamically structured markets. The conclusions are set out in Section 4.7.*

4.1 Introduction

In the introduction to the previous chapter, the historical evolution of the different strategies available for minimising the cost of energy operation of energy entities was presented. While these entities were pure consumers with respect to the energy retailers, the only option to save was to consume less (demand reduction) or to do so in periods of time in which energy prices were lower (demand shifting). When the end user has its own generation system, it goes from a pure consumer to a self-consumer. However, after satisfying all their demand, they may have an excess of energy. In recent years, and with the aim of promoting the use of energy from renewable sources, the governments of many countries have developed laws that oblige retailers to buy these energy surpluses from end users with renewable generation. In this case, the end users become prosumers. There are different systems that define the way in which traders compensate prosumers for their excess energy: Net Balance, Net Purchase and Sale, etc.. Fundamentally, all of them establish the limits imposed on the amount of compensable excess, as well as the form of monetisation of the same (discount/payment). Whatever the compensation scheme, prosumers, in order to optimise their energy operation can now maneuver not only to minimise the cost of their demand (outcomes) but also to maximise the return of their production (incomes). To maximise the utility of their production, prosumers can fundamentally implement two strategies: i) producing more renewable energy in periods when energy is more expensive (supply shifting), if the type of generating source allows it, and ii) determining the optimal use of production at each moment (storage/self-consumption/sale), as was done in the previous chapter. Normally, the schemes that energy retailers use to compensate prosumers for their renewable production are rigid: either the prices of the compensated energy coincide with those of the energy offered but the compensation is in the form of a discount on future consumption, or the energy is compensated monetarily but up to a certain maximum limit. This rigidity, among many other reasons, has made the concept of peer to peer energy sharing [32] appear in recent years.

4.2 Related work

When classifying existing energy trading proposals, one of the main aspects to take into account is the mathematical framework used to model the market. This framework depends fundamentally on whether the problem of energy allocation between the different players is considered to be solved in a centralised or decentralised manner. In the case of centralised approaches, peers follow the orders of a central controller which is assumed to know all the information about buyers and sellers [33]. Single objective maximisation techniques such as convex optimisation [34], particle swarm optimisation [35] or stochastic programming [36] have been proposed to compute a centralised solution. However, it may seem more realistic to use a decentralised framework, since in most cases the scenario consists of multiple users interacting with each other trying to maximise their own utility without taking into account the utility of other users nor the grid conditions. The decentralised solution usually relies on a Game Theoretic

Approach, either by means of a leader-follower model (Stackleberg game) [37], or by means of non-cooperative game model [38].

An auction can also be modelled as a mathematical game defined by a set of players (buyers and/or sellers), a set of actions (offers) available to each player and a payoff vector corresponding to each combination of strategies. The payoff of each player under a combination of strategies is the expected utility (or expected profit) of that player under that combination of strategies, which is determined by the auction mechanism. Although there are different mechanisms for matching the set of individual offers, this thesis focuses only on double auctions (DAs), which were introduced in Subsection 2.1.2.

In general, when dealing with DAs for energy marketing, due to the specific nature of energy itself, the following particularities apply:

- Energy Auctions are Share Auctions [39]: energy is an infinitely divisible good, although it can always be sold as an aggregate in fixed-size packages. However, it is difficult to define a standard size that allows all agents to offer all the quantity they want, especially if their energy transfer capacities or residence market time are different.
- Dynamic Structure: some energy entities that may be considered market agents are inherently mobile (e.g. electric vehicles), so is their connection and disconnection from the physical medium on which the energy exchange takes place (and therefore their entry and exit from the market). Those agents that are not mobile can also access and exit the market in a variable way over time, as their consumption or production varies. Furthermore, speculative agents, those who do not seek to buy/sell a certain quantity but rather to maximise the profit either by buying or selling, continuously vary their role in the market depending on which of them expect to have greater deal probability and/or greater expected profits.
- Dynamic Information: P2P energy exchange markets between end users often use the public electricity distribution network as the physical basis on which to make transfers. For this reason, most peers are also customers of one of the energy retailers that operate using this network. Therefore, these retailers are, at all times, the reliable alternative to the P2P market. That is why the private valuation of each peer is usually a function of the price offered by its retailer, so that the dynamic variation of the latter usually produces a dynamic variation in the former.
- Perishable Good: if the energy is not sold at a given time, and there is no storage system available, or it is full, it may be inevitable to throw that energy away, losing the ability to capitalise it.
- Non-immediate transfer: once a purchase-sale agreement has been reached, the transfer of the good from buyer to seller does not take place immediately, as is the case with most goods. In contrast, the transfer time is not negligible, and depends on the injection capacity of the seller and the absorption capacity of the buyer, i.e, depends on the power of their respective converters. A derivation of this is that, in the case of agents whose permanence in the market is not constant, but occurs during a certain period of time, the energy they can offer/demand at

each moment decreases linearly with the time elapsed. In these cases there is therefore a trade-off between trading as soon as possible or waiting if the profit obtained is expected to be higher by trading later, even if less quantity can be traded.

There is extensive literature on the use of DAs in energy markets. Table 4.2 presents a classification of some of these works according to the following aspects:

- Type of auction: if it is continuous, discrete, or some kind of intermediate ad-hoc typology.
- Existence of the Auctioneer figure: Generally, all DDAs require the presence of an entity that receives the sealed bids, computes the supply and demand curves and calculates the equilibrium price. CDAs, by their very nature, are often open auctions in which the auctioneer is not required, although they could be included for a number of reasons.
- Time decomposition: auctioning, clearing and effective energy transfer procedures can be carried out in parallel over time or, on the contrary, serially over disjointed periods of time.
- Traders' nature: the peers participating in the market may be the same type of prosumer system or entity, in which case they are said to be homogeneous, or belong to different categories with different functionalities or priorities, in which case they are said to be heterogeneous.
- Trader's directionality: if during the same trading session, each trader can either buy or sell, they are called Unidirectional. If they can act as buyers and sellers simultaneously during the same session, they are called Bidirectional or Dual.
- Other characteristics: which may include one or more of the following: i) how the buyer/seller role is selected and whether it is irremovable or may vary between different sessions, ii) what price adaptation strategy is used to try to maximise the potential profit and iii) how the private valuation of the energy from which the purchase/sale limit prices are set is carried out.

Using DDAs for energy trading has the following implications

1. The figure of an auctioneer that hosts the auction and performs the different matching procedures is required. To be able to do the market clearing, the auctioneer must know offers from all traders, which implies a privacy issue and prevent the auctioneer from becoming also a market participant (in addition to its auctioning role), given that it would have all the information and could take advantage of it for its own benefit.

2. Matching is usually done by the auctioneer according to maximisation of social welfare criteria. While the authors agree this is desirable, reality demonstrates that persons and companies are driven by much more selfish optimisation criteria.

Table 4.1 Literature Review.

Reference	Auction Type	Presence of Auctioneer	Temporal Decomposition	Uniformity of peers	Directionality of traders	Role Selection	Price Adaptation
Vytelingum et al., 2010 [40]	CDA	Y	D	Ht	M	F	AA
Ramachadran et al., 2011 [35]	DDA	Y	D	Ht	M	F	RB
Ilic et al., 2013 [14]	CDA	N	D	Hm	M	F	ZI
Majumder et al., 2014 [41]	DDA	Y	D	Hm	M	F	Iter
Taniguchi et al., 2015 [42]	CLFS-DA	Y	D	Hm	B	V	Iter
Reyhanian et al., 2016 [43]	DDA	Y	D	Hm	M	F	–
Flikkema et al., 2016 [44]	DDA	Y	D	Ht	B	F	Cohort
Khorasany et al., 2017 [45]	DDA	Y	D	Hm	M	F	LUF
Donghe Li et al., 2017 [46]	DDA	Y	P	Hm	M	F	N
Xing Yan et al., 2017 [15]	CDA	Y	D	Hm	M	F	SVM
Zhong et al., 2018 [47]	DDA	Y	D	Ht	M	F	N

Abbreviations: Yes (Y), No (N), Convergent Linear Function Submission-based Double-Auction (CLFS-DA), Disjoint (D), Parallel (P), Heterogeneous (Ht), Homogeneous (Hm), Monodirectional (M), Bidirectional (B), Fixed (F), Variable (V), Adaptative-Aggressiveness (AA), Risk-Based (RB), Zero Intelligence (ZI), Iterative (Iter), Cohort-based (Cohort), Linear Utility Functions (LUF), Support Vector Machine (SVM)

3. Another possible DDA problem arises when the negotiation and transfer times are segregated. If both operations are not held in parallel, traders may lose part of their potential transfer time while global trading is in progress. Even if traders can negotiate while transferring, some potential energy transfer time may be lost in the interval between the end of a transfer and the opening of the new DDA session. Either way, time utilisation efficiency falls and the global efficiency diminishes accordingly. This issue is analysed in Section 4.4

It is interesting to note that two types of discrete double auctions can be distinguished, depending on the condition that triggers their subsequent sessions:

Definition 4.2.1 (Timed DDA) In a timed discrete double auction (T-DDA), the time lapse between the k-th session and the subsequent $(k+1)$-th session is constant and equal to $\tau_{k+1} - \tau_k = \Delta_{DDA}$. Once a session is cleared, participants can readapt their offers but must wait until the next session opens to *shout* them. Thus, changes in the S-D schedule occurring inside that period (which could lead to further trading) are not taken into account unless they persist when the $k+1$ session opens at $t = \tau_{k+1}$.

Definition 4.2.2 (Event Triggered DDA) An event-triggered discrete double auction (ET-DDA) is a particular type of DDA in which trading sessions are not determined by a clock (as in the case of timed DDAs), but conducted each time (t_e) there is an event that changes the market structure, and consequently its associated S-D schedule.

4.3 Energy Trading in Static Scenarios with Minimum Required Relative Gains

In this section we introduce a particular case in which a CDA can outperform a Matching-Equilibrium DDA (ME-DDA) even in static conditions (i.e. taking a snapshot of the S-D curve at a given instant). Recall that the ME-DDA mechanism is individually rational (IR), strong budget balanced (SBB), economy efficient (EE) but not incentive compatible (IC), because break-even buyer has an incentive to report a lower value and break-even seller has an incentive to report a higher value. Since we assume that all traders are individually rational (IR), a seller would in principle be willing to accept any price above his PV, while a buyer would be willing to accept any price below his PV. However, in certain cases and/or for some types of assets, traders may impose a minimum markup with respect to their private valuation, below which they are not willing to trade. Take, for example, the case of auctions of services where a commission has to be paid to an intermediary. The trader will therefore not accept to engage in any transaction involving a relative gain less than or equal to the percentage commissioned by the intermediary.

Something similar happens in peer-to-peer (P2P) energy markets. Unless a proprietary network infrastructure has been deployed for P2P exchange, which is very unlikely, the physical transfer of energy takes place over the distribution network. Thus, the DNO may charge (the buyer, the seller or both) a toll for the use of the network and to mitigate any resulting regulatory and quality problems. This toll can be proportional to the economic value of the offer (which depends on the offered quantity and price), or fixed and independent of the value of the offer. Each trader can therefore establish a minimum markup to ensure that what it gains from the market is always greater than what it has to pay to the DNO. In this specific case, the supply curve and the demand curve move in opposite directions, generating two different equilibrium points: the one of the private valuations and the one of the limit prices. Traders between these two points can be either intramarginal or extramarginal, depending on which trader they close deals with. This implies that for certain assignments, some achievements of a CDA may even be of more profit extractive than its equivalent DDA.

4.3.1 Definition of Weak Intramarginals

We argue here that classification of traders between intramarginals (IM) or extramarginals (EM) introduced in Subsection 2.1.1 might not be complete when agents impose a minimum markup on their PV. To illustrate this, Figures 4.1 and 4.2 shows the realisation of two different DA for the same supply and demand schedule. Solid staircases represent private values (PV), dashed lines represent limit prices (LP) and dashed-dotted lines represent actual prices. For each buyer i, its highest possible bid, h_b^{Bi}, equals its limit price. For each seller j, its lowest possible ask, l_a^{Sj}, equals its limit price. The corresponding equilibrium points for PVs, $PV^* \equiv (q^*_{PV}, p^*_{PV})$, and for LPs, $LP^* \equiv (q^*_{LP}, p^*_{LP})$ are also depicted. Note that an ask cannot be closed above the highest limit price among buyers, nor a bid can be closed below lowest limit price among sellers.

In an equilibrium matching DDA (Figure 4.1), buyers ($D1 - D5$) and sellers ($S1 - S4$) would trade up to q^* units at price p^*. The resultant surplus, π_{DDA}, is then equal to the area enclosed by the private valuations of ($D1 - D5$) and ($S1 - S4$), filled with blue diagonal patterns. Sellers $S7$ and $S8$ would not trade because trading at a price p^* lower than their PVs would lead to losses. Buyers $D7$ and $D8$ would not trade because trading at a price p^* higher than their PVs would lead to losses as well. Sellers $S5$ and $S6$, and buyer $B6$ would not trade at at a price p^* because, even obtaining certain relative gain, this would be smaller than their minimum required markup.

Let's now consider a CDA in which buyer $D1$ offers first and trades with seller $S6$ at a price p_{s6d1} lower than h_b^{D1}, and then seller $S5$ offers and trades with buyer $D2$ at a price p_{s5d2} higher than l_a^{S5}. After that buyer $D6$ offers and trades with seller $S2$ at a price p_{s2d6} lower than h_b^{D6}, and then seller $S1$ offers and trades with buyer $D5$ at a price p_{s1d5} higher than l_a^{S1}. Finally, buyers $D3 - D5$ and sellers $S1$,$S3$ and $S4$ manage to trade their remaining units at prices in their acceptable ranges. In this case, total surplus, π_{CDA}, would be equal to the blue patterned areas in Figure 4.2. The white stripe labeled as $\Delta\pi^-$ represents the sum of $\Delta\pi^-_{S2} + \Delta\pi^-_{S1}$, the loss of earning potential that sellers $S2$ and $S1$ experiment for trading with $LP^* - extramarginal$ buyers $D6$ and $D5$, respectively, at prices lower than p^*_{LP}, plus $\Delta\pi^-_{D1} + \Delta\pi^-_{D2}$, the loss of earning potential that buyers $D1$ and $D2$ suffer for trading with $LP^* - extramarginal$ sellers $S6$ and $S5$, respectively, at prices higher than p^*_{LP}. On the other hand, π_{D5},π_{D6},π_{S5}

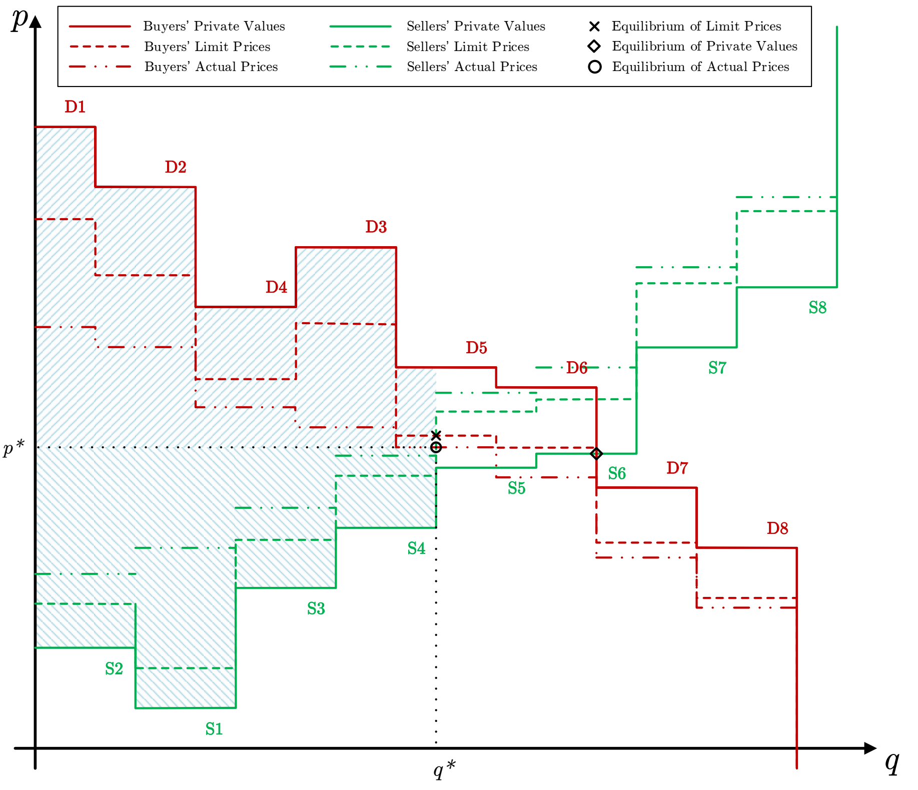

Figure 4.1 Market Clearing for a DDA with Equilibrium Matching.

and π_{S6} represent the profits obtained respectively in the CDA by buyers $D5-D6$ and sellers $S5-S6$. As can be seen, the sum of this profits exceeds the aggregate of losses of earning potential for buyers $D1-D2$ and sellers $S2-S1$, $\Delta\bar{\pi}$, which implies that the global absolute profit extracted is greater for this particular realisation of the CDA than it would have been for the equivalent ME-DDA cleared at p^*. It should be noted that this improvement would have occurred for this S-D schedule even if the ME-DDA participants were truth telling traders placing offers at their limit prices. This reinforces the idea that the traditional classification of traders among IM or EM is not sufficient, at least in those cases where limit prices do not coincide with private values.

For this circumstance to occur given that agents require a minimum markup, not only must there be a particular structure of the supply and demand curve, but also the sequence of offers, which is inherently random, must occur in a particular order. Therefore, it is unusual and unpredictable that a CDA outperforms a ME-DDA. However, the fact that this possibility exists, even in very specific cases, questions whether the current definition of allocative efficiency is complete and economically meaningful.

In any case, this possibility makes it necessary to refine the concepts of intra and extra marginality, given that certain traders cease to be intra/extra marginals in absolute terms,

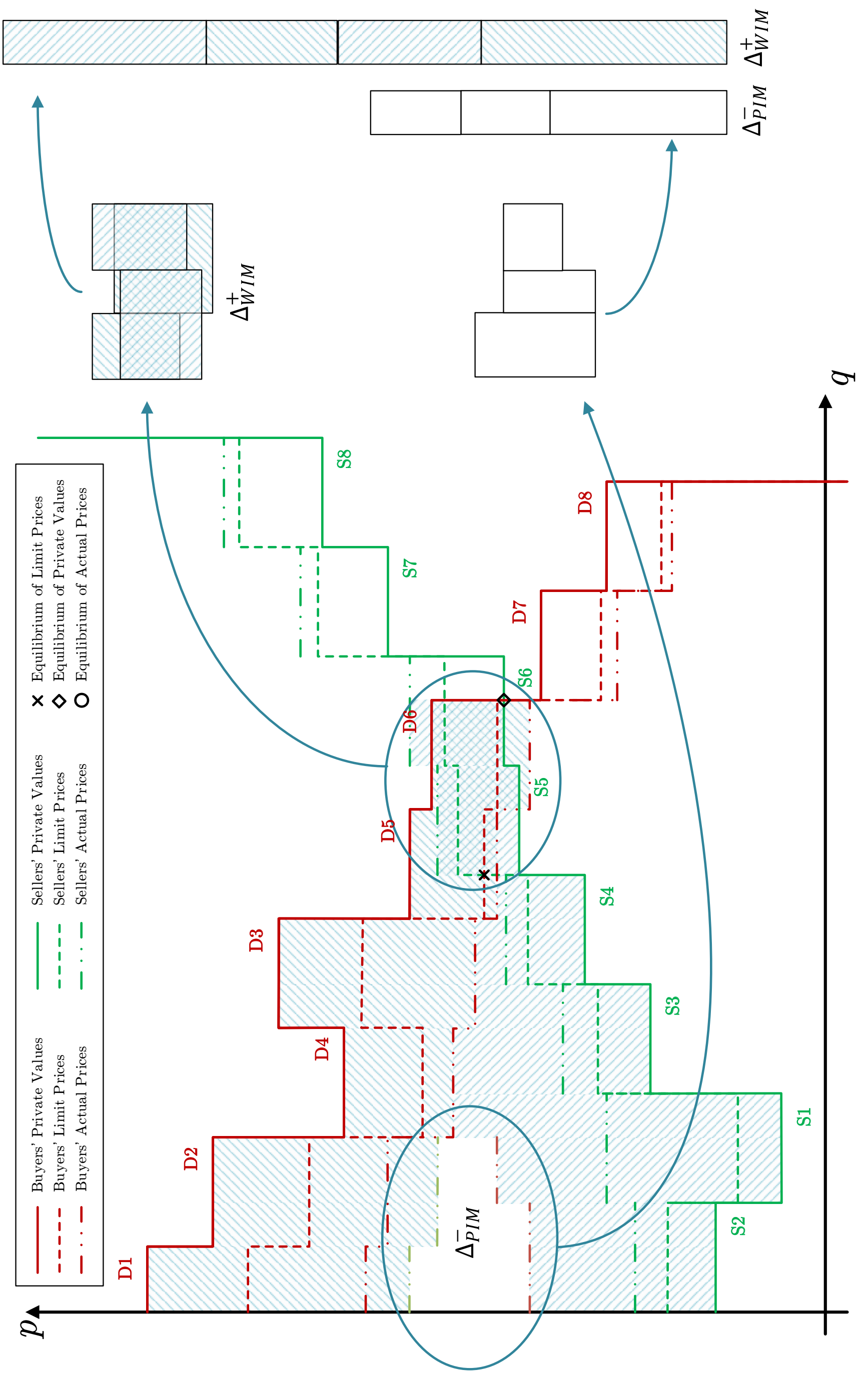

Figure 4.2 Market Clearing in a Perfect Double Auction.

their marginality now depending on the particular trader they manage to trade with.

Let $S(\lambda)$ be the supply staircase as a function of private values in ascending order, $D(\lambda)$ be the demand staircase as a function of private values in descending order, $S(l_a)$ be the supply staircase as a function of limit ask prices in ascending order, $D(h_b)$ be the demand staircase as a function of limit bid prices in descending order. Let assume that minimum required relative gain is equal for all traders, so that $\lambda^i < \lambda^j \implies l_a^i < l_a^j$ and $\lambda^i > \lambda^j \implies h_b^i > h_b^j$.

Then it is possible to break a given S-D schedule into the following:

Definition 4.3.1 (Pure Intramarginal Supply and Pure Intramarginal Demand)

$$S_{PIM}(p) \stackrel{\text{def}}{=} S(p) : S(l_a) \leq q^*_{LP} \tag{4.1}$$

$$D_{PIM}(p) \stackrel{\text{def}}{=} D(p) : D(h_b) \leq q^*_{LP} \tag{4.2}$$

Then it is possible to define $\mathcal{P}_S = \{\forall t : S(t) \in S_{PIM}\}$ to be the set of Pure Intramarginal Sellers (PIMS) and $\mathcal{P}_B = \{\forall t : D(t) \in D_{PIM}\}$ to be the set of Pure Intramarginal Buyers (PIMB), where t is an arbitrary trader, $S(t)$ is the supply offered by t if it is a seller and $D(t)$ is the demand bid by t if it is a buyer. When a PIM trader manages to trade, it always contributes positively to achieving the maximum theoretical sum of profits.

Definition 4.3.2 (Weak Intramarginal Supply and Weak Intramarginal Demand)

$$S_{WIM}(p) \stackrel{\text{def}}{=} S(p) : S(\lambda) \leq q^*_\lambda \wedge q^*_{LP} < S(l_a) \leq q^*_\lambda \wedge \lceil S(l_a) - q^*_{LP} \rceil^+ < D(h_b) \tag{4.3}$$

$$D_{WIM}(p) \stackrel{\text{def}}{=} D(p) : D(\lambda) \leq q^*_\lambda \wedge q^*_{LP} < D(h_b) \leq q^*_\lambda \wedge \lceil D(h_b) - q^*_{LP} \rceil^+ > S(l_a) \tag{4.4}$$

where $\lceil \cdot \rceil^+ = max(0, \cdot)$. Weak intramarginal supply (resp. demand) lies between the equilibrium quantity of price limits and that of private values (first and second requirements). The third condition forces weak intramarginal supply limit ask prices to fit below the limit bid prices of pure intramarginal demand. Conversely, weak intramarginal demand limit bid prices must fit above the limit ask prices of pure intramarginal supply.

Then it is possible to define $\mathcal{W}_S = \{\forall t : S(t) \in S_{WIM}$ to be the set of Weak Intramarginal Sellers (WIMS) and $\mathcal{W}_B = \{\forall t : D(t) \in D_{WIM}$ to be the set of Weak Intramarginal Buyers (WIMB). When a WIM manages to trade, it doesn't necessarily causes a reduction of the maximum achievable profit. Actually, it might contribute to extract the maximum achievable profit if, as in the previous motivation example, the surplus it obtains exceeds the reduction of earning potential caused by its participation in the market.

Definition 4.3.3 (Extramarginal Supply and Extramarginal Demand)

$$S_{EM}(p) \stackrel{\text{def}}{=} S(p) \notin S_{PIM} \cup S_{WIM} \tag{4.5}$$

$$D_{EM}(p) \stackrel{\text{def}}{=} D(p) \notin D_{PIM} \cup D_{WIM} \tag{4.6}$$

Then it is also possible to define $\mathcal{X}_S = \{\forall t : S(t) \in S_{EM}$ to be the set of Extramarginal Sellers (XMS) and $\mathcal{X}_B = \{\forall t : D(t) \in D_{EM}$ to be the set of Extramarginal Buyers (XMB). When an EM manages to trade, it always produces a reduction of the maximum achievable profit, either because the loss of earning potential it might cause to its intramarginal counterpart, and/or because its participation in the market hinders another different intramarginal from trading within the same session.

Finally, it is posible to define the set of all intramarginals, $\mathcal{I}$, as the union of pure and weak intramarginal sets.

$$\mathcal{I} = \mathcal{P} \cup \mathcal{W}$$

Definition 4.3.4 (Perfect Information Double Auction) Given a set $\mathcal{B}$ of buyers and a set $\mathcal{S}$ of sellers, which define a static S-D schedule, a Perfect Information Double Auction (PDA) is a DA that implements a matching algorithm $\mathcal{M}_{\mathcal{B},\mathcal{S}}$ involving all the intramarginals $\mathcal{I}$, and only them. For this algorithm to be carried out, there must be a centralised auctioneer who has perfect knowledge of both the private values and the limit prices (or alternatively the minimum markup) of all traders.

A possible implementation of such $\mathcal{M}$ algorithm, the one used in the foregoing comparisons, is to match weak intramarginals, from the last to the first, with pure intramarginals, starting with the first. Once the weak intramarginals are exhausted, the rest of the pure intramarginals combine with each other until all are done.

To approximate the cost of maintaining privacy and not sharing such information, a series of simulations were designed and realized to compare the performance of a CDA with that of a ME-DDA, and in turn to compare both with the ideal case of a PDA, for different values of minimum required relative gain. In such experiments, a CDA and a ME-DDA are simulated. Both are populated by the same set of agents with independent identically distributed (i.i.d.) static private values. Traders use the same price adaptation mechanism (Zero Intelligence Plus[1] - ZIP [48]) when participating in both the CDA and the ME-DDA. Within each of the two markets, buyers try to buy as much energy as they can (up to the safety maximum imposed by their storage) and sellers try to sell as much energy as they can (up to the safety minimum imposed by their storage). Traders are present in both markets from the first to the last session, and their roles, once chosen during market initialisation, are monolithic (they do not alternate between being buyers and sellers). Their private valuations also remain constant, so it can be said that the markets are both completely static.

Additional simulations were carried out for different values of the total number of traders (to see if market cardinality influences efficiency). The effect on efficiency of the market imposing (or not) an upper limit on the size of traded goods (on the size of energy packages, in this case) was also analysed.

For this static analysis, it was considered that, after a deal is reached, energy exchange between buyers and sellers is immediate (i.e. performed at infinite power). Both markets are run during the same number of sessions, until it is ensured that price adaptation procedures achieve exhaustion of supply and demand. Both markets therefore run until

[1] The ZIP algorithm is explained in Apéndice A

additional transfers are impossible (because the supreme among buyers' limit prices is below the lowest among sellers' limit prices).

Figure 4.3 shows the total profits extracted in the CDA[2], DDA and PDA, for different markup values. Each graph corresponds to a scenario of number of traders and maximum allowed size for traded packages.

For CDAs, the lower the markup, the more likely it is that EM traders manage to trade, especially during the initial sessions when the price adaptation mechanism has not yet had time to evolve. But also, as the markup increases, transfers involving EM traders, although less probable, are more harmful in terms of allocative efficiency reduction. That is why the extracted profit initially increases as the markup does, and then decreases. As can be seen, beyond certain required minimum relative gains, the profits extracted by the CDAs are consistently larger than those obtained by the ME-DDA, both being lower than the ideal case of full information of the PDA. However, some CDA realisations achieve allocative efficiency values of over 95% (with respect to the perfect information case) and achieve this with the advantage that traders do not need to disclose any sensitive information, such as limit price or private valuation.

Figure 4.4 is equivalent, but shows instead the aggregate value of traded energy for the different types of DA.

The analysis show that the volume of traded energy is larger in CDAs for most markup values, at the expense of letting transactions involving extramarginal traders. Only for large markup values, the accurate knowledge of the limit prices means that transactions with weak intramarginal but not extramarginal are included, so that no pure intramarginal is displaced from the auction.

4.4 Energy Trading: Time Use Implications

How often must a T-DDA be triggered? Or alternatively, how does the selection of Δ_{DDA} affect performance? The question of the optimal frequency of trading in DDAs has also been addressed in the literature on financial markets [49]. This work looks at discrete markets with static composition but whose members receive *signals* (i.e. information that change their private valuations) in a dynamic way over time, concluding that the allocative inefficiency in this dynamic market can be decomposed into two parts: one part due to strategic behaviour and the other due to delayed responses to new information. The authors also state that if new information arrives as a Poisson process, the optimal trading frequency can be much higher than the information arrival frequency, eventually tending to a CDA.

Making a wide interpretation of the term signals, we can equate the stochastic arrival of information with the stochastic arrival of traders to an energy market. Therefore, the delay between the occurrence of one of these (un)joining events and the next market

[2] For each CDA, given that the profits extracted depend on the order of the sequence of the offers, which is totally random, 5 realisations have been done with different seeds for random values generator. The graph shows error bars in which the value is the average of the profits obtained and the extremes are the minimum and maximum values within the 5 realisations.

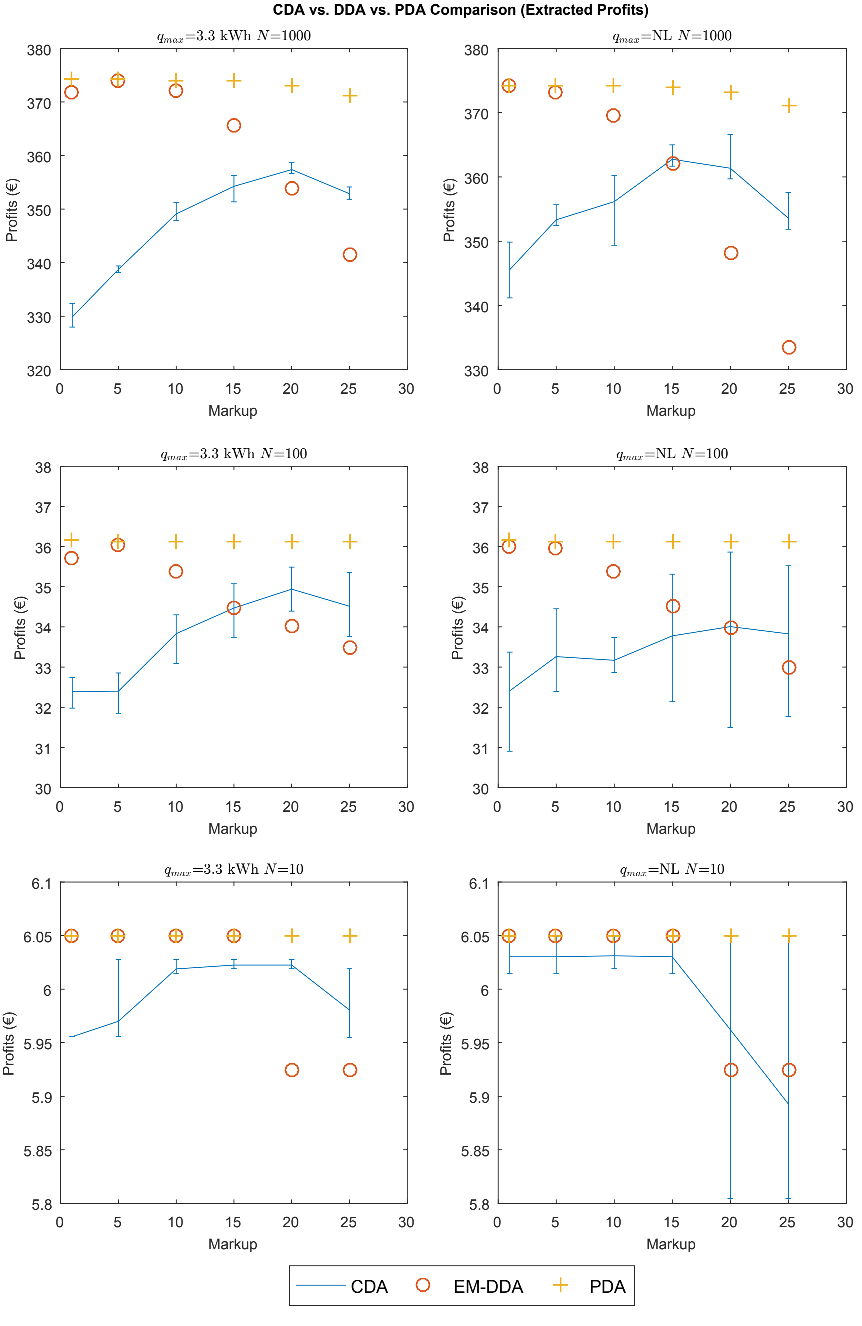

Figure 4.3 Profit extraction comparison between CDAs, ME-DDAs and their corresponding PDAs, for different static scenarios.

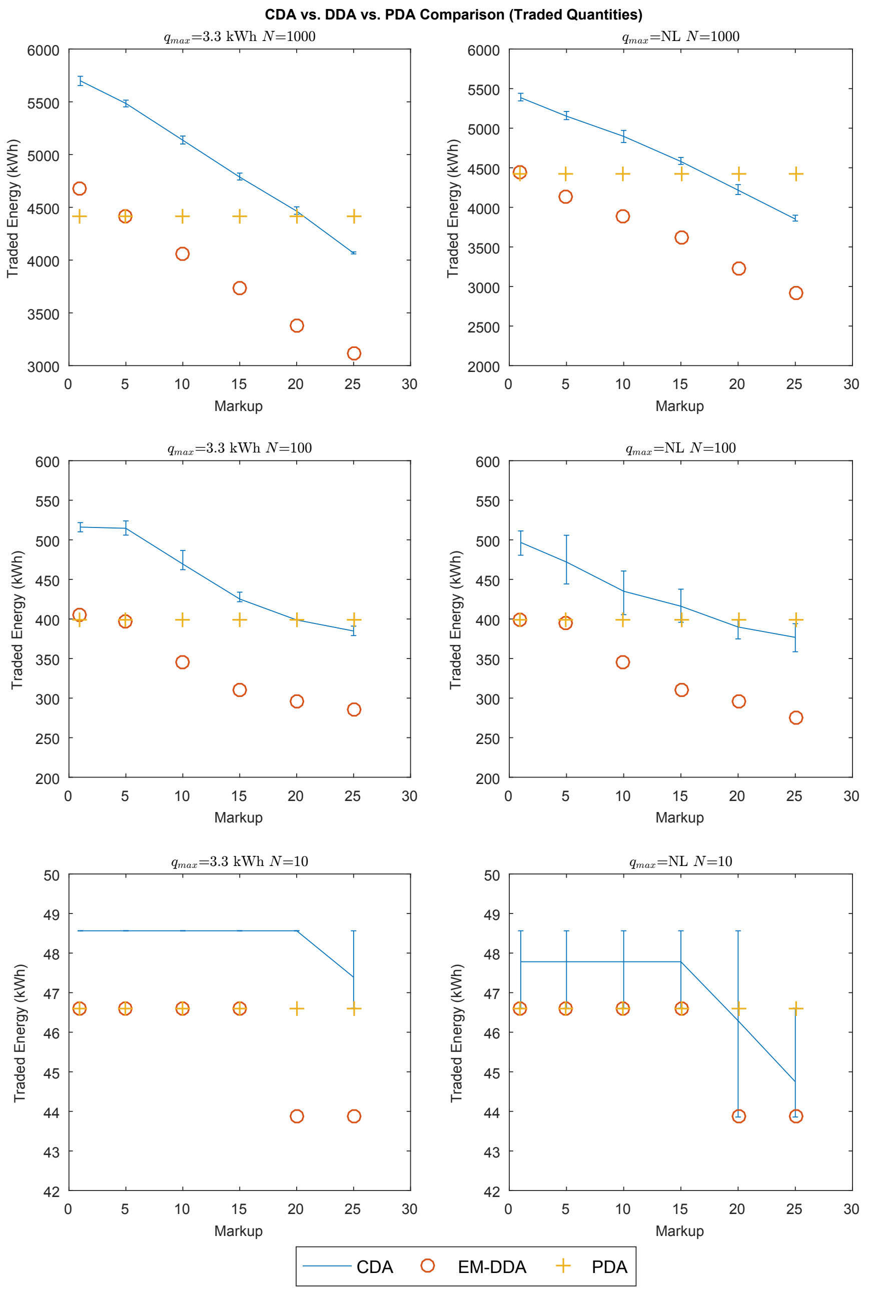

Figure 4.4 Trading Volume comparison between CDAs, ME-DDAs and their corresponding PDAs, for different static scenarios.

session constitutes a delayed response to the new information that modifies the supply and demand curves, and might therefore modify the clearing price.

Such dead times can occur not only between the physical arrival of the trader until it has the actual possibility to access the market, but also after each completed transfer. In this sense, when a trader enters the DA willing to trade a certain amount of energy, two situations can occur:

- The operator of the physical link through which the energy is transferred can allow it to trade directly with all its available energy, so that, after a single deal, it would not need to re-interact in the market.
- On the other hand, it may be necessary to divide all available energy into portions. Some of the reasons that would make this energy bundling necessary could be: i) the market not allowing multi-unit trading, ii) that the operator of the physical link, due to its limitations, imposes limits on the potentially transferable energy in a certain period of time or iii) that the trader itself, in anticipation of future price evolution, would like to trade one part immediately and another in later moments.

In this second case, and if we define t_{-1} as the moment of completion of the immediately preceding transfer, there may be two additional situations, depending on the type of auction.

- If the auction is a timed DDA, the agent should wait for the next session (t_{DDA^+}) to submit a new offer, so the time between t_{-1} and t_{DDA^+} is *idle* time and therefore represents a temporal inefficiency. Furthermore, if once it access the market at t_{DDA^+} its offer falls in the extramarginal side of the auction, it won't trade, therefore losing the following ΔT until the next session opens.
- If the auction is a CDA, the agent tries to trade as soon as possible (i.e. the instant after its t_{-1}) with the agents that may be available. Although it may take some time for the trader to adapt its offer to reach an agreement on the continuous market, this improves liquidity, as each trader makes the most of its potential transfer time.

Therefore, when comparing a DDA whose sessions are conducted every ΔT), with a CDA realised over the same ΔT, the obvious question seems to be how the efficiency in the utilisation of potential transfer time affects the efficiency in profit extraction. In order to define time utilisation efficiency some auxiliary definitions are needed:

- Connection Time (T^i_{con}) ≡ Total period between a trader i connects to the physical transfer system (at t^i_{con}) until its physical disconnection (at t^i_{dis}).
- Access Time ($T^{i,j}_{acc}$) ≡ Period between a trader i connects to the physical transfer system (or completes an ongoing transfer) until it can place offers on the market. Here, $j = 1$ implies the period following the first connection and $j > 1$ for the access period after the end of the $(j-1)$-th transfer.

$$T_{acc}^{i,j} = \begin{cases} t_{DDA^+} - max(t_{end}^{i,j}, t_{con}^{i}) & \text{, for DDAs,} \Longrightarrow T_{acc}^{i,j} \in (0, \Delta T_{DDA}) \\ 0 & \text{, for CDAs} \end{cases}$$

- Negotiation Time ($T_{neg}^{i,j}$) ≡ Total period of time needed for trader i to determine if its possible to reach an agreement after its j-th access to the market. In DDAs, this time is constant for all traders and all market sessions, and is equal to the sum of the period given for offer submission (T_{sub}) plus the time needed to calculate the equilibrium point and perform the market clearing (T_{clr}). With proper synchronisation and current computing capacity this time is practically negligible. After this time, the auctioneer informs the traders whether their offers managed to trade (intramarginal traders) or not (extramarginal ones). In CDAs, this time varies for each trader and trading attempt, and is equal to the sum of the time required for trader i to perform the $k^{i,j}$ price adaptation procedures (each one of them involving T_{adapt}) needed until a deal is reached, with $k \in (0, \infty)$. Note that, in a CDA, this time might not be bounded if a deal is not possible for a given S-D configuration.

$$T_{neg}^{i,j} = \begin{cases} T_{DDA} = T_{sub} + T_{clr} \cong 0 & \text{, constant for } \forall i, \forall j \text{ in a DDA} \\ k^{i,j} \cdot T_{adapt} & \text{, variable, in a CDA} \end{cases}$$

- Trade Time ($T_{trade}^{i,j}$) ≡ Total period between trader i access the market until it reaches its j-th trading agreement.

$$T_{trade}^{i,j} = T_{acc}^{i,j} + T_{neg}^{i,j}$$

- Effective Transfer Time (T_{eff}^{i}) ≡ Effective period of time that a trader i could use for the physical transfer of energy.

$$T_{eff}^{i} = T_{con}^{i} - \sum_{\forall j} T_{trade}^{i,j}$$

  where $j \in (1, \infty)$ is the number of consecutive trading attempts (ended either in deal or no deal) realised by a particular trader during its total connection time.

Finally, it is possible to define the following ratio:

Definition 4.4.1 (Temporal Efficiency)

$$\eta_t^i = \frac{T_{eff}^{i}}{T_{con}^{i}} \tag{4.7}$$

which constitutes another performance indicator to be taken into consideration when comparing a CDA with a timed DDA in dynamic scenarios.

Figure 4.5 displays an example in which 4 Electric Vehicles (EVs) trade energy while parked in the same parking lot. EVs 1 and 4 are buyers, while EVs 2 and 3 are sellers. Parking Events timeline indicates arrival instants (a_i) and departure instants (d_i) for each EV ($i \in [1,4]$). The DDA and CDA timelines each show a possible realisation of each type of DA, with their characteristic times defined as above, and with e_{bs} being the amount of energy transferred between buyer EV b and seller EV s. The upper bar graph shows the sum of the amounts of energy that each EV transfers when participating in the DDA or CDA, respectively.

It can be seen how, thanks to greater temporal efficiency in the CDA, the total quantities exchanged by EVs are greater than for the DDA (i.e. the CDA-based market shows a higher liquidity than the DDA-based one). To compare both in economic terms it would be necessary to compare the total profits extracted in the CDA (in which the total amount transferred is greater but in which the agreements may not be totally efficient if they involve extramarginal traders), with those obtained in the DDA (less total amount transferred but with a guarantee of total efficiency in terms of profit extraction, given that extramarginal ones are left out). In other words, in certain cases, the greater temporal efficiency of a CDA may compensate for its possible inefficiencies in terms of profit extraction when it is compared to a timed DDA.

4.5 Energy Trading in Dynamic Scenarios

The previous section shows how the random nature of price exploration in CDAs can make them more profit extractive than their discrete equivalents, at least when traders require a minimum relative gain. Otherwise, when any relative profit level greater than zero is acceptable, an equilibrium matching DDA is, by definition, the same or more efficient than any CDA. This holds for the case of static markets, whose S-D schedule remains constant during the interval between two consecutive sessions of the DDA. But, what happens when the S-D schedule varies over time? This section analyses how market dynamism affects performance comparisons between CDAs and DDAs for energy trading.

When it comes to auction based markets, the term dynamic can refer, at least, to the following aspects:

- *Market Structure*. If the traders who make up the market (and the role they play) are the same throughout the auction, this is said to have a static structure. If the traders (and/or the role they play) vary in time throughout the auction, this is said to present a dynamic structure.
- *Agents' Information*. If, once the agents entry in the auction with a defined role, their private valuation remains constant over time the auction is said to be information-static; otherwise it is said to be information-dynamic.

Usually, the existing works in the literature address each of these two cases separately. They either study the design of mechanisms for dynamic populations with fixed information [50, 51, 52] or for fixed populations with dynamic information [53, 54, 55, 56].

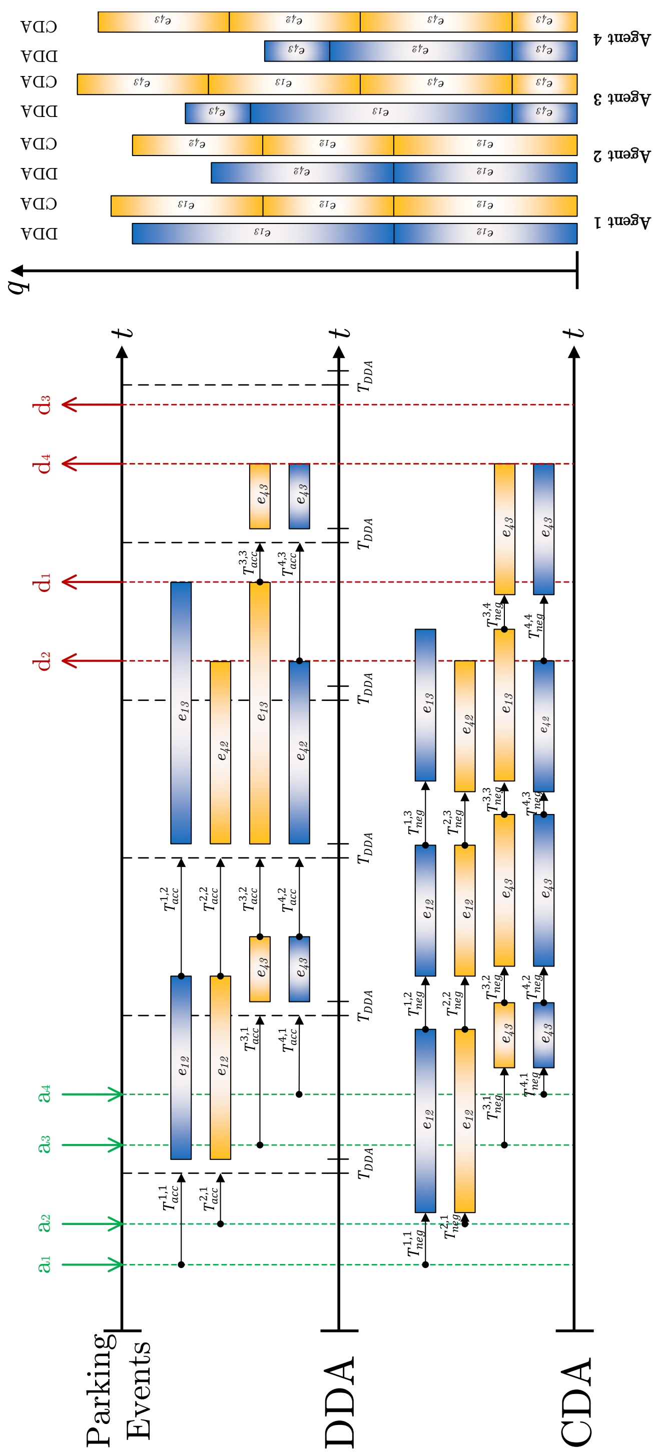

Figure 4.5 An example of Efficiency in Time Utilisation when comparing CDA vs DDA.

The case of markets with a dynamic structure is especially common in energy applications, where traders can join or leave the auction in a variable way over time (e.g. EVs occupying/releasing parking lot spaces, or households with micro-generation from renewable sources that only enter the market when they have a surplus, this being stochastic over time).

Figure 4.6 shows such a case in which a set of EVs arrive and join asynchronously to a DA-based energy market. The temporal trace depicts how the arrival instants can be distributed between two consecutive sessions of a hypothetical T-DDA (in t_{DDA^1} and t_{DDA^2}). It is assumed that traders 1,2 and 3 act as monolithic buyers, and that traders 4 and 5 are monolithic sellers as well. It should be noted that even when they are connected to the market, each EV is unaware of the presence of the others, so extramarginal trades may occur without this implying that any of them is a non-rational economic decision maker. The benchmark for calculating profit extraction efficiency and liquidity would be the case where traders 1-5 would have to wait for the opening of the DDA session immediately after their arrival (in t_{DDA^2}). S-D staircase of the bottom row in Figure 4.6 corresponds to the T-DDA case. As can be seen, total extracted profit in this scenario is $\pi = 9$ monetary units (m.u.), while the total amount of exchanged energy is $q_{ex} = 4$ energy units (e.u.).

Since the continuous nature of time is intractable on a computer, it is common practice to emulate CDAs by simulating CDA sessions in equally spaced time instants (discrete-time CDA) and to calculate the efficiency based on the equivalent ME-DDA for the same S-D curve in each of those instants. In the first row below the temporal trace there is a possible realisation of the auction, were it continuous, in any two moments of time t_1 and t_2 such that $t_{DDA^1} < t_1 < t_2 < t_{DDA^2}$. At t_1 seller 4 trade two out of its three available energy units with buyer 2, and the remaining unit with buyer 1. Although the three traders involved are intramarginal, the ideal quantity allocation would have been for seller 4 to sell two units to buyer 1 and only one to buyer 2. Therefore allocative efficiency is less than one ($\eta_\pi(t_1) = 7/8$). At t_2 the deal between buyer 1 and seller 5 is completely intramarginal ($\eta_\pi(t_2) = 1$). As can easily be seen, the average efficiency calculated as the mean of the efficiencies of both sessions of the discretised CDA is $\overline{\eta_\pi} = 15/16 < 1$. However, the sum of the profit extracted is $\sum_{t_1,t_2} \pi(t) = 9$, equal to the one that would have been extracted in the case of the reference DDA. It is therefore observed that the same profit is extracted with the same liquidity through the use of the CDA, and yet the efficiency calculated according to its traditional definition gives a value lower than one, leading to the erroneous conclusion that the CDA is worse than the equivalent DDA.

The second row of the figure shows what would happen in an ET-DDA. The first session would take place when the first seller (trader 4) arrives at $t = t_{arr^4}$, while the second one would take with the arrival of the second seller (trader 5) at $t = t_{arr^5}$. As can be seen, this version of the DDA does not outperform the results obtained with the CDA either.

But also, in an energy market with a static structure, the agents' information can vary dynamically. Let us think, for example, of a market in which private valuation is based on the price of the energy that the retailer is offering at each moment. Any time change

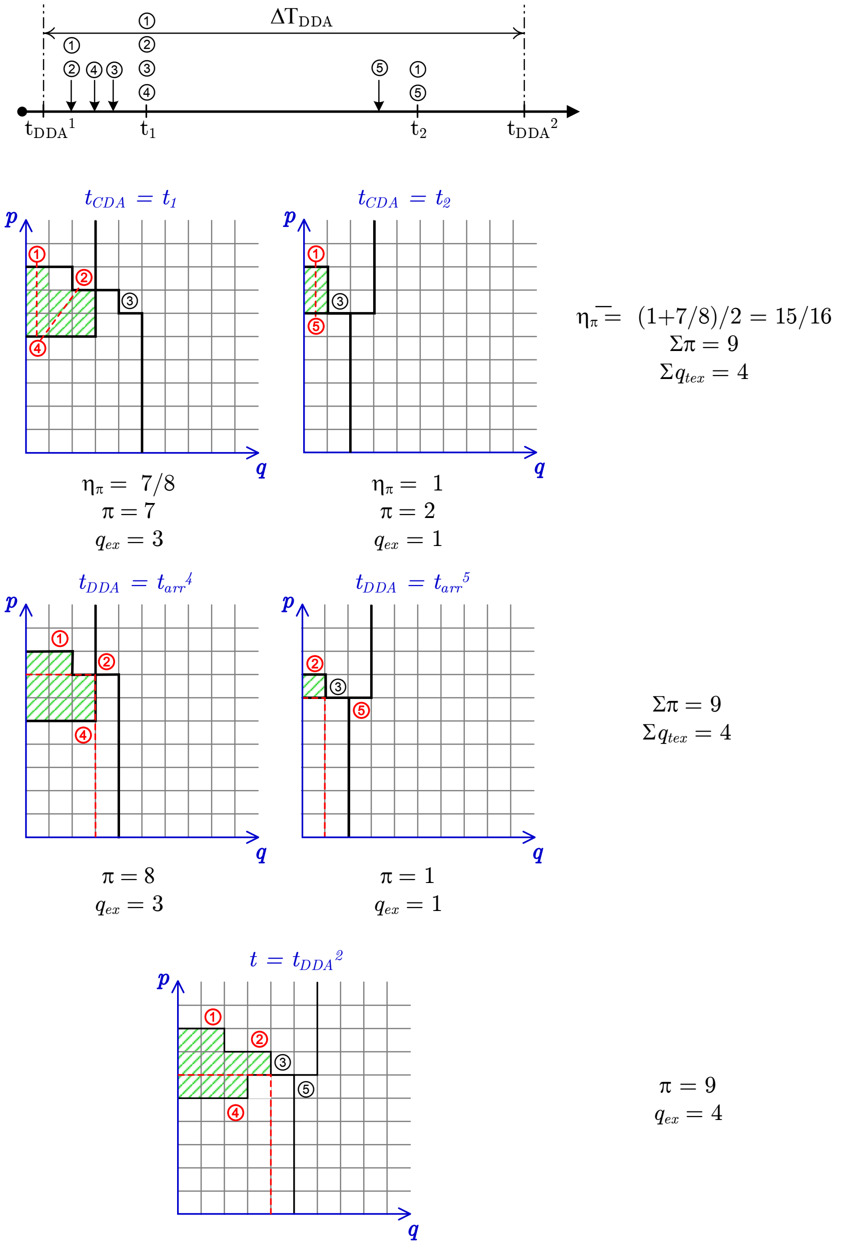

Figure 4.6 An example of how Profit Extraction Efficiency can be misleading in auctions with dynamic structure. Bold red numbers indicate traders that manage to trade at each instant.

in the price of the latter causes a change in the private valuations of those traders who use it as a reference. If traders have the possibility to choose between several energy retailers, their private valuations can change asynchronously as long as the retailers' price variations are asynchronous.

There is a consensus that in CDAs, moving towards the theoretical equilibrium price and thereby approaching the unit efficiency of the equivalent DDA requires a period of time that is proportional to the speed with which traders (re)bid. Weber et al. [57] argue that the use of inherently inefficient CDA may be justified if the cost of waiting for market closure and clearing in the equivalent DDA is higher than the cost of aforementioned inefficiency. They go on stating that measuring the efficiency of CDAs in the static case, which for them is the one in which the traders' PV do not vary, can be misleading because in the case of constant PVs, CDAs are not necessary. According to them, a CDA would only be useful if the private valuations of traders change over time, which they refer to as the dynamic scenario, and in this case, the average efficiency of the CDA is expected to be much lower ($\approx 85\%$) than that attributed to them in the static case ($\approx 98\%$).

Despite its inefficiency, the use of a CDA may be indicated even in those cases where PVs remain constant, since some of the following circumstances may occur:

- For security or privacy reasons, traders may be unwilling to disclose their private valuation and/or limit prices to the centralised DDA auctioneer.
- Traders may not be willing to accept trading at a single (equilibrium) price for the sake of social welfare, but instead try to maximise their individual profit by closing deals directly with other traders.

4.6 Comparative Analysis of Double Auctions in Dynamic Scenarios

In most modern double auction markets, traders are arriving and departing at different times. These markets are also called *online double auctions*. The main challenge for the auctioneer in an online double auction is to make decisions without knowing the traders/orders that have not yet arrived, which is defined as an adversarial setting. Even if traders are required to report their active time before arrival, the calculation of such maximum social welfare becomes an intractable combinatorial problem as the number of agents increases. It would be necessary to check all possible combinations of allocation between buyers and sellers, taking into account that they are not all at once and that the quantities offered are a function of the instant of time in which the session takes place. In his PhD dissertation [58], Zhao demonstrated that there is no deterministic and truthful online double auction that is also competitive for efficiency in an adversarial setting.

In view of the foregoing, we just performed an empirical analysis to compare different types of double auctions in scenarios in which the structure of the underlying market varies dynamically. Three types of double auctions are compared: a CDA, a T-DDA and an ET-DDA. We assume that the latter is also a PDA regarding the clearing of each session. The rationale behind this decision is to compute the profits extracted when the central auctioneer has full knowledge of the private information of all agents and is also immediately informed of any changes in the market structure (and can therefore implement additional trades as soon as possible). The total extracted profit is compared with those obtained in the case of using the other two simple types of double auctions used for the static case (ME-DDA and CDA).

The case study simulates a day (T = 24 hours) of energy trading between $n_{EV} = 1000$ electric vehicles (EVs) that coincide in the parking lot of a large workplace. EVs always act as one-way traders. As in the static case, private valuations are i.i.d. values drawn from the same distribution. All vehicles are equipped with the same trading agent software that automates the price adaptation (using the ZIP algorithm). Each vehicle has its own time of arrival and departure from the car park, associated with the owner's working hours. In addition, while the car is parked, the trading agent tries to buy and/or sell energy autonomously, being able to change its private valuation or its role in the market (change from buyer to seller or vice versa) along its parking time. Therefore, this example case contemplates the two fundamental types of temporal market dynamics.

For the same set of market players (EVs) both a CDA and a set of timed DDAs with different $\Delta T_{DDA} \in \{5,10,15,30,60\}$ are simulated. As is usual in similar previous works, the CDA is emulated realizing discretised sessions every $\Delta T_{CDA} = 1s.$, this being the minimum time granularity for arrival/departure and role changing events.

Figure 4.7 depicts the total sum of profits made by all participant traders. For each value of minimum required relative gain $\mu \in \{1\%,10\%,25\%\}$ two different scenarios have been tested, depending on whether the size of the energy blocks that agents can trade is limited (in this case to 3.3 kWh) or not (NL). Each graph corresponds to a scenario of minimum required markup and maximum allowed size for traded packages.

Figure 4.8 is similar to the previous one, but depicts trading volumes achieved for each type of DA.

It can be seen how, in this type of dynamic context, the ME-DDA behaves best in terms of profit extraction, especially for small values of Δ_{DDA}. In both the CDA and the ET-PDA, traders are able to trade practically at the same time they (re)enter the market, at the cost of doing so in S-D snapshots with little volume offered (clearing is instantaneous and practically one by one). Paradoxically, the DDA seems to benefit from the fact that its price adaptation is slower, giving rise to clearings that involve more traders and therefore a price adaptation that is more representative of the global set of traders. It is observed however how, as Δ_{DDA} increases, the extracted profit progressively decreases, due to the loss of efficiency of utilisation of the potential transfer time.

On the other hand, the CDA continues to be the type of auction that offers the best result in terms of liquidity. This is something to take into account in other scenarios where the owner of the network charges traders on the basis of the amount of energy transferred rather than on the basis of the amounts negotiated. It is also important when the aim is to maximise the amount of renewable energy used, rather than the economic benefit obtained therefrom.

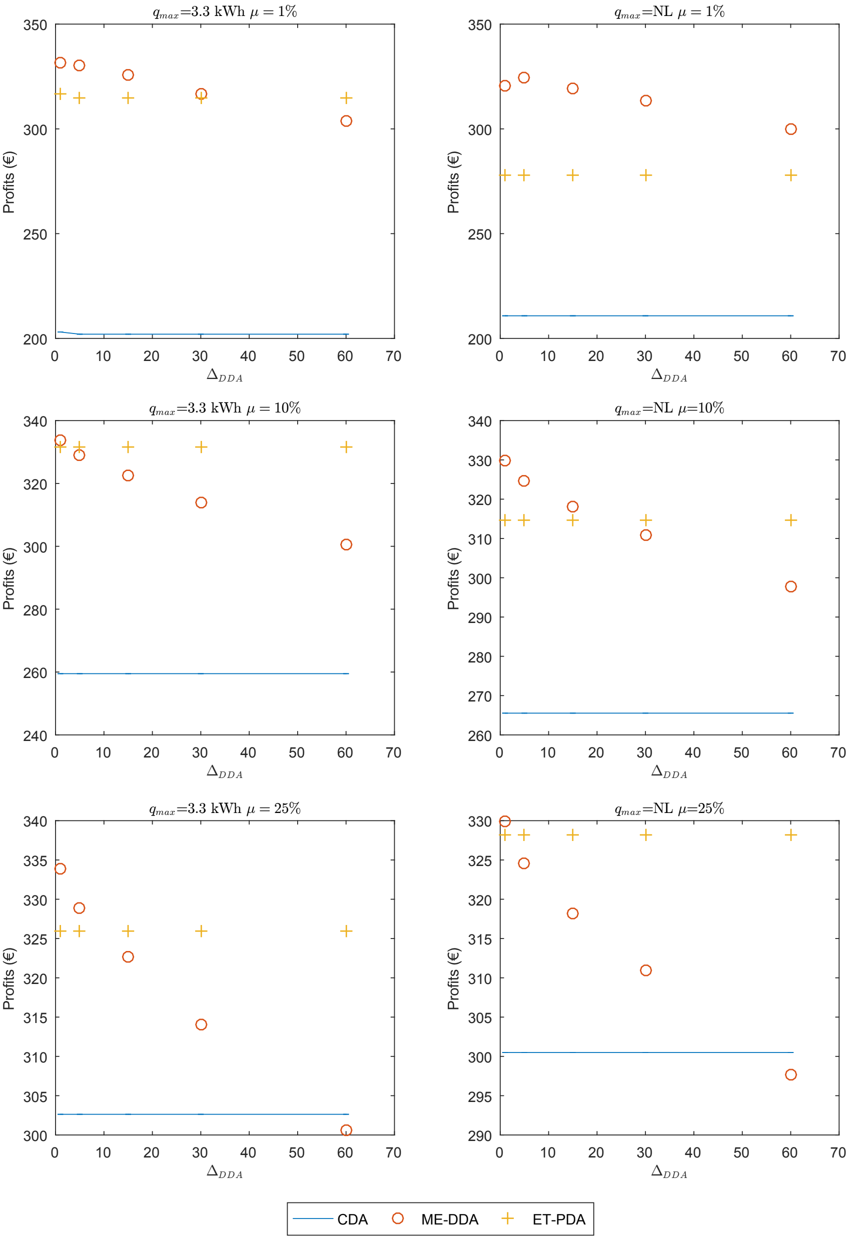

Figure 4.7 Profit extraction comparison between CDA, ME-DDA and ET-PDA, for different dynamic scenarios.

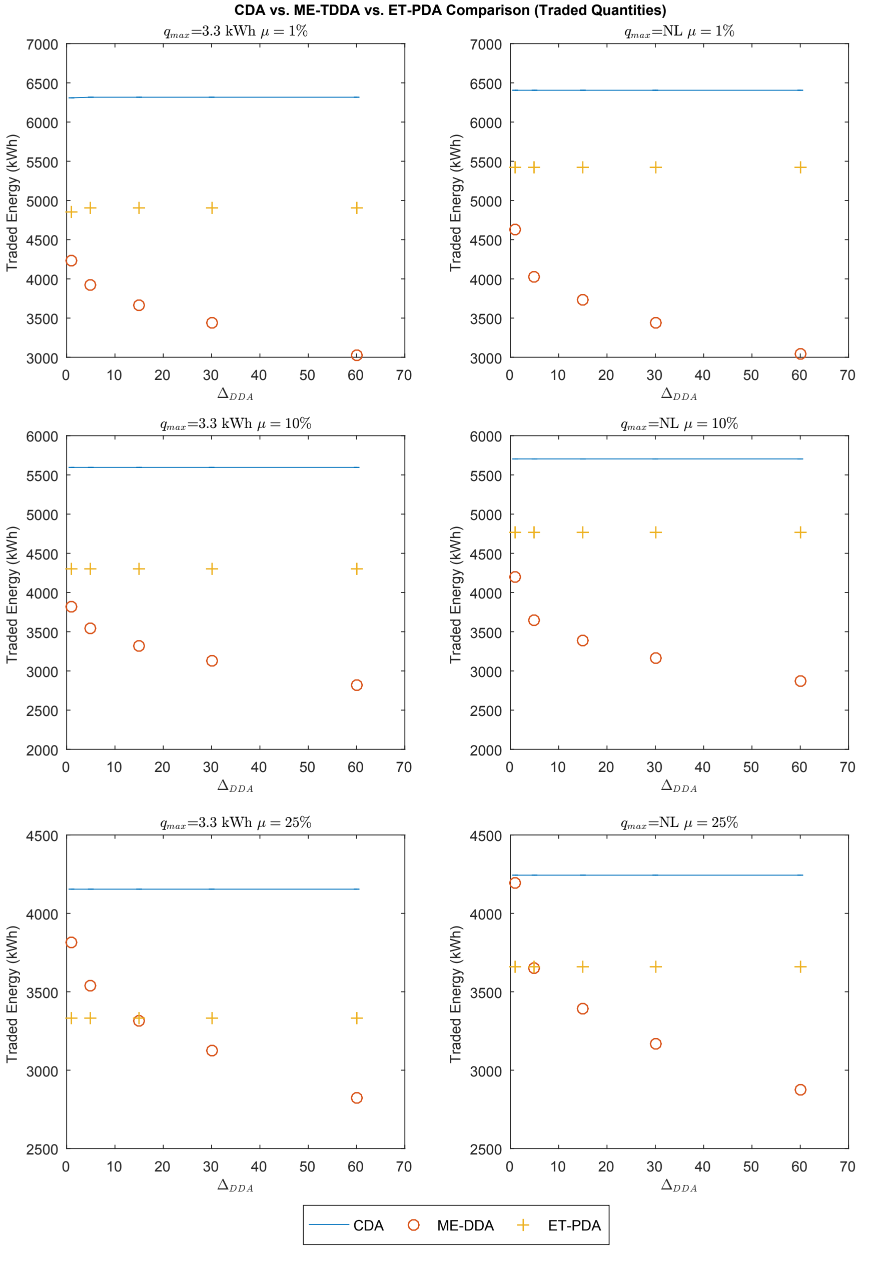

Figure 4.8 Trading Volume comparison between CDA, ME-DDA and their ET-PDAs, for different dynamic scenarios.

4.7 Conclusions

Double auctions are a family of economic models suitable for use in P2P energy markets between end-users. However, the very nature of energy as a tradeable good imposes a number of constraints that make it difficult to design efficient allocation mechanisms, especially in the case of dynamic contexts such as the energy markets. Discrete auctions have the advantage of thickness, while continuous auctions have the advantage of timeliness. Depending on the specific case, one will do better than the other. Therefore, when choosing a particular type of DA structure, attention must be paid to the particularities of traders as well as to the form of monetisation imposed by the operator of the network on which the physical energy transfers are made.

5 A Power P2P Market to Enhance Real-time P2P Energy Interactions between End Users

Those who have knowledge, don't predict.
Those who predict, don't have knowledge.

Lao Tzu, 6th Century BC

THIS *chapter proposes a new type of Peer-to-Peer energy market based on the trading of power quotas, and studies the effects of establishing such an exchange market between end users belonging to the same microgrid (MG). A Continuous Double Auction (CDA) structure, presented in Section 5.2, is used to allow power trading. This also requires an EMS that contemplates the existence of such a market and is capable of participating in it automatically, which is developed in Section 5.3. As a case example, the electrical operation of a neighbourhood of 40 houses is used, and various scenarios with different photovoltaic (PhV) installation penetration levels are analysed in Section 5.4. Results suggest the potential benefits of the use of this type of eP2P exchange structures, which include but are not limited to: savings on electricity bills, better use of renewable sources and reduction in energy storage systems (ESS) utilisation. Simultaneously, new questions raise about the business model, especially for traditional electrical retailers.*

5.1 Disadvantages of Time-ahead Energy Markets

The most common form of energy trading between private parties is through *energy packages*. A particular energy entity can predict that it will incur an energy deficit in the immediate future, and estimate the magnitude of that deficit. The opposite may also occur, that is, an entity has (or expects to have) a surplus of energy that it is interested in selling. Once the quantity to be commercialised and the price requested have been determined, both the buyer and the seller can go to the market, either continuous or discrete, to make their corresponding purchase or sale offers.

This marketing format presents two fundamental problems:

1. It is subject to the accuracy of deficit/surplus estimates by potential buyers/sellers. If a client over estimates its deficit and acquires more than it actually consumes, an imbalance occurs. Conversely, if a selling entity overestimates its surplus (either because it overestimates its generation level or because it underestimates its consumption), it may not be able to meet its sales commitments.

2. Precisely because of this, it is almost inevitable for both buyer and seller to have an energy storage system. In this way, a buyer could derive to its storage an eventual excess of purchased and not consumed energy, for later use. Similarly, upon an eventual underestimation of the energy surplus, a seller could use stored energy to fulfill the selling agreements previously reached.

Technically, the P2P imbalances mentioned in Problem 1 could also be traded through market mechanisms, similar to how the spinning-reserve market does it for the wholesale electric market. In fact, this can represent a financial opportunity for peers with storage capability. However, this still requires the presence of ESSs, which are expensive and whose intensive use leads to their degradation and therefore to additional expenses.

Many existing proposals for trading of energy packages use a Discrete Double Auction (DDA) based market [44, 41, 47]. A DDA seems the obvious choice for time-ahead energy trading, as it provides full allocative efficiency if no minimum markup is imposed by traders over their private values, as explained in Chapter 4. However, as also explained in the previous chapter, a DDA requires the figure of the auctioneer, has a worse temporal efficiency and can be disadvantageous when traders require a minimum relative gain on their private valuations in order to accept an offer.

As an alternative for time-ahead trading of energy packages, the deployment of a real-time power market is proposed here. Real time means here that energy is traded in the form of power quotas, which are placed on the market at the same time that the situations of power surplus or power deficit of the traders occur. In order to enable this type of continuous interaction over time between end users, a theoretical framework is needed, consisting of two fundamental elements:

- A market that allows the continuous and asynchronous shouting of both bids and asks, that can only be implemented through a continuous double auction (CDA). Such a market is presented in Section 5.2.

- To modify the energy management system (EMS) of each energy entity likely to participate in the negotiation of power quotas (houses, buildings, electric vehicles, etc.) so that it includes a trading agent that allows it to automatically participate in the market. In addition, the EMS needs to consider the existence of the market in order to adjust its power flow balance calculations to ensure the satisfaction of total demand at all times. These modifications are issued in Section 5.3.

5.2 A CDA-based Power Market

Any end user with a smart-meter can continuously monitor its power consumption. Those users who have renewable production sources can also track their generated power. The instantaneous difference between these values of consumed and generated power determines the potential roles that the corresponding user can adopt in the market. Those users who do not have renewable production are restricted to play always the role of buyers. On the other hand, prosumers can act as a buyer or seller depending mostly on the sign of its power balance, but also on other factors, as explained later. Anyway, in order for the overproduction of some prosumers to cover the deficit of other consumers, there must exist a structure that allows the immediate negotiation of this positive and negative power quotas.

Power trading between prosumers is carried out using a market based on a CDA [6]. Being double, both power deficit peers (buyers) can initiate offers to buy, which are called *bids*, and power surplus peers (sellers) can launch offers to sell, called *asks*. Both types of offers take the form of quantity-price pairs $o = (q,p)$. As the market is continuous, an offer is closed at any time when there is a buyer/seller willing to purchase/supply that power quota at that price. In this particular market, offers that are not closed automatically disappear after a while (i.e. there is no limit order book).

If we were to take a snapshot at a specific moment in time, we would see how each seller injects into the grid an amount of power equal to the sum of all the active sale-transactions it maintains with its various buyers. Alternatively, at each moment, a buyer absorbs from the grid an amount of power equal to the sum of all the active purchase transactions it maintains with its different sellers. The best way to visualise the active transfers is by means of a chord diagram[1] like the one presented in Figure 5.1.

In the real functioning of a continuous market, the different offers arise asynchronously at any moment of time, as the different situations of surplus and deficit of the participants in the market occur. To overcome the difficulty of simulating this continuum, and as it is usual in similar previous works [59], the CDA is emulated realizing discrete market sessions with a frequency comparable to the frequency of variation of the negotiable stock (power). In this case, the simulation step used to perform the power balance is equal to one minute (coinciding with the temporal resolution of the consumption and generation data), and therefore the discretised CDA sessions are executed with the same temporal granularity. Each of these discrete sessions remains active until

[1] Paul Kassebaum (2020). GitHub circularGraph (https://www.github.com/paul-kassebaum-mathworks/circularGraph)

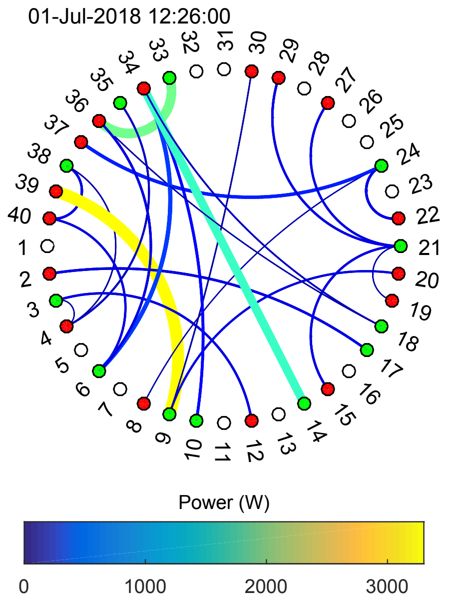

Figure 5.1 Chord Diagram showing active power transfers between 40 peers for a particular minute of a summer day. Green nodes represent sellers, red nodes represent buyers while white ones represent traders that are either idle on the market or that could not agree any transfer yet.

a certain number of unmatched offers is reached, which is an indication that, even having adapted their prices after each of the previous offers, there is no possibility of new deals between traders (either due to exhaustion of supply or demand, or due to price incompatibility). The concatenation of the outputs from these sessions produces quasi-continuous price evolution profiles such as those shown in Figure 5.2.

In a real implementation, the *market* could be an internet-based software application in which the different traders broadcast their bids and asks. In this continuous market the interactions are direct between traders, so the figure of the auctioneer is not necessary. In exchange, when an offer is agreed, the trader who launched it is responsible for broadcasting the deal notice accompanied by the price of the offer. In this way, the remaining traders can adapt the prices of their future offers, by using the price adaptation mechanism implemented by their EMS. The implementations details of the communication protocols necessary for the operation of the market app are beyond the scope of this thesis.

The price per unit of power varies throughout the day, with an upper limit being the energy price offered by the utility, which is the alternative to the P2P market. In this case a lower limit has also been imposed for the valuation of the sellers, but in case there is no such limit, it would be zero (traders are supposed to be economically rational, so none of them trade unless they make a profit above their minimum markup).

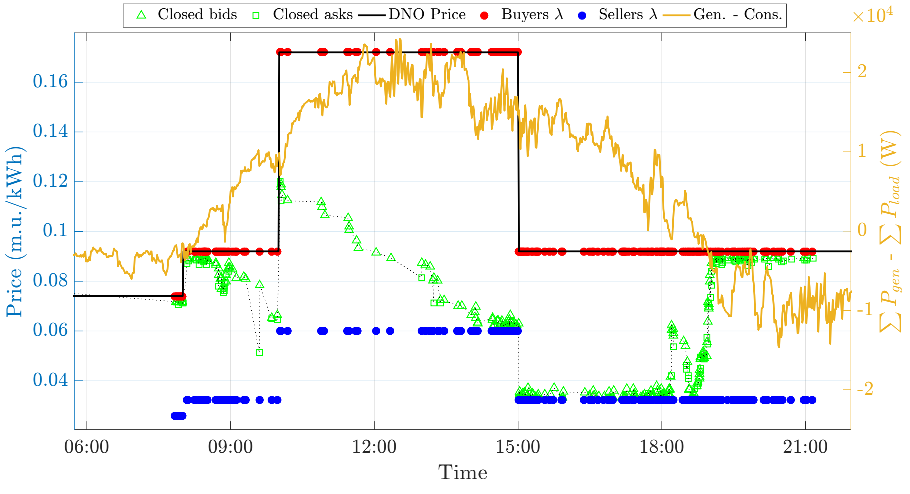

Figure 5.2 Example of realisation of the eP2P market between 20 peers (DRG Penetration = 45%) for one summer day. The deviation of prices depends on the market power of sellers and buyers: when there is excess supply buyers have more bargaining power and prices fall; when there is excess demand sellers can demand more for their power and prices are closer to the one offered by the utility.

Of course, within this range, prices behave according to the basic law of supply and demand: when power demand is greater than supply, prices rise; when there is excess supply, prices fall.

5.3 An Energy Management System with Trading Capabilities

The market is the virtual space where transactions are arranged by matching bids with asks. The physical result of these agreements is the transfer of energy between the peers involved, which is carried out at the power agreed in the transaction that originates the transfer. Logically, this generates additional power flows that modify the power balance, which the EMS has to be aware of. In addition, the EMS of each energy entity should contemplate the possibility of its participation in the market, and communicate with the software that automates the processes that allow such participation. This software is usually called a *Trading Agent* (TA). Although, in general, EMS and TA can be independent pieces of software, in this work the TA is considered an intrinsic function of the EMS, and therefore it is contained in the latter.

The three objectives of the EMS, in order of importance, are:

1. To control the power flows to ensure that demand is met at all times.
2. To maintain the State Of Charge (SOC) of the Energy Storage System(s) within predefined safety levels.

3. To maximise, as far as possible, the profits obtained through the participation in the P2P market.

5.3.1 Power Management

The first two objectives can be analysed together. The aim is to select the most suitable power sources at any given time to meet the demand within the security operational limits imposed by the storage systems, if these are available. The difference between renewable production (P_{gen}) and consumption profiles (P_{load}) determines the power-balance situation of a peer from an energy-economic point of view:

- A deficit situation occurs when consumption is greater than generation ($P_{load} > P_{gen}$). Let's assume first the case of an islanded prosumer. The first option would be to make up for the deficit by using its ESS ($P_{sto} > 0$), if available. If the SOC of the ESS makes its use impossible, or if such ESS does not even exist, the only remaining option for the deficit prosumer is to perform Demand Side Management (DSM) procedures to reduce consumption. Let us now consider the much more common case in which the prosumer is connected to the local distribution grid. In addition to the above measures, it can always cover the deficit by buying energy from the utility company ($P_{util} > 0$) or try to obtain it from the P2P market ($P_{P2P} > 0$), if it is available.

- If the consumption is exactly the same as the generation ($P_{load} = P_{gen}$), the entire energy demand of the system can be satisfied by self-consumption.

- The surplus situation appears when the consumption is lower than the generation ($P_{load} < P_{gen}$). If the system is islanded and does not have storage, excess production is lost; if it has an ESS, the surplus can be stored ($P_{sto} < 0$) until the ESS is fully loaded, after which time the subsequent excess is lost. If the system is connected to the distribution grid, in addition to the above considerations, it may in some cases try to sell the surplus to the eP2P market ($P_{P2P} < 0$) or to the utility company itself ($P_{util} < 0$).

For any given time t, the following two equations (Power Balance equation and Energy Storage Content equation) drive the microgrid:

$$P_{gen}(t) - P_{load}(t) + P_{P2P}(t) + P_{sto}(t) + P_{util}(t) = 0 \tag{5.1}$$

$$E_{sto}(t) = E_{sto}(t_0) + \int_{t_0}^{t} P_{sto}(\tau) d\tau \tag{5.2}$$

with the following constraints:

$$E_{sto}^{min} \leq E_{sto}(t) \leq E_{sto}^{max} \tag{5.3}$$

$$E_{sto}(t) < E_{sto}^{MktMin} \implies P_{P2P}(t) \geq 0 \tag{5.4}$$

$$P_{util}(t) > 0 \implies P_{P2P}(t) \geq 0 \tag{5.5}$$

$$P_{sc}(t) = \min[P_{gen}(t), P_{load}(t)] \tag{5.6}$$

where $P_{sc}(t)$ is the amount of generated power used for self-consumption. Equation (5.4) imposes a conservative limit on the SOC of the ESS, below which the prosumer cannot act as a seller in the market. In this way it can be ensured that surplus is only sold when the level of storage provides a certain room for manoeuvre in the face of possible future needs. Equation (5.5) makes it impossible for an end user to be simultaneously a net buyer with respect to the utility and a net seller with respect to the P2P market. Basically, this restriction prevents peers from reselling energy obtained from the utility. Equation (5.6) states that generated energy is primarily used for self-consumption. Only if there is a surplus after satisfying all the instantaneous demand, it can be stored or offered in the market.

5.3.2 Trading Agent

To allow peers to participate in the eP2P-market, EMSs include a trading agent software that automatically performs private valuation determination, role selection, and price adaptation (see Figure 5.3).

Private Valuation Determination Before going to the market in search of profits, each trader's agent must first establish a private valuation (λ) of the good to be traded, i.e. what value (in monetary units) it gives to each unit of power/energy. In this chapter, end users (either prosumers or pure consumers) acting as buyers value the energy at the price at which they would buy it from the utility (so that buying at any price below means savings). Prosumers acting as sellers must value their excess energy at a price lower than that the utility is offering at any given time (so that buyers might find P2P prices more convenient than the utility ones).

Role Selection Role selection is performed based on the balance between generated power (if available) and consumed power. Peers with surplus go to the market as sellers trying to trade that surplus whenever the SOC of their storage system is greater than a certain level SOC_{Mkt}^{min}. If the SOC is lower than this level, the surplus is used to charge that storage. Deficit peers go to the market as buyers trying to wipe out that deficit.

Price Adaptation The trading agent must be able to adapt the prices of bids/asks to the outcome of each offer. For example, if a better offer remains open, it is evident that the TA must try to further adjust the profit margin to have market chances. Similarly, if someone notifies the closing of an offer at a less competitive price than the one my TA is requesting, it may adjust the offer in search for an even higher profit. TA software

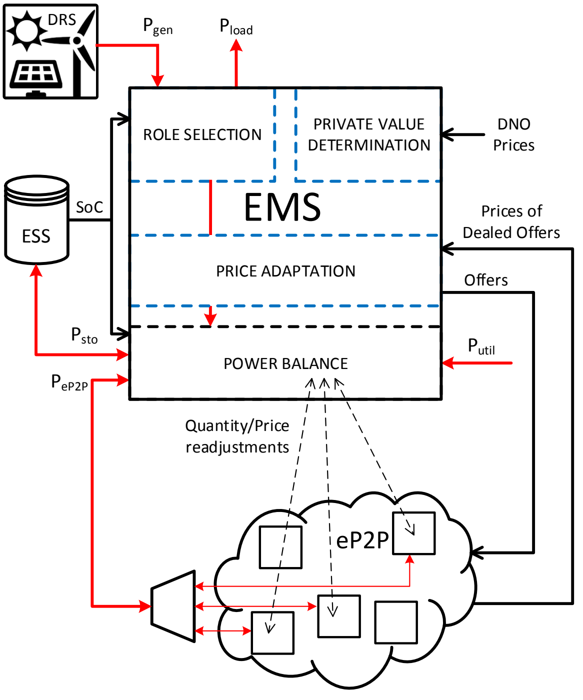

Figure 5.3 Block diagram of the EMS and its external interactions. Blue dashed line blocks integrate the Trading Agent. The red arrows represent power flows, while the black arrows represent information flows.

here uses the well-known ZIP algorithm to perform price adaptation after each offer made within the auction.

Quantity/Price Readjustments Bids and asks made by one peer can be covered by another at any time, so $P_{P2P}(t)$ can vary abruptly between t and any infinitesimally later $t^+ = t + \Delta t$, with $\Delta t \longrightarrow 0$. The EMS is responsible for continuously adjusting the terms $P_{sto}(t)$ and $P_{util}(t)$ in (5.1) to accommodate these variations. Alternatively, unpredictable variations of $P_{load}(t)$ and $P_{gen}(t)$ may make it necessary to modify one or more of the active transactions. The EMS is also responsible for renegotiating such transactions in the following cases:

- A peer acting as a seller ($P_{P2P}(t) < 0$) whose surplus decreases to a level below the aggregate of its current sold power ($P_{gen}(t^+) - P_{load}(t^+) < P_{P2P}(t)$) notifies its buyers, one by one from less to more profitable for the seller itself, of the reduction in the power quota assigned to the corresponding transfer. If the reduction in the surplus suffered by the seller is large enough, it may be necessary to cancel one, several or even all ongoing transfers altogether.

- A peer acting as a buyer ($P_{P2P}(t) > 0$) whose deficit decreases to a level below the aggregate of its current purchased power ($P_{gen}(t^+) - P_{load}(t^+) > P_{P2P}(t)$) notifies its sellers, one by one from less to more profitable for the buyer itself, of the reduction of the power quota assigned to the transfer. If the deficit reduction suffered by the peer buyer is large enough, it may be necessary to completely cancel one, several or even all ongoing transfers.

- A peer acting as a buyer ($P_{P2P}(t) > 0$) whose deficit increases ($P_{gen}(t^+) - P_{load}(t^+) > P_{P2P}(t)$) notifies it directly to the sellers with whom it maintains active transfers, one by one starting with the most profitable, and tries to increase the share of power allocated to the transaction. Depending on its surplus situation, the corresponding seller may increase the quota or keep it stable.

In order to be able to make these readjustments, the EMS maintains an updated *Transfer List* in which each transaction fills a row with the following fields : i) Transfer Identifier, ii) Transfer Type (purchase or sell), iii) Identity of the counterpart of the transfer, iv) State of the transfer (ongoing or finished), v) Transfer start time, vi) Nominal price of the transfer, vii) Current value of instantaneous power being transferred, viii) Relative profit of the transfer for current transfer price and private valuation and ix) Energy transferred from the beginning of the transfer according to the followed power profile.

Content of each row of the Transfer List	
Field	**Description**
Id	Alphanumerical identifier of the Transfer.
Type	Purchase Transfer (1) or Sell Transfer(-1).
Cp. Id	Identifier of the Transfer Counterparty.
State	Ongoing (1) or Finished (0).
t_{start}	Transfer start time.
$\mathbf{p}$	Time profile of nominal power prices.
q_{nom}	Current value of instantaneous power being transferred.
π_{nom}	Nominal value of the total profit that can be obtained if the transfer is completed (for energy packages).
π	Relative profit of the transfer for current transfer price and private value.
$E(t) = \int_{t_{start}}^{t} q_{nom}(\tau) d\tau$	Energy transferred from the beginning of the transfer according to the following power profile.
π_{ex}	Extracted profit so far corresponding to this transfer.
η	Power rate at which the transfer is taking place.
t_{comp}	Completion Time: Time before which the transfer must be finished (for energy packages).

The algorithm that governs the quantity readjustments of the ongoing transfers is explained in Algorithm 1.

Algorithm 1 Transfer Readjustment Algorithm for peer k

Data
    $\Phi(t)$ Gross Power Balance: $\Phi(t) \stackrel{\text{def}}{=} P_{gen}(t) - P_{load}(t)$
    $\beta(t)$ Aggregated Purchased Power: $\beta(t) \stackrel{\text{def}}{=} \sum_{\forall m \in M} P_m(t)$; $\beta(t) \geq 0, \forall t$
    $\sigma(t)$ Aggregated Sold Power: $\sigma(t) \stackrel{\text{def}}{=} \sum_{\forall n \in N} P_n(t)$; $\sigma(t) \leq 0, \forall t$
    $TL(t)$ Transfer List of peer k updated to time t
Result
    $\beta(t^+)$
    $\sigma(t^+)$
    $TL(t^+)$
    $P_{P2P}(t^+)$ Power Market Result: $P_{P2P}(t) \stackrel{\text{def}}{=} \beta(t) + \sigma(t)$
while 1 **do**
    if $\Phi(t) < 0 \land \sigma(t) > 0$ **then** ▹ Cancel all selling transfers
        $n \leftarrow 1$
        while $n \leq N$ **do**
            $q_{nom}(n,t^+) \leftarrow 0$
            $n \leftarrow n+1$
        end while
        $\sigma(t^+) \leftarrow 0$
    else if $\Phi(t) > 0 \land \beta(t) > 0$ **then** ▹ Cancel all purchase transfers
        $m \leftarrow 1$
        while $m \leq M$ **do**
            $q_{nom}(m,t^+) \leftarrow 0$
            $m \leftarrow m+1$
        end while
        $\beta(t^+) \leftarrow 0$
    else if $\Phi(t) > 0 \land \Phi(t) < -\sigma(t)$ **then** ▹ Rearrange selling transfers
        $\Delta\sigma \leftarrow \Phi(t) + \sigma(t)$
        Sort ↓ TL ▹ Sort active selling transfers from lowest to highest relative profit
        $n \leftarrow 1$
        while $\Delta\sigma < 0 \land n \geq N$ **do**
            ▹ Notify peer $i = cp(n)$ intention to reduce sellings up to $\Delta\sigma$
            $q_{nom}(n,t^+) \leftarrow \min(0, q_{nom}(n,t) - \Delta\sigma)$
            $\Delta\sigma \leftarrow \Delta\sigma + [q_{nom}(n,t^+) - q_{nom}(n,t)]$
            $\sigma(t^+) \leftarrow \sigma(t) - [q_{nom}(n,t) - q_{nom}(n,t^+)]$
            $n \leftarrow n+1$
        end while

else if $\Phi(t) < 0 \wedge -\Phi(t) < \beta(t)$ **then** ▹ Rearrange purchase transfers
$\Delta\beta \leftarrow -\Phi(t) - \beta(t)$
Sort $\downarrow$ TL ▹ Sort active buying transfers from lowest to highest relative profit
$m \leftarrow 1$
while $\Delta\beta < 0 \wedge m \geq M$ **do**
▹ Notify peer $j = cp(m)$ intention to reduce purchasing up to $\Delta\beta$
$q_{nom}(m,t^+) \leftarrow \max(0, q_{nom}(m,t) + \Delta\beta)$
$\Delta\beta \leftarrow \Delta\beta + [q_{nom}(n,t) - q_{nom}(n,t^+)]$
$\beta(t^+) \leftarrow \beta(t) - [q_{nom}(m,t) - q_{nom}(m,t^+)]$
$m \leftarrow m + 1$
end while
else if $\Phi(t) < 0 \wedge -\Phi(t) > \beta(t) \wedge \beta(t) > 0$ **then** ▹ Try to enlarge buying transfers
$\Delta\beta \leftarrow -(\Phi(t) + \beta(t))$
Sort $\uparrow$ TL ▹ Sort active buying transfers from highest to lowest relative profit
$m \leftarrow 1$
while $\Delta\beta > 0 \wedge m \geq M$ **do**
▹ Notify peer $j = cp(m)$ intention to enlarge purchasing up to $\Delta\beta$
$q_{nom}(m,t^+) \leftarrow q_{nom}(m,t) + \min(\Delta\beta, \Phi^j(t) + \sigma^j(t))$
$\Delta\beta \leftarrow \Delta\beta + [q_{nom}(m,t) - q_{nom}(m,t^+)]$
$\beta(t^+) \leftarrow \beta(t) + [q_{nom}(m,t^+) - q_{nom}(m,t)]$
$m \leftarrow m + 1$
end while
end if
end while

Once a transfer finishes, the amount of the transfer is calculated as the product between the aggregate energy sold and the nominal price, and charging can be made immediately.

Since the market runs continuously over time, the EMS must adjust power flows while there are no changes from the market in the form of new transactions or adjustments of ongoing transfers. Sellers store in their ESS the portion of their surplus that they do not manage to sell (if any). The buyers, on the other hand, need to supply the additional power they cannot obtain in the P2P market (if any). If they do not have storage availability, they buy the post-market deficit directly from the utility. If they have an ESS they must establish a private valuation for the power/energy stored in that storage. If the instantaneous price of the utility is higher than their private valuation, it is advantageous to discharge the ESS to wipe the power deficit; if, on the other hand, the utility is currently supplying energy at a price lower than its private valuation, a prosumer prefers to purchase the deficit directly from the utility.

The algorithm that drives demand satisfaction at all times is explained in Algorithm 2.

Algorithm 2 Demand Satisfaction

Data
- $\Psi(t)$ Net Power Balance: $\Psi(t) \stackrel{\text{def}}{=} P_{gen}(t) - P_{load}(t) + P_{P2P}(t) + P_{stg}(t)$
- $B_r(t)$ Current ESS Level
- B_{max} Maximum allowed ESS Level
- B_{min} Minimum allowed ESS Level
- κ_{stg} Maximum ESS charge/discharge power
- $\lambda(t)$ Private Value
- $\vartheta_{util}(t)$ Energy Price offered by the utility

Result
- $P_{stg}(t^+)$
- $P_{util}(t^+)$
- $B_r(t^+)$

while 1 **do**
    if $\Psi(t) > 0 \wedge B_r(t) < B_{max}$ **then**
        ▷ Recharge ESS until fully loaded
        $P_{ch}(t^+) \leftarrow \min(\Psi(t), \kappa_{stg})$
        $P_{util}(t^+) \leftarrow -(\Psi(t) - P_{ch}(t))$
    else if $\Psi(t) < 0$ **then**
        ▷ Still got deficit. Either drain from ESS or buy from the utility
        if $\lambda(t) < \vartheta_{util}(t) \wedge B_r(t) \geq B_{min}$ **then**
            $P_{dis}(t^+) \leftarrow -\max(\Psi(t), -\kappa_{stg})$
            $P_{util}(t^+) \leftarrow -(\Psi(t) - P_{dis}(t))$
        else
            $P_{util}(t^+) \leftarrow -\Psi(t)$
        end if
    else if $\Psi(t) = 0$ **then**
        ▷ Perfect Balance
        $P_{util}(t^+) \leftarrow 0$
    end if
    $E_{ch}(t) \leftarrow \min(\int_{\Delta t \to 0} P_{ch}(\tau) d\tau, B_{max} - B_r(t)))$
    $E_{dis}(t) \leftarrow \max(\int_{\Delta t \to 0} -P_{dis}(\tau) d\tau, B_r(t) - B_{min}))$
    $B_r(t^+) = B_r(t) + E_{ch}(t) + E_{dis}(t)$
end while

5.4 Case Study

5.4.1 Description

As an example case in which to establish an eP2P market, a residential neighbourhood in the city of Córdoba (Andalusia, Spain) has been taken. Peers are a set $\mathcal{H}$ of $n_{\mathcal{H}} = 40$ single-family homes, some of which are supposed to have photovoltaic (PhV) generation systems. There are three possible installed PhV powers, $P_{phv} \in \{1,3,5\}$ kWp, and each of them has an associated ESS of adequate capacity, $B_{max} \in \{2.5,5,7\}$ kWh respectively.

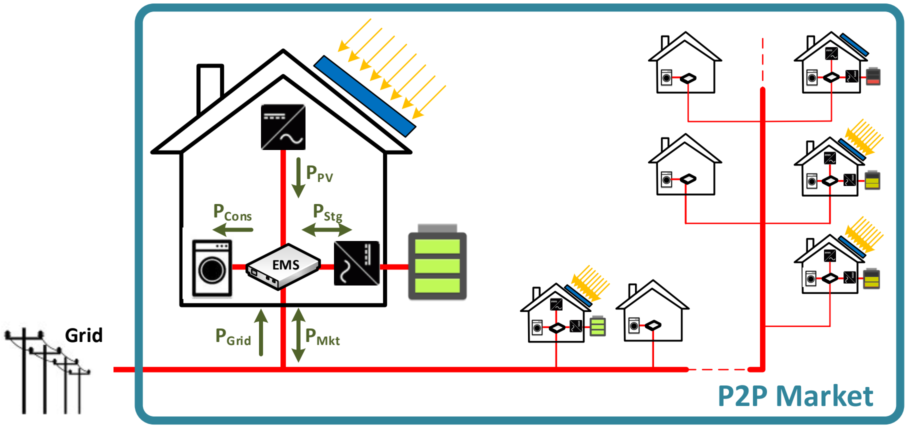

Figure 5.4 Diagram of the Case Study.

Since the houses are located in close geographical vicinity, it is assumed that they all receive the same solar irradiance profile. Therefore the shape of their PhV generation profile is the same, the magnitude being scaled depending on the peak power of the PhV installation for each household.

An extended version of the bottom-up stochastic model of [60] was used to build the consumption profiles, which take into account not only lighting and heating and cooling systems but also the most common household appliances. Based on the number of inhabitants of the house, which is an input parameter, and considering the meteorological conditions (irradiance and temperature) at each moment, the model generates high temporal resolution (1 min) stochastic consumption profiles for a period of one year.

Regardless of whether they have distributed generation or not, all households have an EMS with trading capabilities, and everyone is considered to be continuously participating in the market (see Figure 5.4).

Two different scenarios have been contemplated regarding the possibility of commercial interaction with the distributor. In the first case, DNO does not buy any production surplus from end users, so they either sell it on the eP2P market, store it in their storage systems, or lose it. In the second case, the DNO buys the surplus following a *Net Purchase and Sale System* (NPSS), according to the Spanish legislation. With this system, a prosumer i can inject all their surplus ($\mathcal{S}_i$) into the network, being compensated into its monthly bill. Compensated energy within a certain billing period T ($E_c^i(T)$) can never be higher than consumed one (there cannot be a positive balance of the prosumer with the DNO), so that $E_c^i = \min\left(\sum_{\forall t \in T} E_{DNO}^i(t), -\mathcal{S}_i(T)\right)$. The compensated energy is discounted at the voluntary price for the small consumer (VPSC), $\overline{\vartheta}_c$. In this case, the average value for the VPSC in 2017 is taken, $\overline{\vartheta}_c$ = 0.05 €/kWh.

In general, the net cost of energy for any peer over a certain period of time can be calculated as:

$$\Phi^i(T) = \sum_{\forall t \in T} E^i_{DNO}(t) \cdot \vartheta(t) - E^i_c(T) \cdot \overline{\vartheta}_c + \sum_{\forall \omega \in \Omega_i} \mathcal{A}^i_\omega(T) \tag{5.7}$$

being $\mathcal{A}^i_\omega(T)$ the amount of money corresponding to each transaction ω in the set Ω_i of all eP2P transactions dealt by user i within T.

Another important parameter is the total amount of renewable energy harnessed by each peer i with generation capacity

$$RW^i(T) = E^i_c(T) + \sum_{\forall t \in T} E^i_{sc}(t) + E^i_{eP2P}(t) + E^i_{sto}(t) \tag{5.8}$$

where E^i_{sc}, E^i_{eP2P} and E^i_{sto} represent renewable energy used for self-consumption, sold in the eP2P market or stored into the ESS, respectively.

Finally, in order to consider possible differences in the level of utilisation of storage systems, the following index is defined that takes into account the absolute amount of energy exchanged by the batteries:

$$B^i(T) = \sum_{\forall t \in T} E^i_{ch}(t) + |E^i_{dis}(t)| \tag{5.9}$$

where E^i_{ch} and E^i_{dis} are the amount of energy charged or discharged from the i-th end user ESS, respectively.

5.4.2 Tests and Results

In order to test how the eP2P market affects the economic-energy performance of the households in the example, the operation of the first full fortnight (Day 1 to Day 14, both included) has been simulated for two different months of the year: the coldest (January) and the hottest (July). The number of sellers depends directly on the number of houses with renewable generation. Three possible levels of penetration of PhV installations have been thus considered $PhV_{pen} \in \{15\%,30\%,45\%\}$.

The comparison is made between the energy operation of the residential cluster $\mathcal{H}$ with and without the possibility of eP2P trading. The four performance indicators used (Energy Cost Comparator, Renewable Energy Use Comparator, Battery Usage Comparator and Renewable Energy Harnessing Rate) are defined below:

$$\Delta\Phi(T) = \frac{\sum_{\forall h \in \mathcal{H}} \Phi^h_{P2P}(T)}{\sum_{\forall h \in \mathcal{H}} \Phi^h_{NoP2P}(T)} - 1 \tag{5.10}$$

$$\Delta RW_{use}(T) = \frac{\sum\limits_{\forall h \in \mathcal{H}} RW^h_{P2P}(T)}{\sum\limits_{\forall h \in \mathcal{H}} RW^h_{NoP2P}(T)} - 1 \tag{5.11}$$

$$\Delta B_{use}(T) = \frac{\sum\limits_{\forall h \in \mathcal{H}} B^h_{P2P}(T)}{\sum\limits_{\forall h \in \mathcal{H}} B^h_{NoP2P}(T)} - 1 \tag{5.12}$$

$$\Gamma_{RW}(T) = \frac{\sum\limits_{\forall h \in \mathcal{H}} RW^h_{P2P}(T)}{\sum\limits_{\forall h \in \mathcal{H}} PV^h_{gen}(T)} - 1 \tag{5.13}$$

Results (see Table I) show that the possibility of eP2P trading significantly reduces the total cost of energy (sum of energy expenses for all houses), while increasing the use of renewable energy (sum of PhV energy actually used to meet the aggregate consumption of all houses) and reducing the absolute use of storage systems. The magnitude of this reduction varies according to the level of penetration of the PhV installation, which is logical considering that, with current settings, a seller only exists if there is an instantaneous production surplus.

Figure 5.5 shows the difference in terms of the sources used to satisfy aggregate demand. It can be seen how, during solar radiation hours, the eP2P market consistently replaces the energy supplied by the DNO.

Unlike net balance schemes, the NPSS system does not allow a positive balance for peers with production capacity. Therefore, a prosumer does not monetise any injected energy that exceeds its consumption. On the other hand, the eP2P market allows it to make an economic profit from this surplus production, even above its own consumption (see Figure 5.6).

5.5 Discussion

This chapter shows how the implementation of an eP2P market for the continuous negotiation of instantaneous power quotas makes it possible to reduce the global cost of energy for a set of peers that can be heterogeneous. At the same time, by establishing a new commercialisation option for the surplus of renewable production, greater use is made of this type of clean energy. The savings amount depends on the proportion of peers with generation capacity, which is given by the percentage of penetration of DRG systems. The more penetration, the greater the production and the greater the supply, but also the more energy unused. It also depends on whether the distributor is legally forced to compensate the prosumers for their excess production, although the savings are relevant in both cases.

This cost reduction for prosumers is at the expense of a revenue reduction for the DNO which, depending on the scenario, globally bills between 6.41% and 50.29% less energy in the case of eP2P presence. However, given that the net operating margin on sales of the energy distributors is rather narrow (around 5% in 2017 according to Spanish

Table 5.1 Results.

SCENARIO	$\Delta\Phi_{cost}(\%)$			$\Delta RW_{use}(\%)$			$\Delta B_{use}(\%)$			$\Gamma_{RW}(\%)$		
PhV_{pen}	15	30	45	15	30	45	15	30	45	15	30	45
Coldest	-3.86	-11.23	18.73	+50.19	+64.5	+36.16	-43.1	-27.21	-7.06	78.30	69.54	62.86
Coldest with NPSS	-2.95	-9.99	-22.99	+27.72	+43.81	+29.96	-43.1	-27.21	-7.06	100	100	81.69
Warmest	-20.47	-41.47	-60.11	+104.1	+90.63	+52.79	-34.18	-31.82	-14.07	50.59	55.99	47.87
Warmest with NPSS	-20.30	-40.85	-60.57	+97.65	+78.60	+45.82	-34.18	-31.82	-14.07	100	100	69.80

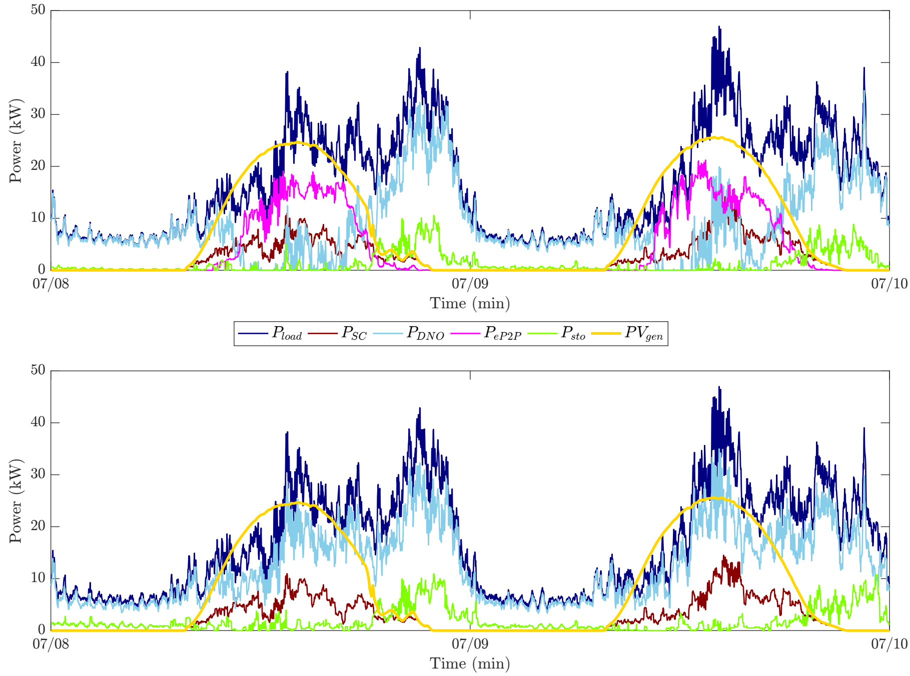

Figure 5.5 Aggregated power balance with (upper) and without (lower) eP2P market, for summer day for a 40 houses neighbourhood with $PV_{pen} = 30\%$.

National Commission on Markets and Competition), even such large reduction in sales volume has a small absolute impact in terms of profit. Although not contemplated in this article, the distributor itself could charge each eP2P operation for lease and maintenance of the network on which the transfer is made. In fact, preliminary calculations show how, by establishing fees between 3.41% and 5.95%, the revenue obtained by the DNO through the eP2P equals the losses derived from the reduction in its direct sales volume. Furthermore, one of the open questions is to study another type of benefits that eP2P trading may have (regarding regulation capabilities, anti-islanding, reduction of future network expansion costs [61]) in order to make it convenient for the distributor to allow energy exchanges.

As an additional benefit, a reduction is achieved in the use of prosumers' energy storage systems, which in principle should result in an increase in their lifetime and therefore in a reduction in the costs of maintenance and replacement. In fact, with this kind of continuous power market, storage systems are not strictly necessary, since traded energy is transferred immediately to be consumed instantaneously. In addition, problems related to forecast do not affect, since only real instantaneous production and consumption are used to determine trading offers.

Future research efforts will focus on improving the role selection strategy for those peers with storage capabilities, with a twofold objective: i) to consider the possibility that they can act as sellers even if they are in a situation of instantaneous deficit and ii)

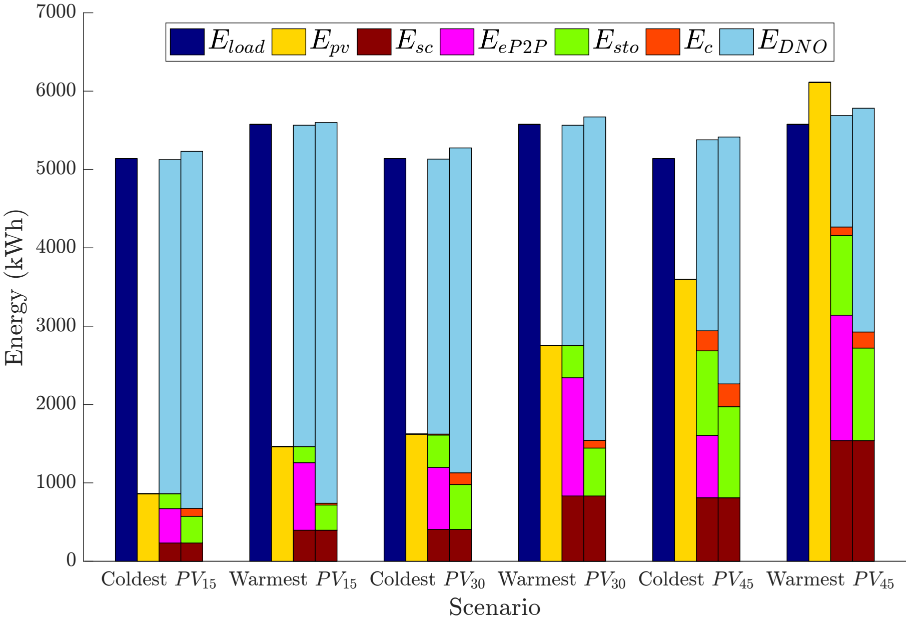

Figure 5.6 A stacked bar diagram showing the aggregate energy breakdown of the 40 houses for a full fortnight assuming that the prosumers all have a NPSS scheme. For each group, the relationship between the first and second bar determines the portion of the load that could ideally be satisfied with renewable energy. The third bar shows, in the case of eP2P marketing possibility, the use of RE broken down into the different forms of harnessing. The fourth bar is identical to the third but without eP2P market.

that they are able to analyse the market price evolution forecast in order to decide at what moments of the day it is potentially more convenient to trade.

6 A Stochastic MPC Based Controller to Optimise End Users Participation in Energy and Power Integrated Markets

Prediction is very difficult, especially if it's about the future.

NIELS BOHR, 1922 NOBEL LAUREATE IN PHYSICS

THIS *chapter expands the analysis carried out in previous chapters, extending it to the case in which energy entities have several P2P markets available with different marketing formats and/or mechanisms. Specifically, as is explained in Section 6.2, each entity can trade energy in the form of packages and in the form of power quotas, yielding two parallel markets, one discrete and the other continuous, which overlap over time. Section 6.3 presents the structure of an EMS that allows the entity to participate simultaneously in both markets while optimizing its energy operation, through the use of a strategic advisor based on Stochastic Model Predictive Control, the formulation of which is specified in Section 6.4. Section 6.5 explains the changes in role selection that are required for the power dispatcher in Chapter 5 to operate in an integrated manner with the optimal energy plan determined by the strategy advisor. Section 6.6 introduces a case study and shows the tests performed and the results obtained.*

6.1 Introduction

Chapter 3 proposed a strategy for saving energy by jointly optimising the scheduling of demand and the choice of optimal power sources to satisfy it. Starting from Chapter 4, the possibility of improving the energy operational economic result not only by minimising the cost, but also by maximising the return, is considered. That chapter stated that certain aspects of energy exchange must be taken into account when choosing the most appropriate auction structure to maximise the return derived from energy trading. Subsequently, in Chapter 5, a structure is proposed for the trading of energy in the form of real-time power quotas, rather than doing it by trading energy packages ahead of time. The findings indicate that there is no one-type-fits-all double auction structure for different forms of energy trading. Therefore, it seems logical to assume that several of these structures may be available to end users, who could in principle participate simultaneously in all of them. This chapter proposes an EMS structure that optimises the energy operation of end users, taking the existence of several energy markets in consideration, and automating the participation in them. These end users can be generally heterogeneous and include both prosumers and pure consumers.

6.2 Integrated Energy Packages and Power Quotas Markets

As explained in the previous chapter, there are fundamentally two forms of energy trading in P2P markets. On the one hand there is the traditional way, which is to negotiate energy packages (EPs) of fixed or arbitrary size, ahead of time. In other words, the agreement between buyer and seller, and possibly the physical transfer of the energy between them, occurs in a time period prior to that of the actual consumption of the transacted energy. In general, this requires that both buyer and seller have the corresponding ESS to store the energy before its transfer/consumption. There is the possibility of operating without ESS, in which case the seller negotiates the transfer of an energy package that is not yet physically possessed, and the buyer negotiates the purchase of an energy package that is expected to be consumed. However, any divergence between the forecasts and the actual values (of generation and/or consumption) would cause a breach of the agreed transaction, with the corresponding power imbalance for the grid.

The alternative form, presented in Chapter 5, is to commercialise power quotas (PQ) either for supply or demand, that are negotiated (and adapted) in real time. In this way, energy transfer occurs simultaneously with energy consumption.

In general, various forms of energy trading can coexist, associated with both continuous and discrete double auction structures. In our specific case, we propose the coexistence of a market for the trading of energy packages, based on a DDA, with another market for the trading of power quotas, based on a CDA.

The discrete market acts as a futures market. Those agents who expect to have more consumption than generation, try to balance this expected deficit through the purchase of energy packages of adequate size in advance. Those agents who have a certain amount of stored energy, and who expect to have more generation than consumption, try to make the surplus profitable through the sale of energy packages. The EMS uses the power quota market as an alternative for continuous time compensation for possible errors in operational predictions. Even if energy packages have been purchased in advance to compensate for an expected deficit, an agent may find itself in an energy deficit situation if predictions fail (i.e. if its actual consumption is higher than expected, or if actual generation is lower than expected). Alternatively, those agents who did not expect to have a surplus can effectively experience it if their consumption is lower than expected or their production is higher than expected. In these cases, they can choose to store the surplus in their ESS, or sell it on the continuous market. In any case, it is assumed that all agents are individually rational (IR): deficit agents only buy in the P2P continuous market if the purchase price is lower than that offered by the energy retailer company; surplus agents only sell in the P2P continuous market if the sale price is higher than the utility they expect to obtain for the consumption of that energy in the future.

6.3 An EMS for Simultaneous Participation in Both Markets

The architecture of the proposed EMS is depicted in Figure 6.1. To enable simultaneous participation in both markets, while performing optimal power dispatch, the EMS needs to track the state of the entity. At any given time t, the entity's state, $x(t) = \{SOC(t)\,,\, BC(t)\,,\, SC(t)\}$, is defined by the state of charge of its ESS, $SOC(t)$, and the buy commitment, $BC(t)$, and sell commitment $SC(t)$, previously acquired and not yet completely satisfied. An agent's state implicitly determines the amount of energy it can bid or ask for in the market.

The EMS might or not include an strategy advisor (SA), explained in Section 6.4, that performs optimisation at each $t_{opt} = \tau_k = k \cdot \Delta T_{DDA}$ immediately prior to each discrete market session. Before such session opens for offers submission, the agent's EMS is assumed to have the following information:

- The following N opening instants of the discrete market, $\{\tau_{k+1}, \ldots, \tau_{k+N}\}$, which are assumed to be evenly spaced over time according to a certain period of time, $\Delta T_{DDA} = \tau_{i+1} - \tau_i, i \in \mathbb{Z}^+$, where N is the length of the prediction horizon, measured in number of intervals of the discrete market. In the case of agents whose permanence in the market is dynamic this implies that they know therefore the number of remaining sessions they have to negotiate, and the corresponding time period they would have to effectively inject/absorb the energy they manage to trade.

- The market history up to a certain past horizon N_h. This includes, for each past trading period $k - i, i \in \mathbb{Z}^+, 1 \leq i \leq N_h$, the set of all individual bids and asks, $\Omega(\tau_{k-i}) = \{\boldsymbol{\varphi}(\tau_{k-i})\,,\, \boldsymbol{\vartheta}(\tau_{k-i}\}$, and their market result, $\mathcal{M}(\tau_{k-i}) = \{\boldsymbol{q}(\tau_{k-i})\,,\, \boldsymbol{p}(\tau_{k-i})\}$.

- Forecasts of consumption profile ($\tilde{P}_{load}(t)$) and generation profile ($\tilde{P}_{gen}(t)$) along certain forecasting horizon ($t \in \mathbb{Z} : \tau_k \leq t \leq \tau_k + N_f$).

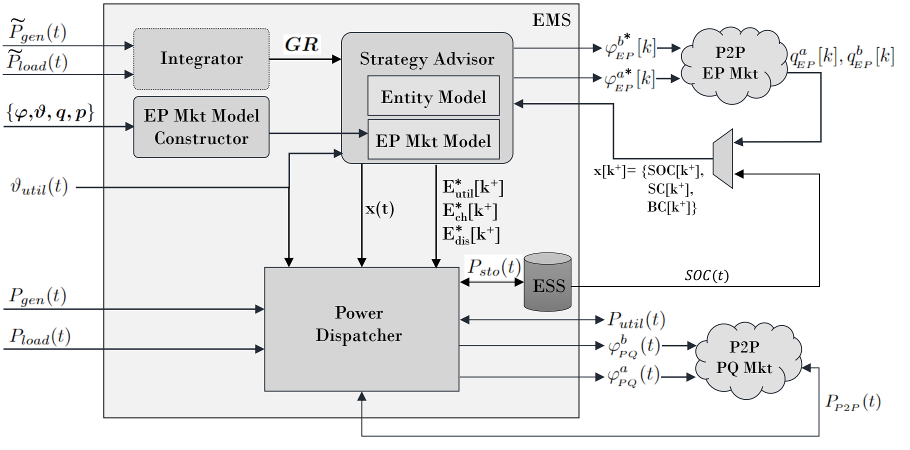

Figure 6.1 Structure of the proposed EMS, allowing the energy entity to participate simultaneously in two eP2P markets, one discrete in which packages are exchanged and another continuous in which power quotas are negotiated.

- The time profile of the price offered by the utility company ($\vartheta_{util}(t)$) along the prediction horizon ($t \in \mathbb{Z} : \tau_k \leq t \leq \tau_k + N \cdot \Delta T_{DDA}$).

6.3.1 Energy Balance Forecasting

Since the time resolution of the consumption and generation forecasts is generally greater than the length of the interval between sessions, the EMS is in charge of carrying out the time aggregation to calculate the interval-wise energy *gross result* vector $\boldsymbol{GR} = \{gr[i]\}$, where[1]:

$$gr[i|\tau_k] = \int_{t=\tau_k+(i-1)\Delta T_{DDA}}^{\tau_k+i\Delta T} \left(\tilde{P}_{gen}(\tau) - \tilde{P}_{load}(\tau)\right) d\tau, \text{ for } 1 \leq i \leq N \tag{6.1}$$

Obviously, it must hold that $N_f \geq N \cdot \Delta T_{DDA}$. The *cumulative gross result*, $\boldsymbol{GR}_c$, vector shows the same dimensions as $\boldsymbol{GR}$, its elements being given by:

$$gr_c[i|\tau_k] = \sum_{k=1}^{i} gr[k|\tau_k], \text{ for } 1 \leq i \leq N \tag{6.2}$$

[1] Please note that parentheses are used to refer to continuous time variables, while brackets denote discrete variables.

Three additional forecast variables can be calculated using the cumulative gross result:

$$PD[\tau_k] = \left\lfloor BC(\tau_k) + \sum_{i=1}^{N} gr[i|\tau_k] \right\rfloor_- \tag{6.3a}$$

$$PS[\tau_k] = \left\lceil (B_r(\tau_k) - B_{min}) + \sum_{i=1}^{N} gr[i|\tau_k] - SC(\tau_k) \right\rceil^+ \tag{6.3b}$$

$$ES[\tau_k] = \frac{\left\lceil PS[\tau_k] - (B_{max} - B_{min}) \right\rceil^+}{PS[\tau_k]}) \tag{6.3c}$$

where $\lceil\cdot\rceil^+$ denotes $max\{0,\cdot\}$ and $\lfloor\cdot\rfloor_-$ denotes $min\{0,\cdot\}$. $PD[\tau_k] \in (-\infty,0]$ is the *predicted deficit*, which equals zero unless the sum of the buy commitments not yet received, $(BC(\tau_k))$, plus the aggregation of the gross result over the prediction horizon is negative. $PS[\tau_k] \in [0,\infty)$ is the *predicted surplus*, which equals zero unless the sum of the current level of energy stock, $(B_r(\tau_k) - B_{min})$, plus the aggregation of the gross result over the prediction horizon, minus the sell commitments not yet satisfied, $(SC(\tau_k))$, is positive. Finally, $ES[\tau_k] \in [0,1)$ is the *excess surplus* which represents the portion of the expected surplus that exceeds the maximum energy stock storage capacity, $(B_{max} - B_{min})$, and which therefore cannot be stored and would be unused if not sold.

Private Valuation The trading agents of all entities have the same way of valuing power in the PQ-Market and energy in the EP-Market. However, the valuation is different for each of the two possible roles (buyer or seller). For the PQ-Market, the private valuation of the buyers is equivalent to the instantaneous price at which the distributor is pricing the energy at each moment, i.e. $\lambda_p^b(t) = \vartheta(t)$. This implies that (rational) buyers never buy P2P power above the distributor's price. On the other hand, sellers value power at 35%[2] of the value offered by the distributor. This implies that the unit price of the sellers is, at most, 65% lower than the instantaneous price offered by the distributor.

For the EP-Market, each trader values the energy as the average cost of its future energy needs, predicted over a future horizon of duration N_p.

$$\lambda_e^i(t) = \frac{\sum\limits_{k=0}^{N_p-1} \hat{q}_i(t+k) \cdot \hat{p}_i(t+k)}{\sum\limits_{k=0}^{N_p-1} \hat{q}_i(t+k)} \tag{6.4}$$

where $\hat{q}_i(t+k)$ is the forecast electrical consumption of the i-th prosumer during the k-th future instant, and $\hat{p}_i(t+k)$ is the utility electricity price for i-th prosumer during the same k-th future instant. However, valuation here also varies depending on

[2] This is an arbitrarily chosen percentage and can be replaced by any other. Different percentages could even be selected for each of the traders.

the role adopted by the trader. Traders which forecast deficit (buyers) directly use the aforementioned value, which implies that a buyer will try to buy energy packages with unitary price below its average energy unit cost within the prediction horizon. Sellers, for their part, adjust their valuation depending on the excess surplus (6.3c) they forecast, considering that rather than discarding the excess of generation over consumption that exceeds the storage capacity of the battery, it is better to lower its value to sell it albeit at a lower price:

$$\lambda_e^s(t) = \lambda_e(t) \cdot (1 - ES(t)) + \varrho \cdot \lambda_e(t) \cdot ES(t) \tag{6.5}$$

where $\varrho \in (0,1)$ is an arbitrary ratio indicating at what percentage of the average energy cost the surplus portion is valued.

Table 6.1 summarises the private valuation for both markets and both roles.

Table 6.1 Summary of Private Valuation of Power (Energy).

	PQ-Market	EP-Market
Buyer	$\lambda_p^b(t) = \vartheta(t)$	$\lambda_p^b(t) = \lambda_e(t)$
Seller	$\lambda_p^s(t) = 0.35 \cdot \vartheta(t)$	$\lambda_e^s(t) = \lambda_e(t) \cdot (1 - ES(t)) + \varrho \cdot \lambda_e(t) \cdot ES(t)$

6.3.2 Markets Forecasting

Knowing the history of submitted offers and their corresponding market results, the EMS can compute the following statistical terms that constitute the model (see Figure 6.3) for the discrete double auction-based energy packages market:

- The sequence of average buying and selling prices (or the average price for uniform pricing) for each past market sessions, $\overline{\mathbf{p}}_{mkt} = \{\overline{p}_{mkt}[k-i]\}, i \in \mathbb{Z} : 1 \le i \le N_h$. As each session corresponds to a specific time instant $t = (k-i)\Delta T_{DDA}$, this is equivalent to calculating the time evolution of the average market spot price during the period covered by the previous N_h sessions.
- Let Θ_k^{mb}, Θ_k^{ub}, Θ_k^{ma}, Θ_k^{ua} be continuous random variables representing, respectively, the prices for matched bids, unmatched bids, matched asks and unmatched asks during the k-th market session. All four have the same support $\mathcal{R}_\Theta = \{0, \vartheta_{util}^{max}\}$, since no one bids below zero nor asks above the highest price offered by the utility along the day. Then it is possible to compute the corresponding probability density functions and cumulative distribution functions (see Figure 6.2) as follows:
  - Matched Bids: $f_k^{mb}(\vartheta^b) = \Pr(\Theta_k^{mb} = \vartheta^b)$ and $F_k^{mb}(\vartheta^b) = \Pr(\Theta_k^{mb} \le \vartheta^b)$
  - Unmatched Bids: $f_k^{ub}(\vartheta^b) = \Pr(\Theta_k^{ub} = \vartheta^b)$ and $\overline{F}_k^{ub}(\vartheta^b) = \Pr(\Theta_k^{ub} > \vartheta^b)$
  - Matched Asks: $f_k^{ma}(\vartheta^a) = \Pr(\Theta_k^{ma} = \vartheta^a)$ and $\overline{F}_k^{ma}(\vartheta^a) = \Pr(\Theta_k^{ma} > \vartheta^a)$
  - Unmatched Asks: $f_k^{ua}(\vartheta^a) = \Pr(\Theta_k^{ua} = \vartheta^a)$ and $F_k^{ua}(\vartheta^a) = \Pr(\Theta_k^{ua} \le \vartheta^a)$

- Liquidity vectors, for both demand, $\mathcal{L}^b = \{\ell^b[k-i]\}$, and supply, $\mathcal{L}^a = \{\ell^a[k-i]\}$, with $i \in \mathbb{Z} : 1 \le i \le N_h$.

$$\ell^b[k-i] = \frac{\sum \mathbf{q}^b[k-i]}{\sum \boldsymbol{\varphi}^b[k-i]} \qquad \ell^a[k-i] = \frac{\sum \mathbf{q}^a[k-i]}{\sum \boldsymbol{\varphi}^a[k-i]}$$

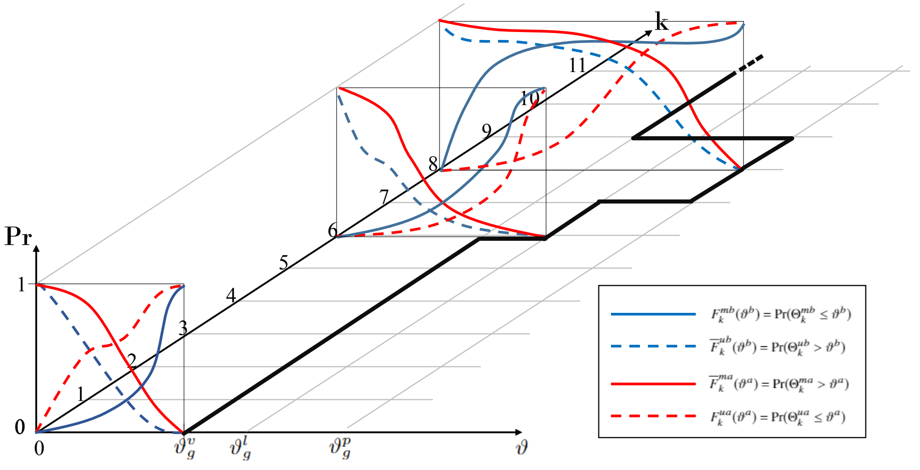

Figure 6.2 Cumulative Distribution Functions (CDFs) and Complementary Cumulative Distribution Functions (CCDFs) are one of the alternatives for modelling the energy packages market. The mathematical definition of each function varies between the different k sessions. Within each session, the support of random variables is determined by the energy price offered by the retailer (in this case an hourly discrimination tariff with off-peak fees, flat fees and peak fees can be observed)..

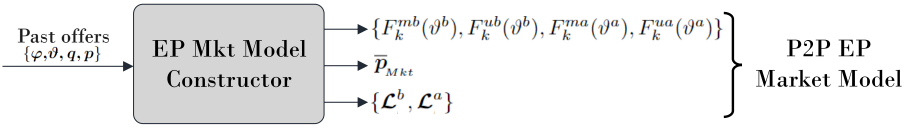

Figure 6.3 Building the probabilistic model for the discrete time energy packages market, based on the history of offers made and their respective results in the market.

6.4 A Strategy Advisor based on Model Predictive Control

The main objective of the strategy advisor is to meet the projected energy demand along the prediction horizon and to do so at the lowest possible cost. To this end, taking into account the existence and availability of the two markets, it generates an optimal dispatch plan that controls the energy flows for each of the sources that the entity has available. The vector of controllable variables is $\mathbf{u} = \{E_{util}[i]\,,\, E_{ch}[i]\,,\, E_{dis}[i]\,,\, \varphi^b[i]\,,\, \varphi^a[i]\}, i \in \{\tau_k,\tau_{k+N-1}\}$. Its components correspond to the following energy quantities: $E_{util}[i]$ is the amount of energy to be consumed from the utility during the i-th period; $E_{ch}[i]$ and $E_{dis}[i]$ respectively correspond to the amount of energy to be charged or discharged from the ESS during i-th period; $\varphi^b[i]$ is the amount of energy that the entity intends to buy at the i-th period, which will be bid in the market session held in $t = \tau_i$; finally, $\varphi^a[i]$ is the amount of energy that the entity attempts to sell in the i-th period, which will be asked in the market session held in $t = \tau_i$. Therefore, the function corresponding to the cost of energy operation of the entity along a certain prediction horizon, N is:

$$\mathcal{J}(\mathbf{x}[k]),\mathbf{u}) = \sum_{i=k}^{k+N-1} E_{util}[i]\cdot\vartheta_{util}[i] + \varphi^b[i]\cdot\tilde{p}_{EP}[i]\cdot(1-\tilde{\ell}^b[i]) \\ - \varphi^a[i]\cdot\tilde{p}_{EP}[i]\cdot\tilde{\ell}^a[i] - (\lceil gr[i]\rceil^+ - E_{ch}[i])\cdot\tilde{p}_{PQ}[i] \quad (6.6)$$

where the tilde ($\tilde{}$) over a variable indicates it is a random variable. By multiplying the price $\tilde{p}_{EP}$ by the buying liquidity complement $(1-\tilde{\ell}^b)$, the expected purchase prices of those market instants with low liquidity are artificially increased. Thus, during optimisation, agents acting as buyers will be more reluctant to plan their purchases at such market sessions. Alternatively, by multiplying the price $\tilde{p}_{EP}$ by the selling liquidity $\tilde{\ell}^a$, the expected selling prices of those market instants with low liquidity are artificially lowered. Thus, during optimisation, agents acting as sellers will be more reluctant to plan their sales at such market sessions.

6.4.1 The expected Value Problem

The economic objective function in (6.6) extends over a prediction horizon. Therefore, its elements refer to the future values of its inputs, which are the controllable variables, and to the future values of the state of the system and its outputs, which would result from the application of those inputs. Optimisation also depends on the forecast profiles of consumption, generation and prices for the two existing markets. These values, as already mentioned, are stochastic and therefore subject to uncertainty. A possible simplification consists in disregarding information on the uncertainty, taking a nominal scenario, and optimizing actions on the nominal scenario. As the common practice for defining a nominal scenario is to replace random variables by their expectation, the resulting problem is called the expected value problem, the solution of which constitutes a nominal plan [62]. At the next decision stage, the strategy advisor will recompute the plan by solving an updated expected value problem on a new nominal scenario that incorporates the observations of the current stage.

In this sense, the following formulation is deterministic, as it is based on nominal consumption, production and price profiles, without taking into account the aforementioned uncertainties. Specifically, within the optimisation, the market-related random variables $\tilde{p}_{EP}[i]$, $\tilde{\ell}^b[i]$, $\tilde{\ell}^a[i]$, $\tilde{p}_{PQ}[i]$ are replaced by their respective expectations, $\overline{p}_{EP}[i]$, $\overline{\ell}^b[i]$, $\overline{\ell}^a[i]$, $\overline{p}_{PQ}[i]$. Since there is no a priori statistical information available on market uncertainty, the expectation of variables in future instants is replaced by the average value of those variables in past isotemporal sessions (market sessions held at the same time period of the day but in previous days).

Thus, the optimisation problem to be solved in each $t = \tau_k$ is the cost minimisation of the energy operation of the entity, which is defined by the formulation (6.7):

$$
\begin{aligned}
\mathbf{u}^*[i|k] = \underset{\substack{E_{util}[i],E_{ch}[i],E_{dis}[i] \\ \varphi^b[i],\varphi^a[i]}}{\arg\min} \quad & \sum_{i=k}^{k+N-1} E_{util}[i] \cdot \vartheta_{util}[i] \\
& + \varphi^b[i] \cdot \overline{p}^b_{EP}[i] \cdot (1 - \overline{\ell}^b[i]) \\
& - \varphi^a[i] \cdot \overline{p}^a_{EP}[i] \cdot \overline{\ell}^a[i] \\
& - (\lceil gr[i] \rceil^+ - E_{ch}[i]) \cdot \overline{p}_{PQ}[i] \qquad \text{(6.7a)}
\end{aligned}
$$

subject to

$$
\begin{aligned}
SOC[i+1] &= SOC[i] - E_{dis}[i] - \varphi^a[i] + E_{ch}[i] + \min\{\kappa_e, BC[i] + \varphi^b[i]\}, && \text{(6.7b)} \\
SC[i+1] &= SC[i] + \varphi^a[i] - \min\{\kappa_e, SC[i] + \varphi^a[i]\}, && \text{(6.7c)} \\
BC[i+1] &= BC[i] + \varphi^b[i] - \min\{\kappa_e, BC[i] + \varphi^b[i]\}, && \text{(6.7d)} \\
\tilde{E}_{load} &= E_{sc}[i] + E_{dis}[i] + E_{util}[i], && \text{(6.7e)} \\
DOD_{max} &\leq SOC[i] \leq 1, && \text{(6.7f)} \\
0 &\leq E_{dis}[i] \leq \min\{\kappa_e, SOC[i] - DOD_{max}\}, && \text{(6.7g)} \\
0 &\leq \varphi^a[i] \leq SOC[i] - DOD_{max}, && \text{(6.7h)} \\
0 &\leq \varphi^b[i] \leq 1 - SOC[i], && \text{(6.7i)} \\
0 &\leq E_{util}[i] \leq \tilde{E}_{load}[i], && \text{(6.7j)} \\
0 &\leq E_{ch}[i] \leq \lceil gr[i] - E_{sc}[i] \rceil^+, && \text{(6.7k)} \\
\varphi^a[i] \cdot \varphi^b[i] &= 0, && \text{(6.7l)} \\
SC[i] \cdot \varphi^b[i] &= 0, && \text{(6.7m)} \\
BC[i] \cdot \varphi^a[i] &= 0, && \text{(6.7n)} \\
0.4 &\leq SOC[k+N-1] \leq 0.6 && \text{(6.7o)}
\end{aligned}
$$

where κ_e is the energy transfer capacity of the entity's converters (i.e. the maximum amount of energy that can be injected into/drained from the grid/ during a single period, and DOD_{max} is the maximum allowable depth of discharge of the ESS. Please note that all variables are normalised with respect to the maximum storage capacity of the entity's ESS, so that both states and control inputs are expressed in units of *batteries*.

Constraints (6.7b) to (6.7d) determine how the system evolves over time, while constraint (6.7e) imposes that the expected load must be always meet, no matter which sources are used. When formulating the problem, a series of design assumptions has been adopted that affect some of the problem constraints:

A.1. Following the prudence concept, quantities sold on the market are immediately deducted from the SOC, even though the physical transfer has not even begun. This avoids the possibility of selling already committed energy. On the contrary, the acquired energy is not assumed as immediately incorporated, but is added over time. This prevents the optimiser from allocating energy that is expected to be acquired in a future instant but will not be available until a later future instant (Costraint (6.7b)).

A.2. Once a purchase or sale agreement has been reached, the physical transfer of the energy associated with that transaction begins immediately and continues uninterruptedly until it is completed (Constraints (6.7c) and (6.7d)). In other words, transfers cannot be postponed.

A.3. Own production is dedicated primarily to self-consumption. Therefore, $E_{sc}[i] = \min\{\tilde{E}_{gen}[i]\,,\ \tilde{E}_{load}[i]\}$ is not a controllable variable but a parameter computed on the basis of the forecast generation and consumption.

A.4. Purchasing energy from the utility for later consumption is forbidden (Constraint (6.7j)). In other words, during periods of low tariff prices, the entity cannot acquire more energy than it needs from the utility in order to store it and consume it during periods of high tariffs.

A.5. In the same market session, each entity can only play one role, either buyer or seller (Constraint (6.7l)). Given that transfers must be started immediately after they are settled, an entity with unsatisfied sales commitments cannot go to the market as a buyer (Constraint (6.7m)); conversely, as long as it has unsatisfied buy commitments, an entity cannot go to the market as a seller (Constraint (6.7n)).

A.6. In the optimisation process, the strategic advisor assumes that future offers will be fully matched in the market (i.e. the optimiser assumes that $q^a[i] = \varphi^a[i]$ and $q^b[i] = \varphi^b[i]$). Immediately after the clearing of the k-th market session, the advisor already knows the real result of the offers shouted in that period. If the offers have not been matched, the available energy differs from that assumed in the optimal strategy profile, so it may be necessary to re-run the optimiser to adjust the values of $E_{util}[k]$,$E_{ch}[k]$ and $E_{dis}[k]$. In any case, given that the optimiser is run before the next market session (for which the results of the immediately previous session are already available), the quantities actually offered, $\varphi^{a*}[k]$ and $\varphi^{b*}[k]$, are always the optimal ones based on the actual state at any given time.

6.4.2 Multiple Scenarios SMPC Approach (MS-SMPC)

From the point of view of each agent, both P2P markets are considered stochastic systems, since the outputs ($m = (q,p)$) for each one of the agent's offers might be different for the same inputs ($\omega = \varphi,\vartheta$)), depending on the offers made by the other participant agents, which are considered an unknown disturbance. Scenario-based optimisation provides an intuitive way to approach the solution to the problem of stochastic optimisation. The idea behind this approach is to compute an optimal finite-horizon input sequence that is feasible under N_s sampled 'scenarios' of the uncertainty, thus obtaining a certain level of robustness [63]. One of the advantages of this approach is that it does not assume a prior knowledge of the statistical properties that characterise uncertainty (e.g. a certain probability distribution function) as is generally required in stochastic optimisation. Each scenario consists of values for some or all of the stochastic processes that affect the system. Furthermore it has been widely used for performing optimal power dispatch (e.g. [64]) and for optimal participation in energy markets [65]. In our case, only the stochasticity of the P2P markets' prices is proposed to be addressed. Therefore, each scenario is a full horizon sample of the prices for the two markets,

$$\begin{aligned}\xi_{(j)}[k] \stackrel{\text{def}}{=} \{p_{EP_{(j)}}[k], \dots, p_{EP_{(j)}}[k+N-1], \ell^b_{(j)}[k], \dots, \ell^b_{(j)}[k+N-1], \\ \ell^a_{(j)}[k], \dots, \ell^a_{(j)}[k], p_{PQ_{(j)}}[k], \dots, p_{PQ_{(j)}}[k+N-1]\}\end{aligned} \tag{6.8}$$

Specifically, within the optimisation, the market-related random variables $\tilde{p}_{EP}[i]$, $\tilde{\ell}^b[i]$, $\tilde{\ell}^a[i]$ and $\tilde{p}_{PQ}[i]$ are replaced by their corresponding values for each scenario, $p_{EP_{(j)}}[i]$, $\ell^b_{(j)}[i]$, $\ell^a_{(j)}[i]$ and $p_{PQ_{(j)}}[i]$.

The offers that determine actual market parameters depend directly on the energy result expected by the different agents, which is given in turn by their consumption and generation forecasts. These predictions depend fundamentally on the climatology, and therefore present a significant level of correlation between consecutive days, as well as between identical days of previous years, provided that the typology of day (workable or weekend) is the same. Therefore, the approach proposed here to build the set of scenarios is to use the set of time series representing market realisations in past days (i.e. the evolution of the average prices and liquidities over similar periods of previous days).

The Multiple Scenarios Stochastic MPC (MS-SMPC) problem then reads as follows:

$$
\begin{aligned}
\mathbf{u}^*[i|k] = \underset{\substack{E_{util}[i],E_{ch}[i],E_{dis}[i]\\ \varphi^b[i],\varphi^a[i]}}{\arg\min} \quad & \sum_{j=1}^{N_s} \sum_{i=k}^{k+N-1} E_{util}[i]\cdot\vartheta_{util}[i] \\
& + \varphi^b[i]\cdot p^b_{EP_{(j)}}[i]\cdot(1-\ell^b_{(j)}[i]) \\
& - \varphi^a[i]\cdot p^a_{EP_{(j)}}[i]\cdot\ell^a_{(j)}[i] \\
& - (\lceil gr[i]\rceil^+ - E_{ch}[i])\cdot p_{PQ_{(j)}}[i] && \text{(6.9a)}
\end{aligned}
$$

subject to

$$
\begin{aligned}
SOC[i+1] &= SOC[i] - E_{dis}[i] - \varphi^a[i] + E_{ch}[i] + \min\{\kappa_e, BC[i] + \varphi^b[i]\}, && \text{(6.9b)}\\
SC[i+1] &= SC[i] + \varphi^a[i] - \min\{\kappa_e, SC[i] + \varphi^a[i]\}, && \text{(6.9c)}\\
BC[i+1] &= BC[i] + \varphi^b[i] - \min\{\kappa_e, BC[i] + \varphi^b[i]\}, && \text{(6.9d)}\\
\tilde{E}_{load} &= E_{sc}[i] + E_{dis}[i] + E_{util}[i], && \text{(6.9e)}\\
DOD_{max} &\le SOC[i] \le 1, && \text{(6.9f)}\\
0 &\le E_{dis}[i] \le \min\{\kappa_e, SOC[i] - DOD_{max}\}, && \text{(6.9g)}\\
0 &\le \varphi^a[i] \le SOC[i] - DOD_{max}, && \text{(6.9h)}\\
0 &\le \varphi^b[i] \le 1 - SOC[i], && \text{(6.9i)}\\
0 &\le E_{util}[i] \le \tilde{E}_{load}[i], && \text{(6.9j)}\\
0 &\le E_{ch}[i] \le \lceil gr[i] - E_{sc}[i]\rceil^+, && \text{(6.9k)}\\
\varphi^a[i]\cdot\varphi^b[i] &= 0, && \text{(6.9l)}\\
SC[i]\cdot\varphi^b[i] &= 0, && \text{(6.9m)}\\
BC[i]\cdot\varphi^a[i] &= 0, && \text{(6.9n)}\\
0.4 &\le SOC[k+N-1] \le 0.6 && \text{(6.9o)}
\end{aligned}
$$

6.5 The Power Dispatcher

After solving the MS-SMPC formulated by Eqs. (6.9), only the first member of the optimal finite-horizon policy is kept and applied to the system, i.e., the SMPC control law is

$$\kappa_{MSSMPC}(\mathbf{x}[k], \xi[k]) \stackrel{\text{def}}{=} u^*[1|k] \tag{6.10}$$

Role Selection Role Selection for the PQ-Market is performed in the same manner as presented in Subsection 5.3.2. As for the EP-Market, two possibilities arise, depending on whether the TA of the entity's EMS implements an SA or not:

- A trading agent that does not have an SA, decides its role based only in its energy balance forecast. If $PD[\tau_k] < 0$ the entity will play buyer, even if it has surplus for the immediate time slot. If $PD[\tau_k] = 0 \wedge PD[\tau_k] > 0$ the entity will play seller, even if it has deficit for the immediate time slot (please remind that both $PD[k]$ and $PS[k]$ are variables that aggregate forecast over a prediction horizon).
- Role selection in trading agents who have a strategic advisor is an inherent result of the strategic optimisation itself. If $\varphi^{b*}[1|\tau_k] > 0$ the entity will play buyer in the immediate market session. Conversely, if $\varphi^{a*}[1|\tau_k] > 0$ the entity will play seller in the immediate market session. If $\varphi^{b}[1|\tau_k] = 0 \wedge \varphi^{a}[1|\tau_k] = 0$ the entity remains idle, reserving itself for future and more potentially beneficial sessions. The possibility of $\varphi^{b}[1|\tau_k] > 0 \wedge \varphi^{a}[1|\tau_k] > 0$ is avoided by the very definition of the optimiser's constraints (6.71) and (6.91).

As mentioned before, the amounts $\varphi^{a*}[k]$ or $\varphi^{b^*}[k]$ implicitly determine the role that the entity will adopt in the imminent market session (remember that only one of them can be non-zero). If the offers are matched, the optimal plan is still valid; otherwise, the optimiser must be run again to resolve the MS-SMPC replacing $\varphi^{a*}[k]$ by $q^{a*}[k]$ and $\varphi^{b^*}[k]$ by $q^{b^*}[k]$.

In either case, the optimal control variables $\{E^*_{util}[k^+], E^*_{ch}[k^+], E^*_{dis}[k^+]\}$ are sent as inputs to the power dispatcher (see Figure 6.1). The function performed by this block is analogous to that described in Subsection 5.3.1. The difference is that in this case, those entities with Strategy Advisor use the continuous eP2P power quota market as a disturbance absorption mechanism, i.e. they go to this market only when the difference between the forecast consumption and generation profiles and the actual ones makes it impossible to operate following the optimal plan defined by the strategic advisor. Meanwhile, those entities whose EMS does not have the Strategy Advisor go to both the EP and the PQ Markets at any given time. In any case, the power demand satisfaction is driven at all times by Algorithm 3.

Algorithm 3 Demand Satisfaction with Integrated Markets

Inputs
  $\{E^*_{util}[k^+], E^*_{ch}[k^+], E^*_{dis}[k^+]\}$ Optimal Plan
  $x(t)$ Current State
  $\vartheta_{util}(t)$ Energy Price offered by the utility
Data
  SOC_{max} Maximum allowed ESS Level
  SOC_{min} Minimum allowed ESS Level
  κ_{stg} Maximum ESS charge/discharge power
Auxiliary
  $\Phi(t)$ Gross Power Balance: $\Phi(t) \stackrel{\text{def}}{=} P_{gen}(t) - P_{load}(t)$
  $\Upsilon(t)$ Result After Rearrangement: $\Upsilon(t) \stackrel{\text{def}}{=} P_{gen}(t) - P_{load}(t) + P_{P2P}(t)$
  $\Psi(t)$ Net Power Balance: $\Psi(t) \stackrel{\text{def}}{=} P_{gen}(t) - P_{load}(t) + P_{P2P}(t) + P_{sto}(t)$
  $E^c_{util}(t)$ Accumulator of energy acquired from the utility during the k period
  $E^c_{ch}(t)$ Accumulator of energy injected into the ESS during the k period
  $E^c_{dis}(t)$ Accumulator of energy drained from the ESS during the k period
Result
  $P_{sto}(t^+)$
  $P_{util}(t^+)$
  $SOC(t^+)$
while 1 **do**
  if $\Upsilon(t) > 0 \wedge SOC(t) < SOC_{max}$ **then**
    ▷ $P_{sc}(t) = P_{load}(t)$
    if $E^*_{ch}[k^+] \geq E^c_{ch}(t)$ **then**
      ▷ The optimal value of energy injected into the ESS has not yet been reached. Charge.
      $P_{ch}(t^+) \leftarrow \min\{\Upsilon(t), \kappa_{stg}\}$
    else if $E^*_{ch}[k^+] < E^c_{ch}(t)$ **then**
      ▷ The optimal value of energy injected into the ESS has already been exceeded. Try to sell the surplus.
      $P_{ch}(t^+) \leftarrow 0$
      $\varphi^a_{PQ}(t) \leftarrow \min\{\Upsilon(t), \kappa_{stg}\}$
    end if
  else if $\Upsilon(t) < 0$ **then**
    ▷ $P_{sc}(t) = P_{gen}(t)$
    if $E^*_{dis}[k^+] \geq E^c_{dis}(t)$ **then**
      ▷ There is still room for discharge in this period. Drain the battery.
      $P_{dis}(t^+) \leftarrow -\max\{\Upsilon(t), -\kappa_{stg}\}$
    else if $E^*_{dis}[k^+] < E^c_{dis}(t)$ **then**
      ▷ The ESS has already supplied all the energy planned for this period. Try to buy the deficit.
      $P_{dis}(t^+) \leftarrow 0$
      $\varphi^b_{PQ}(t) \leftarrow \min\{-\Upsilon(t), \kappa_{stg}\}$
    end if
  end if

Go to P2P PQ Market. $q^b_{PQ}(t)$ and $q^a_{PQ}(t)$ affect $P_{P2P}(t)$
Recompute $\Psi(t)$ with the updated value $P_{P2P}(t)$.
if $\Psi(t) > 0$ **then** ▹ Couldn't sell all the excess.
  if $SOC(t) < 1$ **then** ▹ Store the remaining surplus
    $P_{ch}(t^+) \leftarrow \min\{\Psi(t), \kappa_{stg}\}$
  else if $SOC(t) = 1$ **then** ▹ Sell remaining surplus to the utility
    $P_{util}(t^+) \leftarrow -\Psi(t)$
  end if
else if $\Psi(t) < 0$ **then** ▹ Couldn't purchase all the defitit.
  $P_{util}(t^+) \leftarrow -\Psi(t)$
else
  ▹ $\Psi(t) = 0$ Perfect Balance
  $P_{util}(t^+) \leftarrow 0$
end if
$E_{ch}(t) \leftarrow \min(\int_{\Delta t \to 0} P_{ch}(\tau)d\tau, SOC_{max} - SOC(t)))$
$E_{dis}(t) \leftarrow \max(\int_{\Delta t \to 0} -P_{dis}(\tau)d\tau, SOC(t) - SOC_{min}))$
$E^c_{ch}(t^+) \leftarrow E^c_{ch}(t) + E_{ch}(t)$
$E^c_{dis}(t^+) \leftarrow E^c_{dis}(t) + E_{dis}(t)$
$E^c_{util}(t^+) \leftarrow E^c_{util}(t) + \int_{\Delta t \to 0} \max\{0, P_{util}(\tau)d\tau\}$
$SOC(t^+) = SOC(t) + E_{ch}(t) + E_{dis}(t)$
end while

6.6 Case Study

6.6.1 Description

Such as in Section 5.4, in this case example the entities are a group $\mathcal{H}$ of 100 houses within the same neighbourhood in the city of Córdoba (Spain). Some of these houses ($PhV_{pen} = 45\%$) are supposed to have photovoltaic (PhV) generation systems. There are three possible installed PhV powers, $P_{phv} \in \{1,3,5\}$ kWp, and each of them has an associated ESS of adequate capacity, $B_{max} \in \{2.5,5,7\}$ kWh respectively. Houses with no PhV-installation still has an ESS of $B_{max} = 10$ kWh to be able to participate in the EP-Market. Among the 100 houses, $SA_{pen} = 10\%$ (10 Houses) are randomly selected which form the control set, $\mathcal{H}_c$. These houses are replicated twice, giving rise to three sets:

- Set NoStrat, ($\mathcal{H}_c$): Houses without strategy advisor.
- Set Strat-NonSto, ($\mathcal{H}_{ns}$): Houses with strategy advisor based on expected value scenario according to optimisation problem (6.7).

- Set Strat-Sto, ($\mathcal{H}_s$): Houses with MS-SMPC-based strategy advisor according to optimisation problem (6.9).

The $\mathcal{H}_{ns}$ and $\mathcal{H}_s$ resulting sets (20 houses) are simulated together with the remaining $\mathcal{H}$ houses of the original population, which already include $\mathcal{H}_c$, giving rise to a total population of $n_{\mathcal{H}} = 120$ houses. All houses simultaneously participate in the two different markets. The first one is an PQ-Market similar to the one introduced in Section 5.2. The second one is an hourly EP-Market. The main parameters of both markets are displayed in Table 6.2. The EMS of all houses incorporates two trading agents, one per each market.

Table 6.2 Main Parameters of Integrated Markets.

	PQ-Market	**EP-Market**
Type	D-CDA	DDA
ΔT	1 min [a]	60 min
q_{min}	0.1 (kWmin)	0.25 (kWh)
q_{max}	3.3 (kWmin)	1 (kWh)

[a] Equal to the temporal resolution of the energy operation simulation, thus mimicking a continuous market.

Scenario Generation To generate the scenarios (price evolution and market liquidity profiles), a full month (30 days) of operation of 100 houses (all without strategy advisor) was simulated. These simulations assumed that each agent perfectly knows its generation and consumption profiles, so that offers (and thus prices) reflect the real energy needs/excess of the traders within the simulated days. The results are shown in Figure 6.4. In a real application case, the equivalent of these scenarios obtained by simulation would be the historical data profiles obtained either from similar days in previous years or from the days immediately preceding the current operation day, or from a combination of both.

Operation Costs and Final Stock Valuation In this case study, the net cost of energy for the i-th house over a certain period of time ($T = [t_i, t_f]$) can be calculated as:

$$\Phi^i(T) = \Phi^i_{util}(T) + \Phi^i_c(T) + \Phi^i_{ep}(T) + \Phi^i_{pq}(T) \tag{6.11}$$

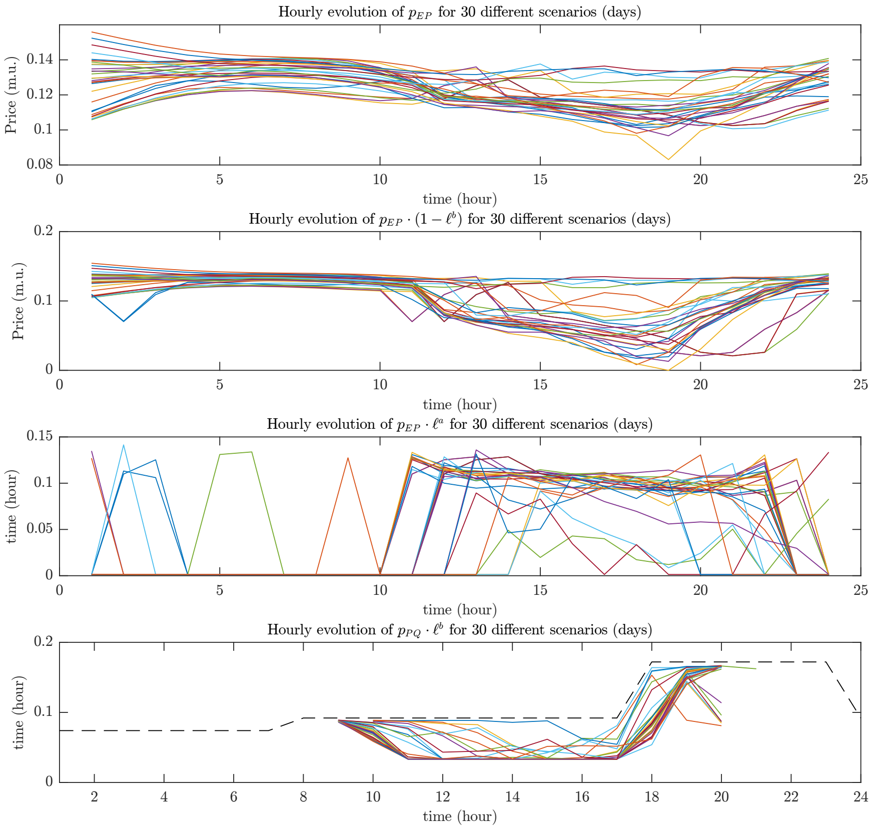

Figure 6.4 Scenarios for the MS-SMPC are the prices and liquidity profiles for 30 simulated days of the same month under comparison (September in this case)..

where

$$\Phi^i_{util}(T) = \sum_{\forall t \in T} E^i_{util}(t) \cdot \vartheta(t) \tag{6.12a}$$

$$\Phi^i_c(T) = E^i_c(T) \cdot \overline{\vartheta} \tag{6.12b}$$

$$\Phi^i_{ep}(T) = \sum_{\forall \omega_e \in \Omega^{ep}_i} \mathcal{A}^i_{\omega_e}(T) \tag{6.12c}$$

$$\Phi^i_{pq}(T) = \sum_{\forall \omega_p \in \Omega^{pq}_i} \mathcal{A}^i_{\omega_p}(T) \tag{6.12d}$$

being $\mathcal{A}^i_{\omega_e}(T)$ the amount of money corresponding to each energy package transaction ω_e in the set Ω_i^{ep} of all eP2P transactions dealt by house i at the EP-Market within T, and $\mathcal{A}^i_{\omega_p}(T)$ the amount of money corresponding to each power quota transaction ω_p in the set Ω_i^{pq} of all eP2P transactions dealt by house i at the PQ-Market within T:

$$\mathcal{A}_\omega = q_\omega \cdot p_\omega \tag{6.13}$$

where q_ω is the traded quantity and p_ω is the unit price of the agreed transaction.

Equation (6.11) is the sum of the cost of energy purchased from the utility (6.12a), plus the revenue of energy compensated by the utility[3] at a price equal to the VPSC ($\overline{\vartheta}_c$) (6.12b), plus the result of trading in the EP-Market (6.12c), plus the result of trading in the PQ-Market (6.12d). By convention, costs have a negative sign, while revenues have a positive sign. In addition, and although it is not directly part of the operating result, a way of computing the value of the energy stored at the end of the operating period in the ESS of each house is necessary:

$$\Phi^i_{B_f} = B^i_r(t_f) \cdot \lambda^i(t_f) \tag{6.14}$$

where t_f is the final instant of the period of comparison and $\lambda^i(t_f)$ is the private valuation of energy for house i in $t = t_f$ according to (6.4).

Comparative Indicators The comparison is then made between the energy operation results of $\mathcal{H}_c$ and those of $\mathcal{H}_{ns}$ and $\mathcal{H}_s$. The analysis is in this case more eminently economic than that of Chapter 5. The following indicators can be computed to compare the operation performance of two sets of houses ($\mathcal{H}_a$ and $\mathcal{H}_b$) (Energy Result Comparator, EP-Market Result Comparator, PQ-Market Result Comparator, Renewable Energy Use Comparator and Battery Usage Comparator) and are defined below:

$$\Delta\Phi(T) = \frac{\left\lceil \Phi^a_{B_f} - \Phi^b_{B_f} \right\rceil^+ + \sum_{\forall h \in \mathcal{H}_a} \Phi^h(T)}{\left\lceil \Phi^b_{B_f} - \Phi^a_{B_f} \right\rceil^+ + \sum_{\forall h \in \mathcal{H}_b} \Phi^h(T)} - 1 \tag{6.15}$$

$$\Delta RW_{use}(T) = \frac{\sum_{\forall h \in \mathcal{H}_a} RW^h(T)}{\sum_{\forall h \in \mathcal{H}} RW^h(T)} - 1 \tag{6.16}$$

$$\Delta B_{use}(T) = \frac{\sum_{\forall h \in \mathcal{H}_a} B^h(T)}{\sum_{\forall h \in \mathcal{H}_b} B^h(T)} - 1 \tag{6.17}$$

[3] Following a NPSS as defined in Subsection 5.4.1.

6.6.2 Tests and Results

Testing the effects of the MS-SMPC-based strategy advisor is a complicated task. First, because the number of optimisation variables grows very fast as the length of the prediction horizon is increased. In turn, the more optimisation variables the problem has, the number N_S of different scenarios needed to reach a certain level of confidence also increases, according to the formula [66]:

$$N_S \geq \frac{z + 1 + \ln(\frac{1}{\beta}) + \sqrt{2(z+1)\ln(\frac{1}{\beta})}}{\delta_x} \tag{6.18}$$

where $\delta_x \in (0,1)$ is the risk acceptability level of constraint violation for the states, z is the number of variables in the optimisation problem, and β is an arbitrary low confidence level ($\beta \leq 10^{-6}$).

Additionally, since the experiments are basically agent-based simulations, it is difficult to guarantee common conditions for entities with/without (non-)stochastic strategy advisor. For each element $h_c \in \mathcal{H}_c$, two identical reproductions are created, $h_{ns} \in \mathcal{H}_{ns}$ and $h_s \in \mathcal{H}_s$. These three elements have exactly the same consumption and generation profiles, and in addition, the parameters of their respective agents are also identical, including those that drive price adaptation and private valuation determination. Therefore, the price evolution of bids and asks is the same for the three entities. What changes between them, and in fact is the origin of the performance variability, is the sequence of roles adopted in the market. Entities in $\mathcal{H}_c$ adopt one or another role in an obtuse manner, without considering the plausible evolution of the market. In contrast, the objective of the strategy advisor is to steer the role selection and the temporal allocation of offered energy quantities so that the entity takes advantage of those hourly sessions with the highest expected revenue.

Each simulation covers a whole week of energy operation during the month of September. Unlike the process of generating the scenarios, in the operation simulations the predicted generation profile does not coincide with the generation profile actually realised. The objective of this setting is to check whether the effect of the stochastic strategy advisor makes the entities that have it obtain a better performance than those having a strategy advisor based on the nominal case, and than those that do not have strategy advisor at all. Figure 6.5 shows the forecast and actual PhV power generation profiles for each week.

Tables 6.3 to 6.8 show the results of the simulations for each of the addends that allow to compute the economic result derived from the energy operation (eqs. (6.11) and (6.14)) of the three replicated sets.

Figures 6.6 to 6.9 are the radar plots[4] of Weeks 1-4, where the different components of the economic result are displayed along with the total results, $\Phi(T = 1\,\text{week})$, themselves.

[4] Víctor Martínez-Cagigal (2020). MATLAB Central File Exchange Polygonal Plot (https://www.mathworks.com/matlabcentral/fileexchange/62200-polygonal-plot).

Table 6.3 Summary of Energy Interactions with the Utility (Aggregation of Purchased and Compensated Energy).

	Utility Interactions														
	E_{util} (kWh)			Φ_{util} (€)			$\overline{\vartheta}_{util}$ (c€/ kWh)			E_c (kWh)			Φ_c (€)		
September	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	329.42	296.49	286.05	-38.9	-35.59	-34.54	-11.81	-12	-12.07	21.97	45.79	50.17	1.10	2.29	2.51
Week 2	372.57	342.33	321.58	-42.75	-39.78	-37.29	-11.47	-11.62	-11.6	13.56	39.76	42.26	0.69	1.99	2.11
Week 3	320.12	256.58	253.01	-36.16	-28.86	-28.23	-11.29	-11.25	-11.15	22.15	34.42	30.21	1.11	1.72	1.51
Week 4	355.48	325.24	322.88	-41.1	-38.18	-38.04	-11.56	-11.74	-11.78	33.25	49.44	50.28	1.66	2.47	2.51

Table 6.4 P2P Energy-Package Market Buying Interactions.

P2P EP-Market Buying Interactions									
September	E^b_{ep} (kWh)			Φ^b_{ep} (€)			$\overline{\vartheta}^b_{ep}$ (c€/ kWh)		
	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	79.45	90.25	99.59	-9.07	-10.22	-11.27	-11.42	-11.33	-11.32
Week 2	78.55	73.05	81.47	-9	-8.33	-9.3	-11.46	-11.4	-11.42
Week 3	78.65	78.7	89.56	-9.13	-9.05	-10.35	-11.61	-11.5	-11.56
Week 4	73.1	82.08	84.57	-8.05	-8.35	-8.67	-11.01	-10.18	-10.25

Table 6.5 P2P Energy-Package Market Selling Interactions.

P2P EP-Market Selling Interactions									
September	E^s_{ep} (kWh)			Φ^s_{ep} (€)			$\overline{\vartheta}^s_{ep}$ (c€/ kWh)		
	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	150.27	176.28	176.35	17.16	20.45	20.47	11.41	11.60	11.61
Week 2	127.79	152.77	148.49	14.72	17.89	17.41	11.51	11.71	11.72
Week 3	157.37	173.89	172.56	18.19	18.19	20.22	11.56	11.71	11.72
Week 4	118.34	135.33	141.59	13.05	15.01	15.69	11.03	11.09	11.08

Table 6.6 P2P Power Quota Market Interactions.

P2P PQ-Market Buying Interactions									
September	E^b_{pq} (kWh)			Φ^b_{pq} (€)			$\overline{\vartheta}^b_{pq}$ (c€/ kWh)		
	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	146.61	89.47	92.9	-7.26	-4.24	-4.21	-4.95	-4.74	-4.54
Week 2	135.24	87.49	98.88	-7.36	-4.10	-4.74	-5.44	-4.69	-4.79
Week 3	129.78	99.38	90.35	-6.33	-4.50	-4.03	-4.88	-4.53	-4.46
Week 4	123.74	75.14	76.72	-6.18	-3.49	-3.46	-4.99	-4.65	-4.52

Table 6.7 P2P Power-Quota Market Selling Interactions.

P2P PQ-Market Interactions									
September	E^s_{pq} (kWh)			Φ^s_{pq} (€)			$\overline{\vartheta}^s_{pq}$ (c€/ kWh)		
	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	301.58	153.05	152.49	14.13	7.61	7.79	4.69	4.97	5.11
Week 2	264.98	114.24	112.71	12.82	6.45	6.06	4.84	5.65	5.38
Week 3	283.68	139.70	140.3071	13.10	7.22	6.94	4.62	5.17	4.95
Week 4	235.54	115.71	115.59	10.49	5.57	5.91	4.45	4.81	5.11

Table 6.8 Valuation of Final Stock of Stored Energy.

Valuation of Final Storage						
September	B_f (kWh)			Φ_{B_f} (€)		
	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	22.66	22.12	21.65	2.73	2.65	2.59
Week 2	31.03	25.55	26.72	3.76	3.08	3.24
Week 3	24.85	27.45	26.61	2.87	3.19	3.10
Week 4	26.77	25.37	25.15	3.10	2.96	2.94

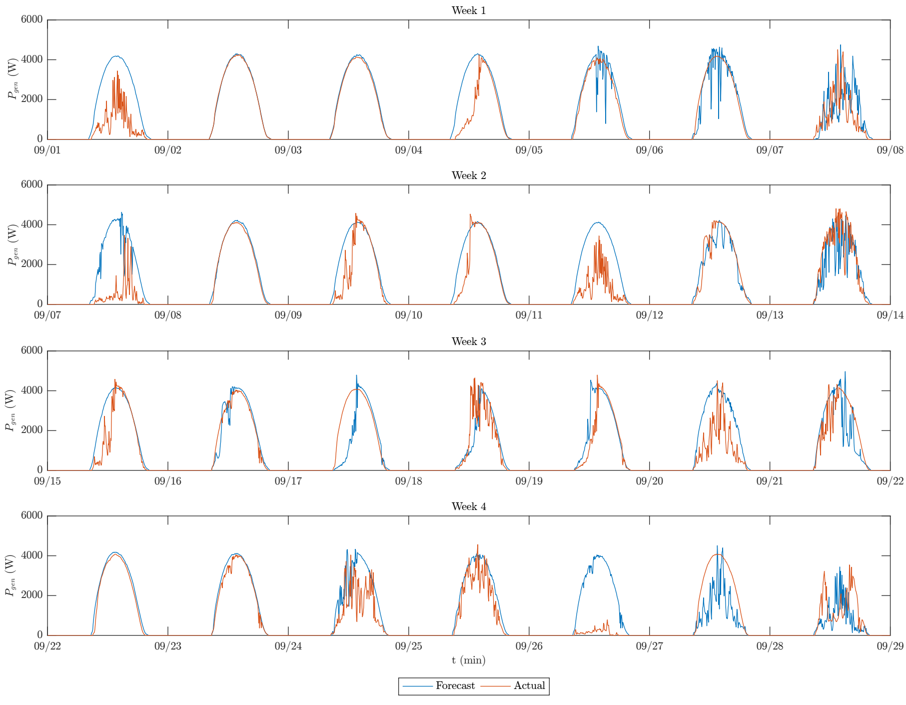

Figure 6.5 Forecast vs. Actual PhV Power Generation Profiles for each week.

Table 6.9 Comparative indicators (with respect to the performance of the set of houses without SA ($\mathcal{H}_c$)) for the set of houses with Nominal MPC-based SA ($\mathcal{H}_{ns}$) and for the set of houses with MS-SMPC-based SA ($\mathcal{H}_s$).

September	$\Delta\Phi_{cost}(\%)$		$\Delta RW_{use}(\%)$		$\Delta B_{use}(\%)$		$\Gamma_{RW}(\%)$		
	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$	$\mathcal{H}_c$	$\mathcal{H}_{ns}$	$\mathcal{H}_s$
Week 1	-13.46	-15.19	-3.05	-2.89	+59.89	+61.46	100	96.95	97.11
Week 2	-14.33	-15.22	-3.47	-3.66	+66.53	+69.36	100	96.53	96.34
Week 3	-33.46	-28.62	-2.76	-3.37	+64.87	+68.52	100	97.24	96.63
Week 4	-10.04	-12.99	-2.72	-1.71	+55.74	+57.97	100	97.28	98.29

6.7 Discussion

This chapter extends the analysis of Chapter 5, proposing the simultaneous participation of energy traders in two energy markets that are parallel in their operation but overlapping in time. The discrete EP-Market acts as a futures market, allowing traders to purchase/sell energy packages in advance of the occurrence of a forecast deficit. The continuous PQ-Market acts as a spot market, in which power quotas are negotiated to balance deficits and excesses instantly. To allow this simultaneous participation, a

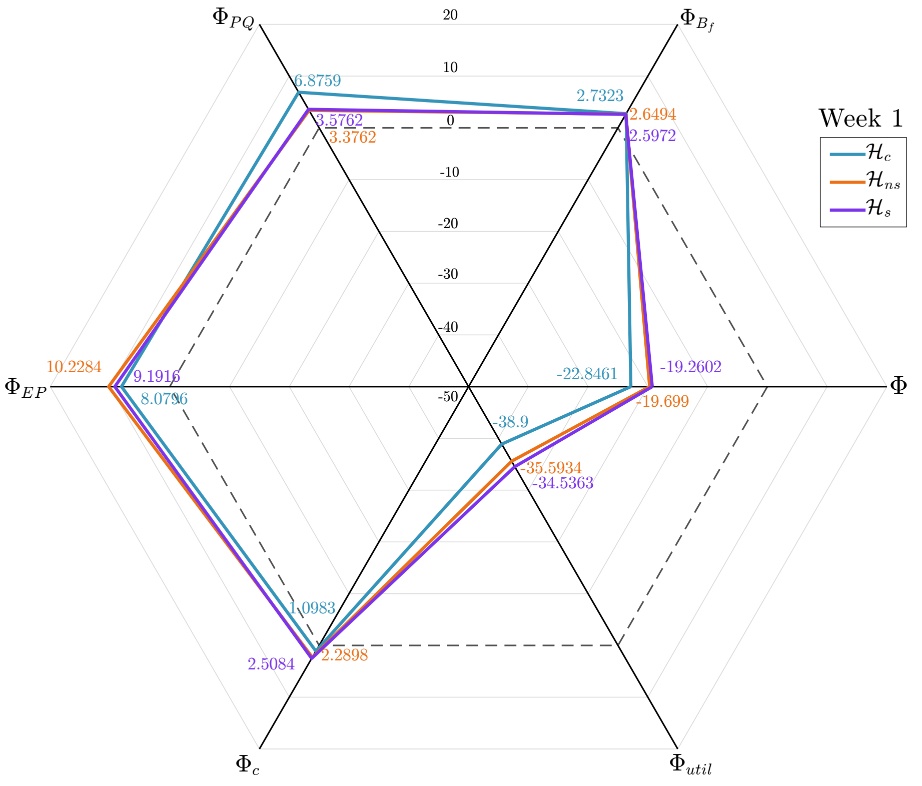

Figure 6.6 Energy Operation Economic Result for Week 1.

series of changes in the structure of the EMS are required to allow the automation of the procedures for determining private valuation, price adaptation and role selection for each of the two markets. Entities with excess generation act as sellers, and have the option of either selling as much as they can as soon as possible (in the immediately following market moments) or offering their excess at certain future market moments where the price obtained is historically more profitable. They must also decide on the quantities offered in the discrete market, taking into account that the stock sold in the futures market is no longer available for sale in the continuous market. On the other hand, entities that foresee having an energy deficit (those whose foreseen consumption is greater than their foreseen generation) have to decide whether to try to anticipate it by obtaining energy packages in the discrete market, which is generally more expensive, or to risk trying to cancel their deficit in the continuous market of power quotas, which is generally cheaper but less liquid. In this sense, the EMS can incorporate the strategy advice functionality, consisting on the determination of the optimal energy operation profile and encompasses the storage utilisation, the energy acquisition from the network and the interactions foreseen in the two eP2P markets. This thesis proposes a possible implementation of this strategy advisor, based on MPC. The chapter includes two variants, one based on a single nominal scenario, and the other based on SMPC, which

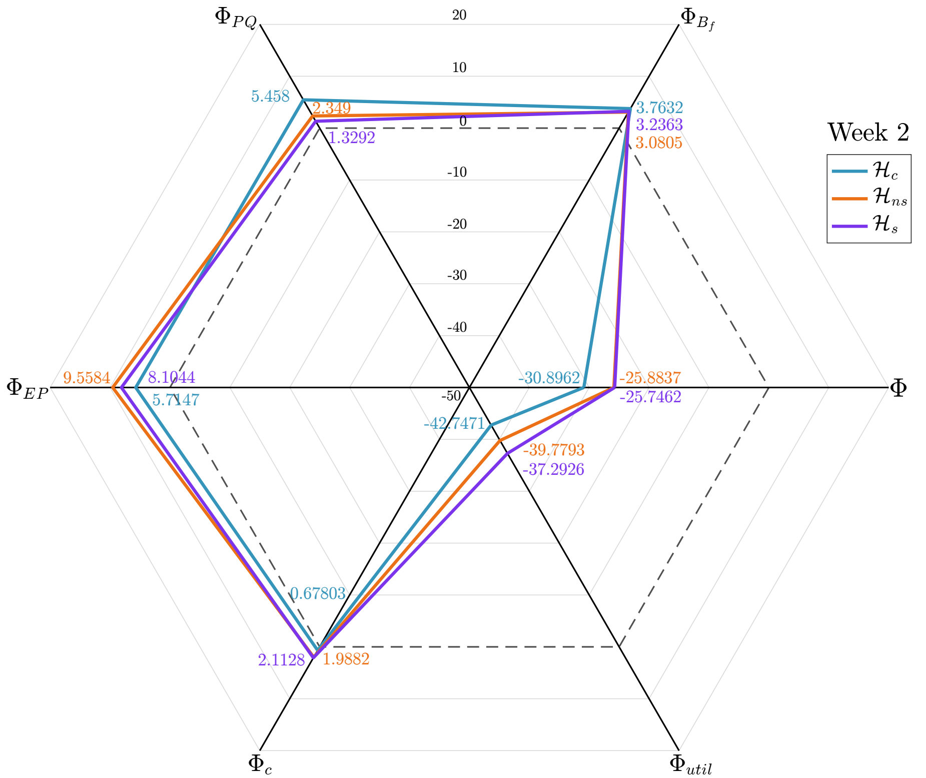

Figure 6.7 Energy Operation Economic Result for Week 2.

optimises contemplating multiple scenarios. Experiments carried out on the case study show that both variants offer an improvement in economic performance of between 10-30% compared to the case of not using a SA. Furthermore, the MS-SMPC-based variant generally performs slightly better than the nominal variant, as it contemplates more possible market price evolution profiles (derived from different PhV generation scenarios), although to state this conclusively it would be necessary to make a deeper statistical analysis which is beyond the scope of this thesis. These savings are mainly achieved by buying less energy from the grid and replacing it with cheaper energy, either previously bought and stored or bought instantaneously; and by selling a greater portion of the surplus energy in market sessions where the price is higher. But it's not all advantages. This improvement is also achieved through an intensification of the use of storage systems, which could lead to a reduction in their lifespan. The translation of depreciation costs into the calculation of energy operating costs is an open issue, both in terms of the selection of the usage level indicator and in terms of the monetisation of such usage.

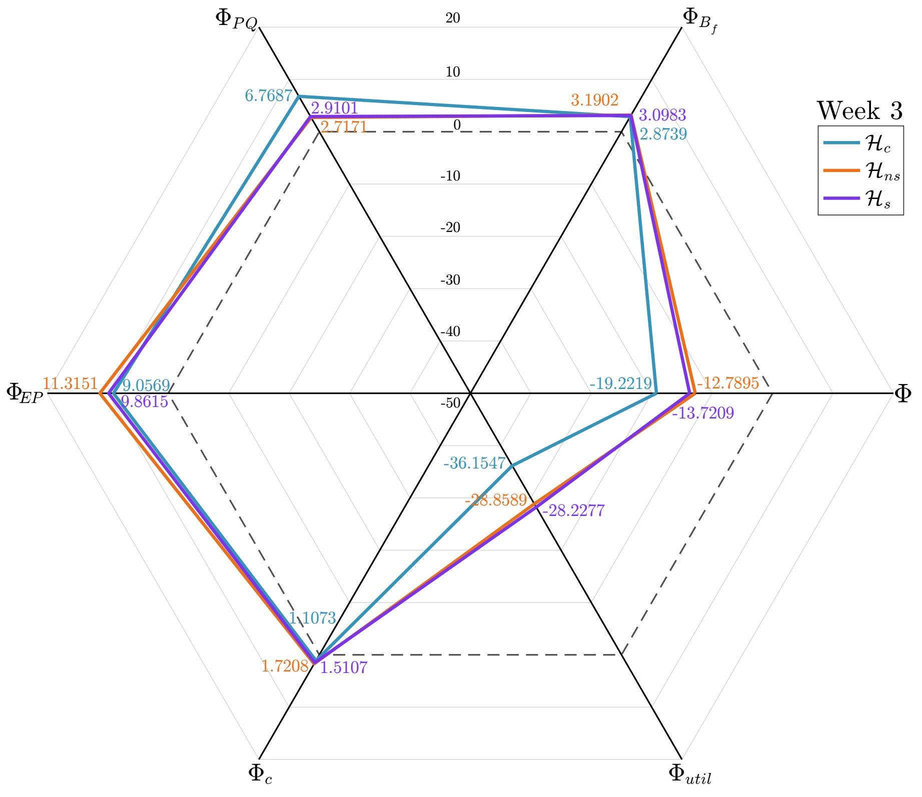

Figure 6.8 Energy Operation Economic Result for Week 3.

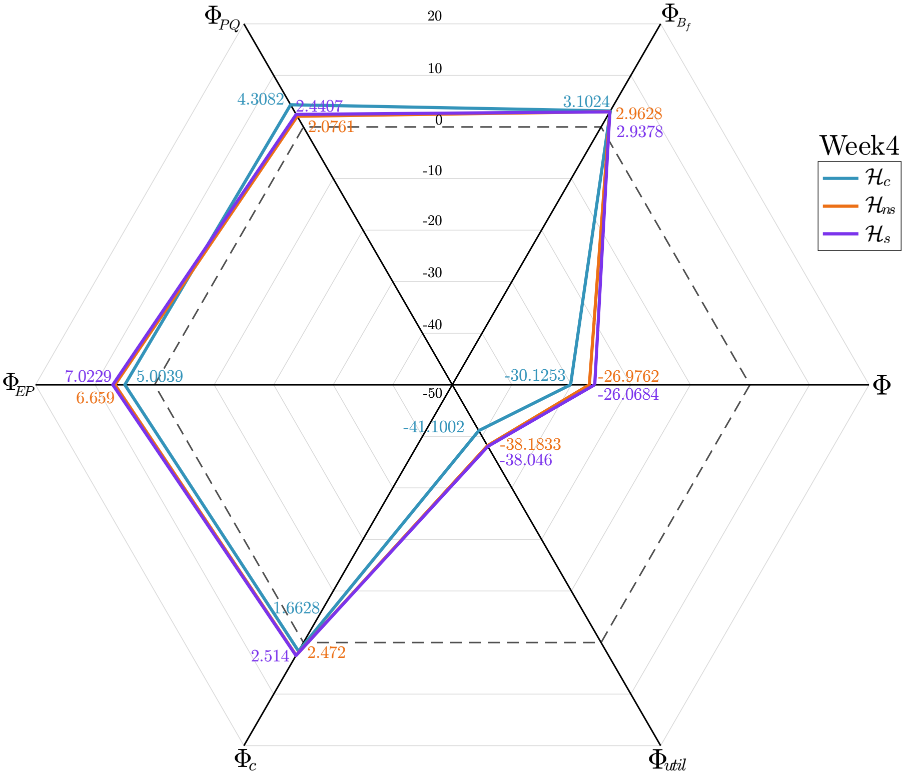

Figure 6.9 Energy Operation Economic Result for Week 4.

Part III

Final Remarks

7 Conclusions

It takes a lot more energy to fail than to succeed, since it takes a lot of concentrated energy to hold on to beliefs that don't work.

MoneyLove, 1978
Jerry Gillies

7.1 Main Results

The performance improvement and the cost reduction of energy storage systems favor the installation of these systems to be generalised in the next years. At the same time, increased environmental awareness and government measures aimed at switching to clean energy sources make it foreseeable that the level of penetration of local renewable generation systems will grow. In this future context, heterogeneous energy entities (households, buildings, industries, vehicles), with also diverse energy roles (pure consumers, prosumers, pure producers, static storers, mobile storers, etc.), shall coexist with traditional energy retailers and compete for energy marketing.

The generic objective of the EMSs that control the energy operation of these energy entities is to guarantee the full satisfaction of the energy demand in a way that is reliable, efficient, and that also maximises the economic result derived from the operation at the energy level. In order to optimise the economic result derived from the entity's energy operation, an EMS may seek the following objectives:

1. Lower demand to reduce consumption.
2. If demand cannot be lowered, but it is (at least partially) shiftable, optimise the timing of the activities that generate demand so that their corresponding consumption occurs when the cost of energy is lower, or when consumption can be satisfied with own production.

3. Maximise the economic utility derived from own production. If self-consumption is the priority option, this implies managing the storage systems so that the production is stored to be consumed in those instants in which its utility is maximum with respect to the alternative, (i.e. purchasing energy from the utility company).
4. Maximise the economic utility derived from any excess production that cannot be self-consumed, which generally implies injecting it into the network, hopefully in exchange for some kind of economic compensation.

Regarding objective 4, the first option is to sell the excess to the utility. In most countries, including Spain, the utility is legally forced to absorb this excess and to compensate the prosumer who produces it. There are different compensation schemes, but most of them are based on deducting the excess production from the prosumer's bill. What fundamentally differentiates them is the price at which the energy is discounted, as well as the maximum compensable energy amount. The other option is to sell the excess energy directly to another end user in exchange for monetary compensation, which is known as Peer to Peer energy (eP2P). This option does not have to be incompatible with the former, but the two can coexist in parallel. For example, once the maximum compensable production the retailer must compensate has been reached, a prosumer may still sell the remaining surplus in a P2P fashion. Or, even if that limit has not been reached, the prosumer may prefer to sell on the P2P market if the revenue obtained on the P2P market is greater than the revenue obtained from utility's compensation.

Precisely, one of the main motivations for the establishment of structures that allow the exchange of P2P energy is to expand the opportunities for end users to capitalise their locally produced renewable energy. Enabling P2P energy interactions broadens the pool of potential buyers, and somehow 'liberalises' the selling price, which is no longer imposed by the law and/or the utility.

Chapter 4 enumerates the specific characteristics of energy as a good that can be traded between peers. Based on these characteristics, the focus is placed on market structures based on double auctions. Since it is impossible to build a market mechanism for double auctions that is simultaneously individually rational, strategically dominant, budget balanced and economically efficient, Chapter 4 introduced a comparison between the two common types of double auctions: the discrete double auction (with sealed offers and uniform pricing), and the continuous double auction (with public offers and discriminatory pricing).

In addition to the traditional P2P energy markets based on trading energy packages, this thesis proposes an alternative way based on trading power quotas. Final consumers with a negative power balance try to wipe out this deficit by means of power bids. Final consumers with a positive power balance bring this surplus into the market in the form of power offers. This marketing form shows two main advantages: first, as both types of offers are made in real time and based on real deficits and surpluses, so transactions are exempt from divergences due to prediction errors; and secondly, since it is a real-time market, any end user can participate in it without the need for an ESS to store energy purchased ahead of time for later consumption. Its main disadvantage, however, is that the transaction does not just involve a closed buy-sell agreement, as in the case of energy packages. On the other hand, since the exchange is in real time, while the transfer is ongoing the involved power quota (and perhaps the instantaneous price of that quota) must be continuously adjusted to reflect changes in the power balances of any of the parties involved. This implies the continuous exchange of messages between each buyer-seller couple involved in an active transfer, which can generate an important volume of information, that in any case is perfectly bearable with current information and communication technologies. Chapter 5 presented a double auction structure that enables this type of market, as well as some modifications that each participant's EMS must undertake in order to synchronise the usual energy operation with the participation in the continuous market.

Assuming the most general case in which a single energy entity can trade its energy both in the form of packages and in the form of power quotas, some changes are necessary in its EMS to: i) contemplate both forms of commercialisation, ii) enable automated participation in all markets and iii) act strategically and simultaneously in each of the available markets to maximise its economic utility.

Chapter 6 proposes a structure in which there is a market for trading packages, with discrete sessions over time and thus based on a DDA, and another market for trading power quotas, which is continuous over time and thus based on a CDA. The EMSs of energy entities use the former as a futures market, in which they try to anticipate situations of excessive deficit or surplus calculated on the basis of their predictions of consumption and generation. An strategy advisor is proposed to determine jointly (i) the optimal energy dispatch in order to meet the expected demand, and (ii) the market participation profile. The first involves defining, ahead of time, which energy sources should be used to meet the demand (either energy from the utility, or self-produced energy, or energy purchased directly from other peers). The second calculates how to fragment supply offers (for a surplus peer) or demand offers (for a deficit peer) over future market sessions in a way that maximises the expected return. This SA is based on an Scenario Based Stochastic Model Predictive Controller. The stochastic model of the market is built on the basis of the knowledge of previous offer streams and their corresponding market results, which allows to generate the different scenarios required by the SMPC. The second market is used as a regulation alternative when, due to prediction errors (either in consumption, generation or prices forecasts), it is necessary to deviate from the optimal energy dispatch calculated by the strategy advisor. The necessary modifications to the structure of the EMS and its algorithms were implemented, and their operation demonstrated in Chapter 6.

7.2 Future Research Directions

There are many possible paths to explore to deepen the analysis of this work. The first has to do with the extension of the strategic advisor regarding the optimal profile of offers. The version presented in Chapter 6 only optimises the temporal profile of offered quantities, leaving aside the determination of offered prices, which is done using an independent price adaptation technique. A possible approach is to approximate the CDFs of Subsection 6.3.2 through mathematical expressions that can be included in the cost function, and to perform probabilistic optimisation that maximises the mathematical expectation of the return bearing in mind that trading chances depend on the price offered. This is considered a feasible way since both the prices and the quantities that form the space of possible offers have a finite support.

The second line that would be worth exploring has to do with experimentation in real environments. This thesis deals with energy interactions between final entities, and it is not easy to have an experimental set-up that includes several real entities or even several electronic equipment (mainly programmable loads and programmable converters) that allow emulating the entities. For that reason, the experiments of this thesis have been carried out in a simulation platform built ad-hoc using OOP in Matlab. Although this allows multiagent simulation of many final entities, important aspects to consider are lost, such as the delay in communications between agents and their effects on system performance.

Finally, it is also interesting to extend the study on the effects that the establishment of this type of P2P markets may have on the economic results of energy distribution and retailing companies. That is to say, to calculate how much they lose but also to investigate new business models that allow them to compensate the loss of income derived from the reduction in the direct sale of energy.

7.3 Communications and Collaborations

International research stays

- Aalborg University. Aalborg, Denmark. Department of Energy Technology. Under the supervision of Professor Josep M. Guerrero.

  August to December 2017.

Participations in conferences

- *Presentation of a scientific article* in the 2nd. International Conference on Smart Energy Systems and Technologies. September 9th - 11th, 2019, Porto, Portugal.
- *Presentation of Doctoral Thesis*. XVII Simposio de Ingeniería de Control y V Seminario de Innovación Docente en Automática. January 30th. - February 1st 2019.
- *Conference attendee* 5th IFAC Conference on Nonlinear Model Predictive Control 2015 (NMPC'15). September 17th - 20th, 2015. Sevilla, Spain.

Publication
Journal articles

- Baez-Gonzalez, P., Rodriguez-Diaz, E., Vasquez, J. C., Guerrero, J. M. (2018). *Peer-to-Peer Energy Market for Community Microgrids* [Technology Leaders]. IEEE Electrification Magazine, 6(4), 102-107.
- Báez-González, P., del Real, A. J., Ridao Carlini, M.A., Bordons, C. (2016). *Day-ahead economic optimisation of energy use in an olive mill* [Control Engineering Practice] 54, 91-103. https://doi.org/10.1016/j.conengprac.2016.05.019.

- *Submitted:* Báez-González, P., Bordons, C., Ridao- Carlini, M. A. *A stochastic MPC based energy management system for simultaneous participation in continuous and discrete prosumer-to-prosumer energy markets*

Conferences articles

- Baez-Gonzalez, P., Rodriguez-Diaz, E., Ridao Carlini, M. A., Bordons, C. (2019). *A Power P2P Market Framework to Boost Renewable Energy Exchanges in Local Microgrids*. [2nd. International Conference on Smart Energy Systems and Technologies]
- Baez-Gonzalez, P. (2019) An Integrated Framework for Modeling and Control P2P Predictive Control. [Doctoral Symposium - XVII Simposio de Ingeniería de Control y V Seminario de Innovación Docente en Automática.]

Part IV

Appendices

Appendix A
Zero-Intelligence-Plus (ZIP)

Each *Zero Intelligence Plus (ZIP)* agent [48] has a profit margin which determines the difference between the agent's reservation price and the offer to be submitted. The agent adapts the instantaneous value of this profit margin, within its range of desired relative gain, in terms of i) its current role, ii) the result of the immediately preceding trading call (if it ended in Deal or No Deal), and iii) its current instantaneous selling/buying price.
Since ZIP strategy is used as the bidding strategy for agents along the thesis, the algorithms used for adjusting the profit margin are shown in pseudocodes Algorithm 4 and Algorithm 5. When an agent i is required to increase or decrease its profit margin at a given time t, a target price ($\tau_i(t)$) is calculated:

$$\tau_i(t) = \mathcal{R}_i(t) \cdot q(t) + \mathcal{A}_i(t) \tag{A.1}$$

where $\mathcal{R}_i(t)$ is a randomly generated coefficient that sets the target price relative to the price $q(t)$ of the last shout in the market, and $\mathcal{A}_i(t)$ is a small random absolute price alteration. The Widrow-Hoff delta rule is then applied to update the profit margin on the transition from time t to $t+1$:

$$\mu_i(t+1) = (p_i(t) + \Delta_i(t)) \div \lambda_{i,j} - 1. \tag{A.2}$$

where $\lambda_{i,j}$ is the private value for a unit j, p_i is the current market price for agent i and $\Delta_i(t)$ is the Widrow-Hoff delta value, calculated using the individual trader's learning rate β_i:

$$\Delta_i(t) = \beta_i(t)(\tau_i(t)) - p_i(t)). \tag{A.3}$$

As the target price varies dinamically, the learning system requires damping to prevent high-frequency oscillations around it. A momentum coefficient $\gamma_i \in [0,1]$ is introduced to be able to modify the rate of variation of the margin through the use of:

$$\Gamma_i(t) = \gamma_i \Gamma_i(t-1) + (1-\gamma_i)\Delta_i(t-1), \tag{A.4}$$

with $\Gamma_i(0) = 0$, in place of $\Delta_i(t)$ in equation A.2 to obtain the update rule used by ZIP agents:

$$\mu(t+1) = (p_i(t) + \Gamma_i(t)) \div \lambda_{i,j} - 1. \tag{A.5}$$

Finally, the shout price $p_i(t+1)$ is calculated using the profit margin $\mu_i(t+1)$ according to the following equation:

$$p_i(t+1) = \lambda_{i,j}(1 + \mu_i(t+1)). \tag{A.6}$$

Algorithm 4 Pseudo code of the algorithm for the ZIP sellers

```
if the last shout was accepted at price q then
    any seller for which p_i ≤ q should raise his profit margin;
    if the last shout was a bid then
        any active seller for which p_i ≥ q should lower his margin;
    end if
else
    if the last shout was an ask then
        any active seller for which p_i ≥ q should lower his margin;
    end if
end if
```

Algorithm 5 Pseudo code of the algorithm for the ZIP buyers

```
if the last shout was accepted at price q then
    any buyer for which p_i ≥ q should raise his profit margin;
    if the last shout was an ask then
        any active buyer for which p_i ≤ q should lower his margin;
    end if
else
    if the last shout was a bid then
        any active buyer for which p_i ≤ q should lower his margin;
    end if
end if
```

List of Figures

List of Tables

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