Demand aggregator optimal strategies: from the bidding to the execution

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BARCELONATECH

PhD program in Statistics and Operations Research

Demand aggregator optimal strategies: from the bidding to the execution

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Barcelona, May 2023

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Firmado por BARBERO MATTIA - el día 24/05/2023 con un certificado emitido por AC FNMT Usuarios

Agradecimientos

Hace más de seis años tuve mi primera entrevista con la que acabaría siendo la directora de mi tesis, Cristina Corchero. En estos seis años han pasado muchas cosas, personas, retos por el camino que me han permitido crecer y ser la persona que soy hoy. Aviso de que va a ser imposible agradecer a cada una de las personas que me han ayudado, motivado, inspirado, apreciado, hecho reír y llorar, ¡así que será un agradecimiento no exhasustivo!

Primero de todo quiero dar las gracias a Cristina, que fue la persona que creió en mi desde el principio. Para mí has sido una inspiración y un apoyo en muchas ocasiones. Antes como directora de tesis y después como socia en BambooEnergy. Como en cualquier relación hay momentos mejores y peores, cosas que te gustaría mejorar y cambiar, pero estoy muy agradecido por la manera en la cual hemos pasado los momentos más complicados con un abrazo, y esa sensación de entendernos con una mirada para mí no tiene precio.

Muchas gracias a mi tutor Javier Heredia por todas las sugerencias que han permitido mejorar mi tesis. To the external referees, I very much appreciate the time and effort you have invested in reviewing my work.

También quería dar las gracias a todos los compañeros de IREC que me acogieron tan bien cuando salté de trabajar en un bar a trabajar en una oficina y me moría de miedo. En particular a esas personas que estuvieron siguiéndome desde el principio. A la Lucia, con la cual empezamos a mirar mercados eléctricos y agregadores en el mundo para imaginarnos como plantear el proyecto REFER, que fue el proyecto que financió mi doctorado. Al Lluc, que es la persona amb la cual possiblement he col·laborat més. Les seves ganes de canviar el món i ajudar les persones, a part de ser un exemple i una inspiració per mi, fan que sigui molt més fàcil anar a la oficina cada dia. Y eso que en IREC hay y había personas increíbles con las cuales sigo manteniendo de las mejores amistades: Jordi, Marta, Alaia, Tonis, Nick, Oriol, Silvia, David, Danis, Anzhelika, Pol, Gerard, muchas ¡gracias!

Y gracias al IREC como institución, por su apoyo económico y logístico. Por financiar mi doctorado, permitiéndome participar a muchas conferencias, publicar artículos, y apuntarme en cursos que me han hecho crecer profesionalmente.

I would also like to thank Innoenergy, for accepting me in their PhD school program first, and then believe in what we developed during this PhD and investing in BambooEnergy. This program was probably the funniest part of my PhD. I could assist in different courses knowing other PhDs in the energy topic, exchanging about what we do, best practices, and drinking lot of beers.

Part of the Innoenergy program was the internship I did in France, with Energy Pool. Je voudrai remercier en particulière à Edouard Perroy et Pierre Guillain pour moi accompagner dans le boulot. Et tous les autres collègues pour moi embrasser très bien, les parties a fut, les promenades at avoir la patience de moi apprendre le français aussi, ils ont été six mois réellement jolis pour moi.

También quiero dar las gracias a todos los compañeros de Bamboo, por estar tan motivados cada día, y para entenderme y ayudarme por si alguna tarde estuve haciendo el doctorado en lugar de estar desarrollando la mejor plataforma para gestión de la flexibilidad, ¡sois los mejores!

No quiero olvidar dar las gracias a todas esas personas que quizás nunca he visto, pero que me han inspirado a través de sus trabajos, ideas, presentaciones. Se que somos enanos encima de hombros de gigantes, y todo este trabajo no habría sido posible sin el trabajo previo y colectivo de muchísimas personas que cada día investigan, se equivocan, y tienen las ganas de empezar otra vez para publicar posibles mejoras en diferentes ámbitos.

Gracias a todos los amigos que tengo en Barcelona y por el mundo. Que son los que me preguntan cómo me va la vida, y después que tal con el doctorado. Es sobre todo gracias a los que en momentos más complicados me han suportado, que me han convencido a no dejarlo, que me han hecho reír, que han tenido la paciencia de escuchar lo poco o mucho que me falta para acabarlo o saber en qué problema me he encallado esta vez, que he podido llegar hasta al final del viaje.

Un reconocimiento también a las personas que cuando acabo de conocerlas me preguntan qué hago y se quedan escuchando unos minutos de si la demanda y la producción tiene que estar en balance, de cómo gestionamos la flexibilidad , etc… Gracias a los que me dicen que lo han entendido y que es muy interesante y gracias a los que me dicen que no entienden de que va, siempre es bueno tener feedbacks sinceros😊

Ultimo, e non per ordine di importanza, a tutta la mia famiglia. Ai miei genitori Gianni e Monica per sostenermi sempre, fin da piccolino. So che non era facile per loro quando me ne andai da casa, però sempre sento una sicurezza sapendo che sono vicino a me, anche se non fisicamente. A mia sorella Marta e mia nonna Sita per le chiamate e i momenti passati insieme. Senza di voi tutto questo non sarebbe stato possibile!

Abstract

Europe is at the beginning of an energy revolution. The old energy paradigm where big, centralized power plants provide energy to passive consumers is ending. Distributed renewable energy resources and electrification of mobility, industrial processes or building heating and cooling devices are changing the way in which electricity is produced and consumed. In addition, the current socio-political tensions and the Ukrainian war boosts European countries to reach the energy independency from other regions and from fossil fuels. In this moment, energy is more expensive than ever, and citizens are every time more conscious about environmental issues and desire to be an active part of the revolution.

In this context, advances in the Information Technology (IT) allows to gather much more information from devices and allow to control them remotely, although their potential in energy-related topics is still untapped. At the same time, European Directives are incentivizing consumers to play an active role in the electricity system and national regulators are transposing the European Directives to enable consumers to actively participate in electricity markets. However, it is not easy for the System Operator to handle the coexistence of consumers and generators in the same markets' mechanisms, due to their intrinsic differences. Demand aggregators are the new market actors that promise to put the consumers at the center of the energy system. Demand aggregator's role is to aggregate, trade, and coordinately manage the flexibility of multiple consumers in electricity markets. Demand-side flexibility is the ability of a consumer to modify its consumption depending on external factors, such as electricity prices or electricity's grid conditions. However, it is not clear what is the best strategy to adopt for Demand Aggregators.

Under this new paradigm, this PhD thesis prospects the optimal strategies of a demand aggregator that manages the flexibility of different types of assets in energy and balancing markets, from the optimal bidding strategies in a day-ahead horizon to the execution and control of the devices in real time. To achieve this main objective, the thesis firstly analyzes the regulation of the four main European balancing markets, with special attention in finding barriers and enablers for a commercial scale development of Demand Aggregators. Once analyzed the framework, the thesis aims to cover the optimal operation of the Demand Aggregator: (1) the thesis explores and proposes three different algorithms to predict the electricity's consumption of different type of consumers, proposing a methodology to compare them; (2) the work proposes a methodology to predict the flexibility of several type of consumption and allow to trade this flexibility in electricity and balancing markets and (3) the thesis proposes two novel mathematical programming models to allow the participation in the Iberian secondary reserve market and the joint participation in short-term energy and tertiary reserve markets.

Results demonstrate the technical and economic viability for Demand Aggregators to participate in the selected markets and the novelty of the proposed methodologies. Further research topics are individuated due to the complexity of the problem, including electricity market's regulatory issues or economical and physicals restrictions to consider when a change in the consumer's behavior is needed. Despite the challenging framework, from the algorithms and knowledge developed during this thesis, the author, with its thesis director, funded in 2020 Bamboo Energy. Bamboo Energy is a company created to commercialize the software developed withing this thesis, making demand aggregation a reality in Spain. Consequently, this thesis presents a success story of how what began, more than five years ago, with the initial steps of energy flexibility in a research environment, ended up with a spin-off that tackles real market business on energy management in demand aggregation applications.

Keywords: Demand aggregators; flexibility; energy markets; Demand Response; balancing services; bidding strategies; optimization; forecast, business models.

Resumen

Europa está a las puertas de una revolución energética. El antiguo paradigma energético donde las grandes plantas de generación producen energía para los consumidores pasivos está acabando. La penetración de recursos renovables distribuidos y la electrificación de la movilidad, de procesos industriales o los equipos de producción de frio y calor en edificios, va a cambiar la manera en la cual la energía se produce y consuma. Además, la actual situación sociopolítica y la guerra en Ucrania aceleran la necesidad para Europa de poner fin a la dependencia energética de otros países y de los combustibles fósiles. Actualmente, la electricidad es más cara que nunca, y los ciudadanos están siempre más comprometidos con el medio ambiente, queriendo ser una parte activa de la revolución.

En este contexto, los avances en el "Internet de las Cosas (IoT)" permiten recoger muchos más datos de los equipos y permiten su control remoto, aunque en el campo energético queda mucho recorrido por hacer para aprovechar todo su potencial. Al mismo tiempo, las directivas europeas incentivan los consumidores a tener un rol activo en el sistema eléctrico y los reguladores nacionales están trasponiendo las directivas para permitir a los consumidores participar activamente en los mercados eléctricos. A pesar de esto, no es fácil para los operadores del sistema gestionar la coexistencia de consumidores y generadores en los mismos mercados, debido a sus diferencias intrínsecas. Los agregadores de demanda son la nueva figura del mercado eléctrico que pondrán los consumidores al centro del sistema energético. El rol de los agregadores de demanda es agregar, ofertar, y gestionar la flexibilidad de múltiples consumidores en los mercados eléctricos. La flexibilidad de la demanda es la habilidad de un consumidor de modificar su consumo dependiendo de ciertas situaciones externas, como podría ser el precio de la electricidad o necesidades del operador del sistema. Aún no está claro cuál es la mejor estrategia para implementar por parte de los agregadores de demanda.

Bajo este nuevo paradigma, esta tesis doctoral explora las estrategias optimas de un agregador de demanda que gestiona la flexibilidad de diferentes activos en mercados eléctricos y de flexibilidad, desde la construcción de la oferta hasta la ejecución en tiempo real. Para alcanzar el objetivo, la tesis primero analiza la regulación de cuatro diferentes principales mercados de balance europeos, con el foco en detectar barreras y facilitadores para un desarrollo comercial a grande escala de los agregadores de demanda. Una vez analizado el marco regulatorio, la tesis intenta cubrir las operaciones optimas del agregador de demanda: 1) la tesis explora y propone tres algoritmos para predecir el consumo energético de cuatro tipos de consumidores, proponiendo una metodología para compararlos; 2) el trabajo propone modelos para predecir la flexibilidad de diferentes activos energéticos y para permitir ofertar esta flexibilidad en mercados eléctricos y de balance y 3) la tesis propone dos novedosos modelos de optimización para permitir la participación de consumidores en el mercado de reserva secundaria y la participación combinada en mercados de energía y de reserva terciaria en tiempo real.

Los resultados demuestran la viabilidad técnica y económica de la participación de los agregadores de demanda en los mercados analizados y la novedad en las metodologías propuestas. También se identifican diferentes líneas de investigación a futuro, debido a la complejidad del problema, que incluye asuntos regulatorios, restricciones económicas y físicas para tener en cuenta cuando se busca un cambio en el patrón de los consumidores. A pesar de las dificultades del contexto, a partir de los algoritmos y conocimientos desarrollados durante esta tesis, el autor, junto con su directora, fundaron en 2020 BambooEnergy. BambooEnergy es una empresa creada para comercializar el software desarollado durante la tesis, haciendo la agregación de la demanda una realidad en España. Por esta razón, esta tesis presenta una historia de éxito de lo que empezó hace más de seis años con los primeros pasos en un entorno de investigación, acabó convirtiéndose en una spin-off disruptiva en el contexto de la gestión de la demanda agregada.

Palabras clave: Agregadores de demanda; flexibilidad; mercados energéticos; Respuesta de la demanda; Servicios de balance; estrategias de oferta; optimización; predicciones, modelos de negocio.

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List of Acronyms and Abbreviations

aFRR	automatic Frequency Restoration Reserves
AGC	Automatic Generation Control
BRP	Balancing Responsible Parties
CAPEX	Capital expenditures
CV(RMSE)	Normalized Root Mean Square Error
DA	Demand Aggregator
DER	Distributed Energy Resources
DR	Demand Response
DSO	Distribution System Operator
EMS	Energy Management System
ENTSO-E	European Network of Transmission System Operators for Electricity
EV	Electric Vehicles
FCR	Frequency Containment Reserves
FRR	Frequency Restoration Reserves
FSP	Flexibility Service Providers
HVAC	Heating, Ventilation and Air Conditioning systems
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
k-NN	k-Nearest Neighbors
KR	Kernel Regression
MAPE	Mean Absolute Percentage Error
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
mFRR	manual Frequency Restoration Reserves
NEMO	Nominated Electricity Market Operators
NN	Neural Networks
OMIE	Operador del Mercado Ibérico de Energía

OPEX	Operating expenditures
P.O.	Operating Procedure
PV	Photovoltaic
REE	Red Eléctrica de España
RR	Replacement Reserves
SCIP	Solving Constraint Integer Programs
SO	System Operator
SOC	State of Charge
TSFA	Time Series Factor Analysis
TSO	Transmission System Operator

Notation

Indices and sets

$\mathcal{B}$	Set of stationary Battery
$\mathcal{H}$	Set of thermal load Assets
$\mathcal{P}$	Set of PV assets
S	Set of shiftable load Assets
T	Set of time steps considered
$i \,€ \{\mathcal{P}, \mathcal{B}, \mathcal{H}, S\}$	Consumption or generation flexible source
$t \,€\, T$	Time interval

Parameters

av	Binary indicating if the load is available to change its consumption or not
b1 [€/kWh]	Expected difference between expected energy upward activation and unbalance price
C	Thermal inertia of the thermal zone, also called capacitance $[kWh/°C]$
C^{act}	Cost per each switch performed by the shiftable load [€]
C^{debt}	Cost per *kWh* not consumed by the end of the day $[€/kWh]$
COP	Coefficient of performance of a thermal load
$direction$	Binary indicating if the activation is upward ($direction = -1$) or downward ($direction = 1$)
E^B	Battery capacity [*kWh]*
E^s	Energetic debt cumulated until the moment during the day [*kWh*]
Flex_obj	Flexibility objective to reach the SO request *[kW]*
m	Minimum bid size of the market *[kW]*
is_up, is_down	Binaries indicating if the aggregator is executing the optimization for the up ($is\_up = 1$ and $is\_down = 0$) or down ($is\_up = 0$ and $is\_down = 1$) tertiary reserve
$\mathcal{M}$	Big Number
$\overline{ME}$	Energetic debt allowed by the asset owner [*kWh*]
mi	Minimum bid size for the intraday continuous markets' [*kW*]

minu	Per unit of the current time step remaining until the next hour
mt	Minimum bid size for the tertiary markets *[kW]*
N	Number of switches until the moment
$\overline{N}$	Maximum number of switches from OFF to ON allowed during a day
NI	Number of frozen time steps due to the aggregator cannot buy or sell energy in the next intraday markets
p^{c}	Expected consumption or generation of a curtailable load [kW]
p^{Bc},p^{Bd} [kW]	Expected charging and discharging power from the battery without any flexibility activation
P^{min}, P^{max}	Minimum and maximum and power of the load [kW]
P^{Md}, P^{Mc}	Maximum discharging and charging power [kW]
p^{S}	Expected shiftable baseline consumption [kW]
pv	Baseline forecasted PV generation [kW]
r	Band ratio between secondary up and down offered band
R	Thermal resistance of the zone's envelope [$°C/kW$]
SOC^{M}, SOC^{m}	Maximum and minimum level of SOC the battery can reach without compromising the device [$\%$]
$SOC0$	Initial State of Charge of the battery [$\%$]
$SOCend$	Expected battery's SOC at the end of the optimization period *[%]*
$type$	Binary indicating the type of control over the thermal asset (1 = ON/OFF, 0 = power output)
$\underline{T}$	Minimum time between a switch from an OFF to an ON status [h]
T^{min}, T^{Max}	Minimum and maximum temperature allowed in a thermal zone [$°C$]
T^{a}	Ambient temperature of the external of the zone [$°C$]
T^{i}	Internal temperature of the zone [$°C$]
$Tdev$	Expected temperature variation [$°C$]
TS	Time from last switch at the first-time step [h]
U^{O}, D^{O}	Accepted up and down secondary reserve band [kW]
w	Penalization for buying or selling in the continuous intraday market *[€/kWh]*
$x0$	Binary indicating the expected initial status of the shiftable load
λ^{act}	Price of the activated flexibility *[€/kWh]*

λ^{B}	Estimated activation price for offered band *[€/kW]*
$\lambda^{eU}, \lambda^{eD}$	Estimated upward and downward secondary activation price $[€/kWh]$
λ^{off}	Offered up or down tertiary reserve price *[kW]*
λ^{sp}	Spot market price *[€/kWh]*
λ^{P}	Deviation penalty rate for reserve offered and not supplied
ϕ	Heating or cooling electric power provided by the thermal load $[kW]$
ϕ	Security factor on the offered secondary band
ϕ^{s}	Solar power entering throughout the window surface $[\mathrm{kW}/m^2]$
η^{c}, η^{d}	Charging and discharging efficiency $[\%]$
ρ^{+}, ρ^{-}	Estimated activation ratio of Up and Down band
σ	Binary parameter indicating if the thermal load is providing heating ($\sigma = 1$) or cooling ($\sigma = -1$)

Variables

A^{P}	Correctly activated flexibility by the aggregator due to the flexibility activation from the SO [*kW*]
B	Expected benefits for secondary market participation [€]
C-7	Consumption during the same hour of the previous week [kW]
D	Type of day
D^{PV}	Photovoltaic's generation reduction *[kW]*
F^{BU}, F^{BD}	Maximum flexibility up and down, respectively, that the battery could provide at a given time.
F^{HU}, F^{HD}	Maximum up and down flexibility that the HVAC could offer at a specific time [kW]
$finalSOC$	Expected SOC at the end of the optimization period *[%]*
$finalT^{flex}$	Expected final temperature deviation due to the flexibility activations [$°C$]
h	Binary indicating if an offer is sent to the SO (1= yes, 0=No)
h'	Transformed hour considered
$hu \;\; hd$	Binary variables that take value equal to 1 if the aggregator reaches the minimum offer upward or downward flexibility in the market respectively
I	Solar irradiation $[kW]$
m	Month

P	Expected penalizations for secondary market participation [€]
P^{Surp}, P^{Lack}	Surplus and lacked power to satisfy the SO flexibility activation [kW]
SOC	State of Charge of the battery [%]
T	Outdoor temperature $[°C]$
T_24	Ambient temperature with a lag of 24 hours $[°C]$
T^{FLEX}	Temperature deviation due to the flexibility activation $[°C]$
Tsun_air	Combination of the irradiation and the ambient temperature $[°C]$
u , d	Binaries to assure that the aggregator activate either up or down flexibility
U^{aux}, D^{aux}	Auxiliary batteries' variables representing the deviation from the power baselines *[kW]*
U^{B}, D^{B}	Up and down flexibilities offered or activated by the battery [*kW]*
U^{H}, D^{H}	Flexibility up and down offered by the thermal load [kW]
u^{H}, d^{H}	Binary indicating if the flexibility activation on the flexible asset is either up or down
U^{OFF}, D^{OFF}	Offered up and down flexibility of the aggregator's portfolio [kW]
U^{S}, D^{S}	Estimation of the total flexibility up or down activated by the aggregator in the secondary market [kW]
U^{S}, D^{S}	Flexibility up and down provided by the shiftable load [kW]
us , ds	Binary indicating if the shiftable asset provides either up or down flexibility
W	Binary to indicate when the aggregator is following the activation order from the SO (1= yes, 0=No)
x	Binary that indicates if the status of the shiftable load is ON (x = 1) or OFF (x = 0)
X^{B}	Binary to establish whenever the battery is providing upward $X^{B} = 1$ or downward $X^{B} = 0$ flexibility
X^{Surp}, X^{Lack}	Binary indicating if there is a surplus or a lack in the flexibility delivery or not.
y	Binary that takes value equal to 1 after a change in the shiftable load status from ON to OFF

All models are wrong, but some are useful. - George Box

Chapter 1 - Introduction

1.1 Motivation

Climate change is an undeniable reality for scientists, most politicians and society as a whole. Accordingly, people and industries are aware about the ecological impact of their activities. Five of the Sustainable development goals from the United Nations are directly energy-related and, according to it, we are in the "Decade of Action" [1]. Technology advances make energy transition a reality; however, this implies deep changes in the society and in the economy as a whole. The objective of this Chapter is to introduce the main trends of the energy sector that bring to the need for Demand Response (DR). In the last Section, the research gap is individuated, and the objectives and the structure of this thesis is presented.

1.1.1 Climate Crisis

During the last decade, before and after the COVID pandemic, the main crisis of our society is the climate change. Our world is warming up at a rhythm never seen before. The last report from the Panel on Climate Change (IPCC) [2] states clearly that we need to reduce global emissions by around 45% on 2010 levels by 2030 and establish net zero emissions by 2050 to preserve the global temperature increase to 1.5 º C in respect to the preindustrial era. The time to act for our species is very short and if we do not do anything, the consequences can be catastrophic, such as an increasing number of heat-related deaths, extreme food and water shortages and extreme weather events that are both more frequent and more severe, among others. Likewise, the recently-published report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services [3] warns of the unprecedented decline of the planet's nature and the acceleration of species extinction rates. All of these can potentially create a big social and environmental crisis.

The production and use of energy accounts for more than 75% of the EU's greenhouse gas emissions and it is in the middle of a transition without precedents [4]. The EU promises massive investments in green technologies through the Green Deal to reach 50-55% renewable share by 2030 and net-zero greenhouse gas emissions by 2050. Specifically, in Spain the objective is to reach 70 % of renewable energy production by 2030 and 100 % by 2050 [5].

Full electrification of heating and transport sector and of some industrial processes is the path foreseen to reach targeted objectives. This trend added to the decrease of the 13 % of the world population that nowadays does not have any access to electricity [6], according to the International Energy Agency (IEA), it is expected that the world electricity consumption doubles until 2050, while renewables are projected to make up over 50% of generation by 2035 [7]. As reported by International Renewable Energy Agency (IRENA) and IEA [8], to achieve these low-carbon goals around USD 3.5 trillion in energy sector would be required every year until 2050, and specifically demand-side investment would need to surge by a factor of ten over the same period.

1.1.2 Distributed energy resources penetration

The energy paradigm is evolving fast. Historically, the energy system structure was vertical, having big, centralized power plant producing electricity. These power plants, apart from being proprietary of big companies' blind with the needs of citizens, they are the most pollutant ones, being their fueled by gas, fuel or coal. Nowadays, we are in the middle of a revolution without precedents in the electricity sector, where smaller and decentralized renewable power plants substitute conventional power plants.

Main renewable technologies are solar, wind and hydropower. Hydropower already contributes significantly to the penetration of Renewable Energy Sources in several countries, but this resource is geographically limited and is strongly conditioned by the morphology of the site [9]. Nowadays, the fastest growing of renewable energy sectors consist of solar and wind power: the rapid decline in the cost of these technologies, as Fig. 1-1 shows, has made them cost-competitive against other fossil or nuclear fuels, and has led to their accelerated deployment [10], without the need of governmental subventions.

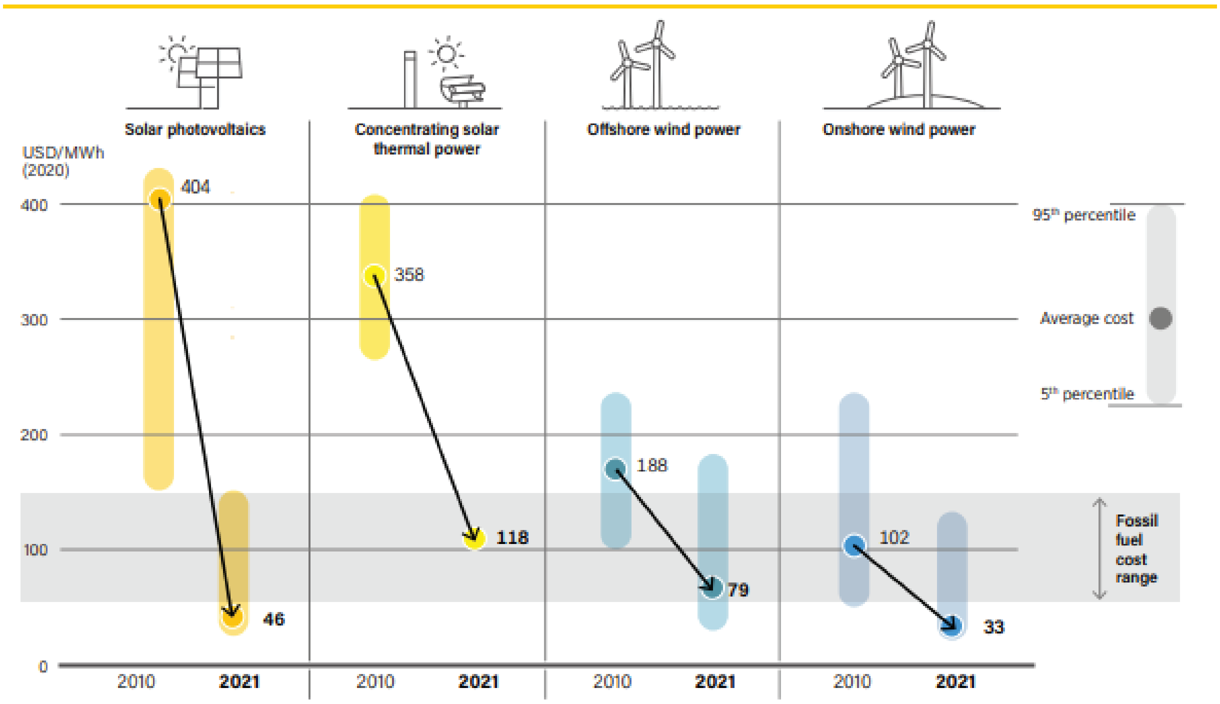


Fig. 1-1 Cost per kWh produced by renewable technology. Source: [11]

The lower costs of the technology with the increase of the electricity price due to the current energy crisis, the increase of people awareness about their environmental impact and the ever-stricter regulation about national emissions creates the perfect condition for a massive rollout of renewable energies. Fig. 1-2 shows the trend in capacity installation for Photovoltaic (PV) panels, wind power plants, hydro and bioenergy. The additional capacity installed of PV has almost increased by a factor of four during the last six years, while the newly installed capacity from wind energy has increased by 50%. These two electricity resources were almost inexistent in 2010. Total renewable installed capacity is expected to increase between a factor of 1.5 and 2 in the next 5 years according to the IEA [11].

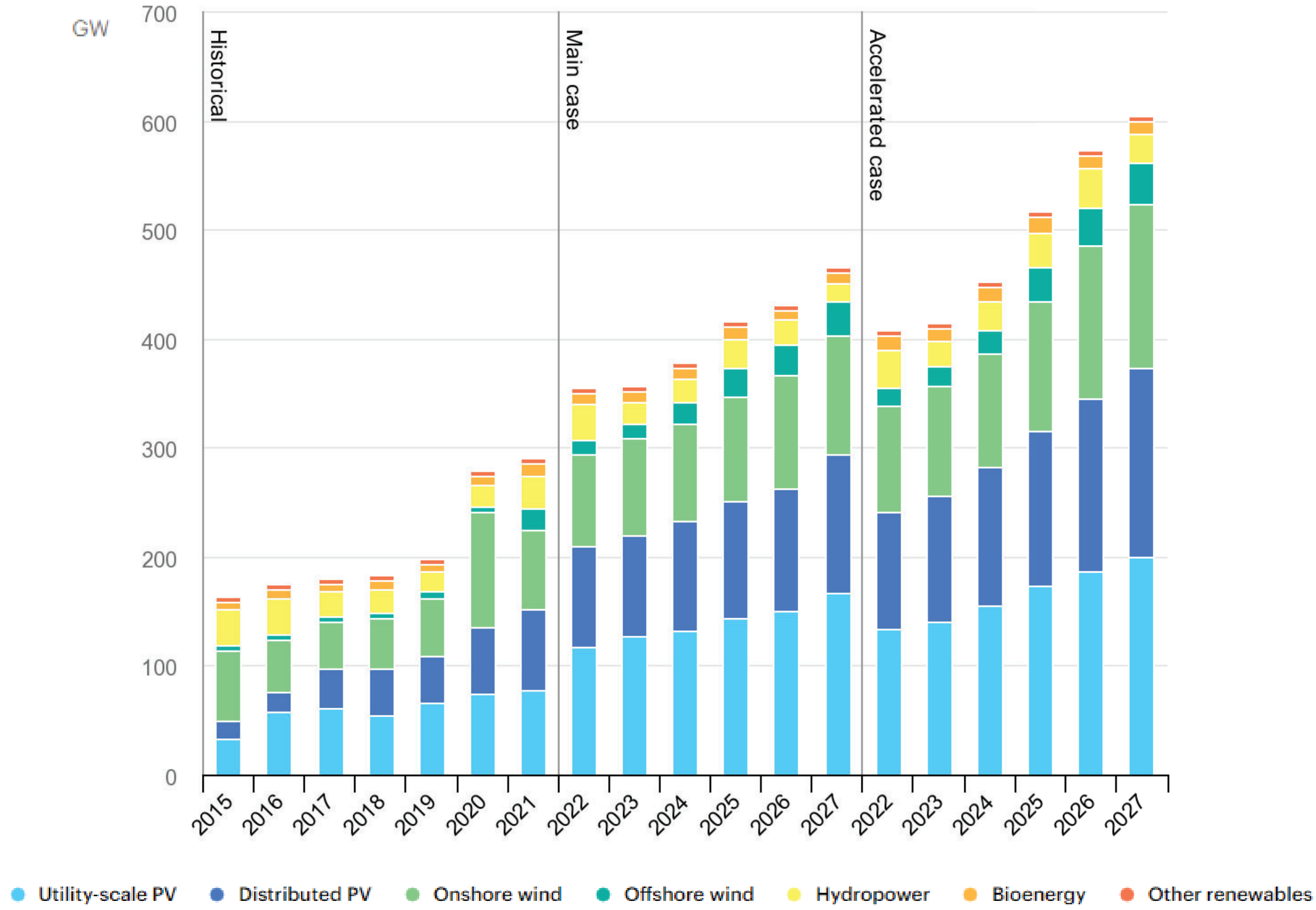


Fig. 1-2 Capacity addition by technology. Source: [12].

Nonetheless, Distributed Energy Resources (DER) are not limited to the generation side. Stationary batteries and Electric Vehicles (EV) fall in the DER definition and are protagonists of the energy transition as well. Fig. 1-3 shows the EV's stocks in the last years by region. The growth is impressive, with China leading the global market. EVs are an example of interdisciplinary challenge, connecting transport and electricity sector. The trend is similar for stationary batteries; the total installed cost of a stationary battery is estimated to fall by an additional 54-61% by 2030 and total electricity storage capacity appears to triple in energy terms by 2030, according to the IRENA [12]. These two resources are not likely to be a passive actor in the energy transition. Their capacity to absorb, store and inject energy back to the grid depending on external conditions, such as energy prices or renewable production, makes them the perfect dance partner of uncontrollable renewable generators.

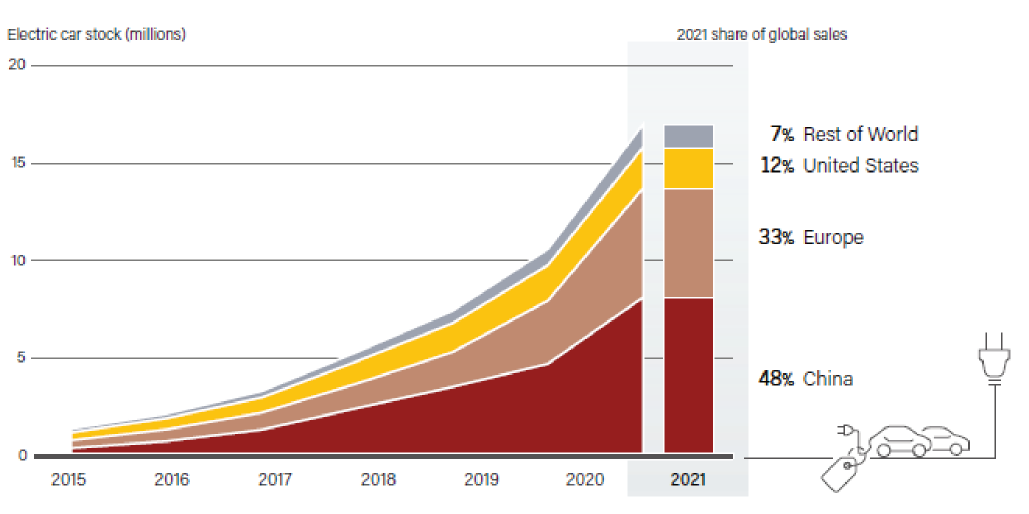


Fig. 1-3 Millions of EV sold by year and region. Source: [13].

1.1.3 Legislative changes – consumer at the center

Historically, the demand side of the energy system has been inelastic, increasing or decreasing only due to industrial crisis or technological disruptions. The latest advances in smart grid and building technologies enable the paradigm of a elastic consumption, modified by external dynamic signals as price. This new paradigm promises to unlock the active participation of the demand in electricity markets and to transform passive consumers into active consumers, also called "prosumers". Prosumers can modify their energy consumption to participate in DR programs. DR is the action taken by a consumer to adapt its consumption to electricity prices or to the need of the System Operator (SO). For instance, smart buildings need to manage their energy flows of generation from local renewable power sources and their internal consumption, and for that purpose they may include solutions to manage their flexible loads. This means that technical barriers are no longer significant on the automation side. The main challenge is to transform these functionalities into products that consumers can trade in electricity markets [14] to reduce their electricity bill while helping the energy transition toward a 100% renewable energy system.

For this reason, it is important to adapt regulation of electricity markets to the last changes in the electricity sector. Electricity market regulation was designed for big, centralized generation power plants. Each country has different regulation regarding DR, but there are some shared laws that should indicate the path for national governments to improve DR programs. The Energy Efficiency Directive 2012/27/EU [15] was an important step forward for DR in Europe; Article 15.4 states that "Member States shall ensure the removal of those incentives in transmission and distribution tariffs […] that might hamper participation of demand response, in balancing markets and ancillary services procurement. Member States shall ensure […], that tariffs allow suppliers to improve consumer participation in system efficiency, including demand response, depending on national circumstances". Article 15.8 meanwhile states that "Member States shall ensure that national energy regulatory authorities encourage demand side resources, such as demand response, to participate alongside supply in wholesale and retail markets. […] Such specifications shall include the participation of aggregators."

The Demand Aggregator (DA) emerged as a new market agent necessary to manage demand-side flexibility [16]. Its role is to aggregate and manage coordinately different flexibility providers (loads and/or DERs), that are not currently able to enter the market due to their small size and/or due to a lack of infrastructure and knowledge, allowing them to participate in electricity markets [17].

The transposition deadline for the fulfillment of the European Directive was the 5th of June 2014, but various countries did not achieve the objective. The necessity of a transition towards a more flexible electricity system that could allow the participation of a higher share of renewable energies, is highlighted by the European Commission in the EU winter package "Clean Energy for All Europeans", released on the 30th of November 2016. It highlights that energy will be traded ever more closely to real time and intraday and balancing markets will gain more importance. The role of the aggregator is reinforced and in the future demand side flexibility and storage resources should be incentivized. Furthermore, the Energy Performance of Buildings Directive EPBD [18] encourages the use of smartness meters that enable the use of DR and allow customers to take ownership of their energy usage.

Considering that in 2013 the figure of the DA did not exist in any European country, these directives undoubtedly boosted DR. However, much work has yet to be done to make the market uniform and to allow the participation of aggregators at all market level. Moreover, various countries, such as Spain, have not yet transposed completely European Directives having their balancing markets closed to prosumers or having strong barriers to their participation. European Directives urge countries to open electricity markets to consumers and demand aggregators to achieve the EU energy and climate policy targets [19].

1.2 Objective of the thesis

The general objective of the doctoral thesis consists of defining and implementing novel statistical and optimization tools and methodologies to facilitate the integration of flexible demand-side resources in the energy system throughout a new market actor: the Demand Aggregator.

The DA will become an important figure that will empower consumers, giving them the possibility to participate in electricity markets, saving money and helping the transition toward a 100 % renewable energy system. Since DA are young actors in the European electricity market, this thesis aims to build a complete DA management tool that allows this new agent to perform optimally.

To reach the main objective of the PhD, several specific objectives have been identified:

1) To analyze critically the European electricity markets' regulation scheme to find main enablers to reinforce and barriers to remove to unlock the full demand-side flexibility potential in Europe.

2) To propose new statistical techniques adapted to forecast electricity consumption.

3) To develop new mathematical models for different type of flexible assets able to consider their rebound effect.

4) To propose a mathematical programming model for the DA optimal bidding strategy in the Spanish secondary electricity market including demand side resources and to develop the complementary model to manage their participation in the market during real time operations.
5) To propose a mathematical programming model for the DA bidding strategy in short – term electricity markets and develop the complementary model to manage demand side flexibility resources in real time.
6) To develop a DA execution tool able to combine all the previous developed modules in a unique platform.

1.3 Framework and structure of the thesis

1.3.1 Framework

This PhD thesis has been possible thanks to the collaboration between IREC (Catalonia Institute for Energy Research) and the UPC (Universitat Politècnica de Catalunya). During the first two years of the thesis the PhD candidate worked on the REFER project [20], which is a RIS3CAT project in collaboration with the Metropolitan Area of Barcelona (AMB) and other companies. The objective of the REFER project is to explore new ways to find flexibility and efficiency in rehabilitated buildings and some initial tests could be performed at the Montgat library.

In addition, in April 2018 the Innoenergy PhD School selected the PhD candidate. The program offers soft-skill courses in top universities, extra activities, and the possibility to create relationships with other international students and companies.

The PhD candidate also performed an external stay in an international company based in France in the Savoie Technolac called Energy Pool, which is one of the firsts companies to act as Demand Aggregator in Europe.

Finally, from the result of this thesis, the candidate co-founded the software company Bamboo Energy in 2020.

1.3.2 Publications and outreach activities

Note: In 2020, once the software company Bamboo Energy is founded, the results of the thesis are protected and the publication of the algorithms and mathematical models is restricted.

1.3.2.1 International Journal papers

i) Canals Casals L, Barbero M & Corchero C. Reused second life batteries for aggregated demand response services. *Journal of Cleaner Production* 2019; 212:99–108. https://doi.org/10.1016/j.jclepro.2018.12.005.
Journal Impact factor: 11.072 in JCR, 110 citacions in Google Scholar in April 2023

ii) Barbero M, Corchero C, Canals Casals L, Igualada L, Heredia FJ. Critical evaluation of European balancing markets to enable the participation of Demand Aggregators. *Applied Energy* 2020;264. https://doi.org/10.1016/j.apenergy.2020.114707.
Journal Impact factor: 11.446 in JCR, 55 citacions in Google Scholar in April 2023

iii) Barbero, M., Casals, L. C., & Corchero, C. Comparison between economic and environmental drivers for demand side aggregator. *Utilities Policy 2020*, *65*, 101077. https://doi.org/10.1016/j.jup.2020.101077
Journal Impact factor: 3.24 in JCR, 3 citacions in Google Scholar in April 2023

iv) Etxandi-Santolaya M, Colet-Subirachs A , Barbero M, & Corchero C. Development of a platform for the assessment of demand-side flexibility in a microgrid laboratory. *Applied Energy* 2023, 331, 1 February 2023, 120359, https://doi.org/10.1016/j.apenergy.2022.120359.
Journal Impact factor: 11.446 in JCR, 0 citacions in Google Scholar in April 2023

v) Barbero M, Canals Casals L, Colet-Subirachs A, Salom J & Corchero C. Demand Response Approaches in a Research Project versus a Real Business. Submitted for review to *Sustainable Energy, Grids and Networks* in April 2023. Second revision in progress.

Journal Impact factor: 5.405 in JCR

1.3.2.2 Conference papers

i) M. Barbero, L. Igualada and C. Corchero, "Overview of the Regulation on Aggregator Agents in Europe," 2018 15th International Conference on the European Energy Market (EEM), 2018, pp. 1-5, doi: 10.1109/EEM.2018.8470015.

ii) N. Chapman, M. Barbero and C. Corchero, "Battery Electric Buses Participation in Electricity Markets and Power Systems," *2019 16th International Conference on the European Energy Market (EEM)*, 2019, pp. 1-6, doi: 10.1109/EEM.2019.8916362.

1.3.2.3 Conference presentations

i) Oral presentation at the conference “European Energy Market 2018” of the Paper “Overview of the regulation on Aggregator agents in Europe” (Lodz, 2018);

ii) Oral presentation at the conference “Jornada técnica del CIGRE” of the paper “Estudio de mercados de flexibilidad de la demanda y algoritmos de agregadores” (Madrid, 2018);

iii) Presentation at the ETIP-SNET Workshop “Energy flexibility in buildings: lesson learnt from the Barcelona pilot” (Madrid, 2018)

iv) Poster presentation at the conference “World Sustainable Energy Days”, of the conference paper “Demand response market participation of a tertiary building equipped with a second life electrical vehicle battery and HVAC” (Wels, 2019);

v) Oral Presentation at the IEA Open Workshop “Energy flexibility in buildings: a key asset in the future energy system” (Barcelona, 2019);

vi) Oral presentation at the conference “European Energy Market 2019” of the paper "Battery Electric Buses Participation in Electricity Markets and Power Systems" (Ljubljana, 2019)

vii) Oral presentation at the conference “APEEN 2020 Energy Transition and Sustainability“ of the paper “Comparison between economic or environmental drivers for demand side aggregator” (Covilha, 2020)

viii) Online oral presentation at the conference “World Sustainable Energy days” of the paper “Data-driven demand flexibility estimation in a commercial buildings from air conditioning and lighting system” (Austria, 2020)

ix) Online oral presentation at the conference “4th workshop of the INTERREG project Smart Edge” (Milan, 2020)

x) Online oral presentation at the conference “APEEN 2021 Energy Transition and Sustainability” of the paper “Detection of spike imbalance prices in the French electricity market using machine-learning methods” (Portugal, 2021)

1.3.2.4 R&D Projects

The work developed in this thesis contributed to the elaboration and development of the following European and Spanish R&D projects:

i) REFER project project funded by ACCIÓ and the European Regional Development Fund (FEDER) under the RIS3CAT Energy Community. Available: https://refer.upc.edu/ca

ii) SABINA H2020 project of the European Union under the grant agreement nr. 731211. Available: https://sabina-project.eu/

iii) Coordinet H2020 project of the European Union, with reference call LC-SC3-ES-5-2018-2020. Available: The CoordiNet Project (coordinet-project.eu)

iv) Electraflex project

v) Adebuild project, financed by MINCOTUR.
vi) Flexauto project, financed by MINCOTUR.

1.3.2.5 Tutoring

During the thesis, the PhD candidate tutored some students with their Master or Bachelor degree or thesis:

i) Co-tutored the Internship of Axel Eriksson with the title “Using Recurrent Neural Networks for Price Forecasting in the Iberian Secondary Electricity Market”, 2019 (Innoenergy Master Student, KTH).
ii) Co-tutored the Internship of Pablo de Juan with the title “Automatized machine learning using AI techniques for electric consumption forecasts”, 2019 (CFIS, FME, UPC).
iii) Co-tutored the Internship of Francesc Martí Escofet with the title “Machine learning techniques for electric consumption forecasts”, 2021 (CFIS, FME, UPC).
iv) Co-tutored the master’s degree thesis of Maite Etxandi Santolaya with the title “Integration of a microgrid laboratory into an aggregation platform and analysis of the potential for flexibility”, 2021. (Master on Energy, UPC).
v) Co-tutored the master’s degree thesis of Saioa Etxebarria with the title “Forecasting building’s flexibility using machine learning models”, 2021 (Master on Mathematical Engineering, UAB).
vi) Tutored the master’s degree thesis of Rafel Orestes Pérez Barceló with the title “Environmental impact of Demand Response participation in electricity markets”, 2022 (Master Smart Electrical Networks and Systems, UPC).
vii) Tutored the master degree internship of Joaquin Costa with the title “Customer Journey definition for a B2B2C model”, 2022 (Master Smart Electrical Networks and Systems, UPC).

1.4 Structure of the thesis

The work developed within the scope of this thesis is organized into seven Chapters (including the present one). The current Chapter discusses the motivation to this thesis, defines the problem under research and its main objectives and presents the framework of the thesis.

Chapter 2 introduces all the basic concepts needed to contextualize the framework of this work. It presents the fundamentals of Demand Response, the different types of flexibility, the role of the DA and the business models that are raising in Europe related to it.

Chapter 3 critically analyzes European electricity markets. Firstly, it presents a brief introduction to electricity market mechanisms. The Chapter also analyzes the existing barriers and enablers for DA from a regulatory, technical, and economic point of view. To complement the analysis, a comparison of the five most important balancing European markets is presented.

Chapter 4 presents three statistical techniques to forecast electricity consumption. These techniques are tested over four different data set and evaluation metrics are proposed to evaluate electricity demand forecasting algorithms in the future.

Chapter 5 describes the mathematical model to characterize different types of flexible assets to permit their participation in balancing and energy markets. Moreover, it describes the algorithms, the variables and the parameters needed to estimate day ahead flexibility.

Chapter 6 presents the mathematical programming models for demand aggregation participation in day ahead and short-term energy and balancing markets. The first proposed model covers the participation in secondary reserve markets of a DA using MILP optimization with risk aversion to deal with uncertainty in activation volumes. The second proposed model covers the DA participation in multiple short-term electricity market sessions.

Chapter 7 describes the main contributions and findings from this thesis, as well as the topics for future work.

Chapter 2 - Context

This Chapter introduces the basis for the work done in this thesis. It describes the concepts needed to understand the framework and the practical scope of the thesis. The needs of demand side flexibility are highlighted from different perspectives. This Chapter also introduces the different types of flexibility considered within this thesis. Finally, it introduces the figure of the DA, how it fits in the new electricity system and the main business models raised in Europe about demand aggregation.

2.1 Demand Side Flexibility needs

Demand Side Flexibility is the ability of a consumer to modify its consumption depending on external factors, such as electricity prices or grid conditions. This Section explains the need of different actors to adopt demand side flexibility.

2.1.1 System Operator

The transition toward a 100 % renewable energy system creates different challenges for System Operators (SO), which role is to keep during all the time the balance between demand and generation. Conventional power plants can easily modulate their production to adapt to the demand. This is not the same for renewable generators, which strongly depends on weather conditions. It can happen that in times of high demand the weather conditions (sun, wind) are not optimal to allow system balance. In this case, the production from renewables might be insufficient to cover all the demand, and, without other sources, conventional peak power plants must be activated. These conventional powers rely on fuel, coal, or gas as their main sources of energy, making them the most pollutant and most expensive. Such peak power plants need to be maintained available during the whole year, although they are used just in exceptional cases. Currently in Spain, to assure the security of the electricity system, the 5% of the electric bills in Spain is reserved to peak power plants to keep their availability during peak hours.

The alternative solution to peak power plant for their flexibility in the generation's schedule is to increase the available flexibility of the loads, also called Demand Side Flexibility (DSF). DSF is one of the solutions to assure the security of supply. In case of high demand and low production, a flexible system can reduce the consumption until the peak is over, avoiding investing in new generation power plants. With this mechanism, consumers are paid for the service provided to the grid, creating extra benefits for them, and avoiding installing new peak gas power plant in the system, and indeed reduce costs for the Transmission System Operator (TSO).

The downside of volatile generation is when there is more production from renewable than electricity demand. In this case, it can occur that electricity prices during that hour becomes negative, as already happens sometimes in Germany and in other countries of the North of Europe. This happens because it is more expensive for some sources such as nuclear to turn down the power plant than pay for producing. However, if no one buys that energy at a negative price, the SO needs to curtail the renewable production to balance with the demand. Wind curtailments in Spain between 2008 and 2013 had an economic impact of around 85 M€ due to a mismatch between generation and demand [21].

Another challenge raised by the deployment of decentralized energy resources and the electrification of heating and transport system is the increased importance of the distribution grid. Until now, the distribution grid was the last part of the electric transportation chain. It connected the high voltage grid, where generators were placed, to the end-users. From now on, distribution grids are taking ever more importance and they need the capacity to manage their network. First, the old unidirectional electricity's flow is moving to a bi-directional flow, where consumers can produce and inject energy into the distribution grid. Secondly, the appearance of EV and electric heating/cooling systems will consistently increase the demand peak at the distribution grid. The power lines were not dimensioned to support such a high electricity demand, creating congestion problems during peak hours. Also in this case, Demand Side Flexibility helps to reduce congestions at the local level, preventing Distribution System Operators (DSOs) to invest in grid reinforcement needs [22]. In this sense, local markets where consumer offer their flexibility in a competitive market to solve congestions are emerging, and they will take always more importance [23].

2.1.2 Consumers

Demand side flexibility is a resource coming from consumers, which modify their electricity consumption behavior to adapt to electricity prices or electricity grid needs. Of course, for doing this, consumers need some incentives.

The first type of incentive is economical. In fact there are two categories of demand response depending on how the economic incentive is presented to the consumer: explicit or implicit [24]. With explicit DR, also called "incentive based", the consumer is expected to receive a payment for the service delivered upon request, triggered by, for example, unbalance between generation and demand or a congestion on the network. This payment can be received directly or through an intermediary. DSOs and TSOs need this type of DR to solve balancing and congestion problems. With implicit DR, also called "price based", the consumers react to a dynamic signal, which is often a time-varying price related to the wholesale market price. It is important to mention that one direct consequence of the renewable's volatility is higher volatility in electricity market prices. Nowadays, it is quite common for example to have an electricity price in the wholesale market that is the double of the price of the previous hour. The later fact opens huge opportunities for demand-side flexibility providers, since if they can adapt their demand to electricity prices, they could take advantage of the market's volatility to reduce their electricity bill.

Consumers can participate in these programs individually, or through the figure of an intermediary, the Demand Aggregator (DA). Those two types of DR are not exclusive and could both be enabled in a certain geographic area. The present thesis focuses on the potential of explicit and implicit DR through the figure of the DA.

Demand side flexibility can also be used to increase the usage from renewable local generation. Self or communitarian consumption is always a better solution than absorbing energy from the grid from an economical and environmental point of view. Adapting the demand to local solar and wind production is another way to reduce load peaks and increase local renewable generation. This is not only an economical incentive, but also social and environmental. Be able to share energy within the neighborhood and consume the energy locally produced by the community reduces costs, enhance investments in local renewable energy generators and support citizen's participation in the energy system [25].

Therefore, the second type of incentive is environmental. Consumer's environmental awareness is gradually increasing. DR is an effective way to help the integration of renewable energies in the mix and increase self-consumption. Even though benefits of DR are widely accepted, a lot of work is missing to measure the real environmental impact of demand response on the short and long term.

Finally, the last incentive for consumers to adopt DR measures come from collateral effects to participate in a DR program. For doing this, consumers need first to monitor their consumption. This is a must-have for participation in whatever DR programs. By participating in a DR program, consumer increase their awareness about their consumption and it helps to detect any unexpected or inefficient behavior or asset.

2.2 Types of Demand Side Flexibility

Although the concept of Demand Side Flexibility is quite new, the electricity system has always had flexibility sources that come from the generation side to balance the demand. However, it would be an error to say that increase generation is the same than decrease the consumption or vice versa. This is because in most cases a decrease in the consumption during a certain period implies an increase of the consumption during another period, what is called rebound effect. This means that in most cases the consumption is moved in the time, but it is not reduced at all. In contrast, a conventional power plant can change its production profile during a certain period without the need to change its scheduling for the next hours. This means that a conventional power plant can increase or decrease the total energy produced over a day.

Depending on how a change in the consumption during a certain period affects the consumption for the next periods, DSF resources can be divided in shiftable loads, deferrable loads, interruptible loads, and storage devices.

2.2.1 Shiftable loads

Shiftable loads are consumptions that can be shifted in the time without any direct affectation of the user's comfort or industrial production. For instance, some domestic appliances such as the washer machine and some industrial processes are considered shiftable loads. These loads can have limit on the time that the process needs to finish. For example, for an industry that produces shoes, the only limitation could be to have finished the scheduled production by 8 p.m., when the daily shift ends, no matter if the process takes place during the morning or during the afternoon. Fig. 2-1 shows the typical rebound effect of a shiftable load. During the flexibility activation the consumption decreases, and it is recovered some hours later.

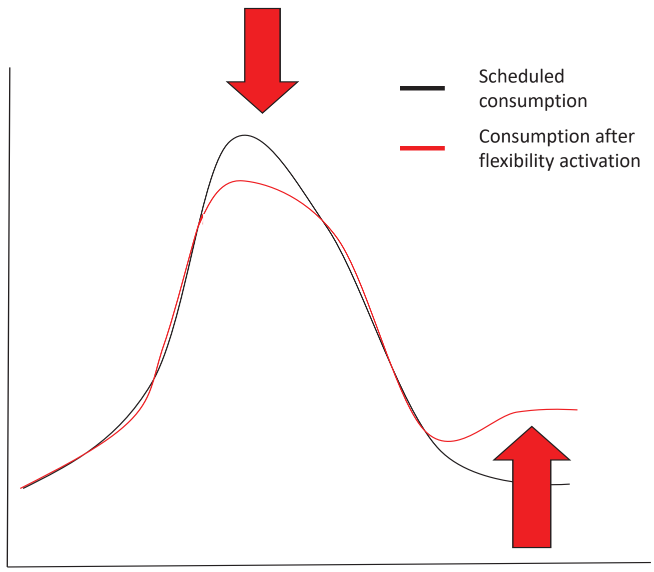


Fig. 2-1 Shiftable load rebound effect

2.2.2 Deferrable loads

A deferrable load has less flexibility than a shiftable load because the energy shifted has to be recovered after a limited time, since their timely usage directly affects the comfort of the user or the productivity of an industrial process.

Typical deferrable loads are thermal loads such as Heating, Ventilation and Air Conditioning systems (HVAC), fridges or swimming pools. For all these types of loads, it is possible to reduce the consumption during a determined period taking advantage from the inertia of the space and from the fact that all these processes have a range of comfort. For example, in the case of an industrial fridge used for conserve bread, the temperature can oscillate between – 10 °C and - 5 °C without affecting the quality of the product. The main condition is to recover that consumption not used in the following time steps to bring the temperature to the operational point. Fig. 2-2 shows the rebound effect of a deferrable load.

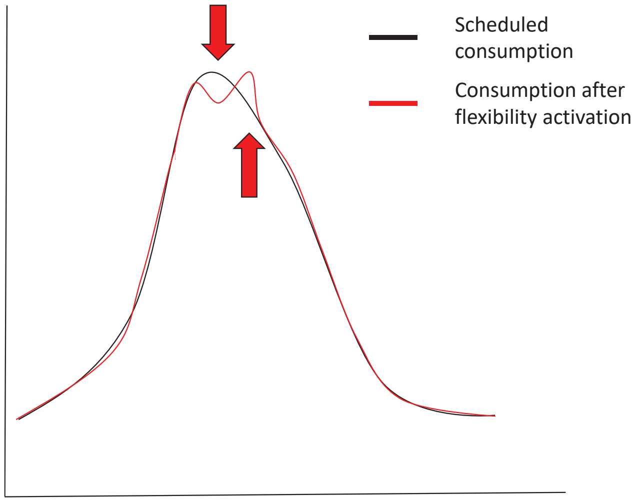


Fig. 2-2 Deferrable load rebound effect.

2.2.3 Interruptible loads

Interruptible loads, on the contrary of shiftable and deferrable loads, do not need to recover the reduced amount of energy, indeed they do not have rebound effect. This hypothesis is valid if the flexibility service provided is worth enough in economic and environmental terms to justify a load reduction. An example of interruptible loads are some industrial processes that can be eliminated during a certain day. Although is not an interruptible load, some building that have renewables installed can interrupt their production to balance the demand with the generation in the system, in this case they are defined as interruptible generation. Fig. 2-3 shows the rebound effect of an interruptible load.

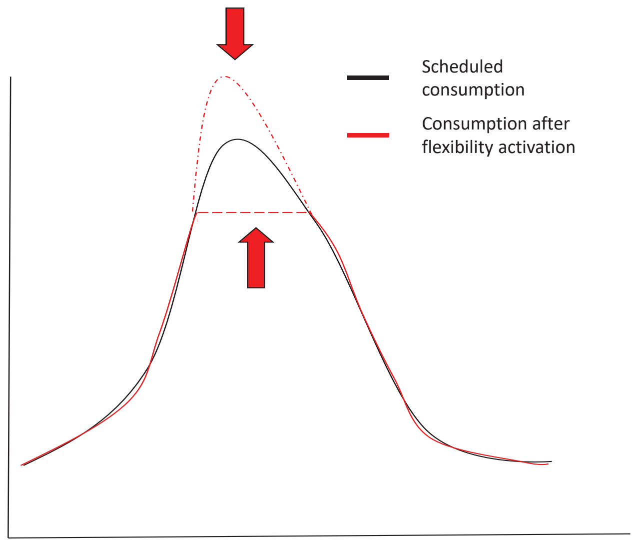


Fig. 2-3 Interruptible load rebound effect.

2.2.4 Storage devices

Storage devices are devices that can absorb energy, store it during a certain time and inject it back when necessary. The most common storage devices are stationary batteries. Their usage is every time more common, and they are used in houses to increase self-consumption or to take advantage of different electricity prices during the day. Their usage does not directly affect the comfort of user, since their usage does not imply to modify the consumption of the site, but it affects the origin of the electricity that is used.

Another type of storage devices are electric vehicles. As explained in the introduction, there is a clear trend in the increase of this technology. EV, on the contrary of stationary battery, have more limitations, since they always need a minimum level of battery charge, depending on the user needs and they are not connected continuously to the grid.

2.3 The demand aggregator

2.3.1 Role of Demand aggregators

The DA is the new electricity market actor who acts as an intermediary between energy consumers, DER owners, DSOs and TSOs and manages in a coordinated way these end-users or take advantage of the services provided by these DERs [16]. Its role was firstly recognized in the Energy Efficiency Directive 2012/27/EU to encourage the use of DR and then reinforced in the EU winter package “Clean Energy for All Europeans” which enhances the use of demand side flexibility and storage resources, strengthening the role of the DA [26].

Aggregators are the key enablers for the active participation of end-users into electricity markets and the provision of network related services. They provide the technology and the electricity sector knowledge that facilitate such participation. Aggregators sum up small flexibility capacities from individual DERs so that the final amount is large enough to build marketable flexibility products. From a technology perspective, the aggregator is linked to various entities, such as the flexible assets, the DSO or the TSO, through a communication interface, which allows it to assess the capability to provide power and energy services. The aggregator can also implement the logic needed to estimate the flexibility, create bids and market products with that flexibility, as well as to operate the end devices to fulfil the market agreements.

Currently, DA in Europe are mainly working with large energy consumers as industries, taking advantage of the flexibility of their production process [27]. However, literature is also focusing on residential and tertiary buildings' flexibility, as they represent about the 40 % of the global energy consumption [28] and have a great flexibility potential.

Consumers participation in electricity markets is not simple to manage, since technical requirements for participating in these markets are strongly generation oriented [29]. To allow consumer participation in electricity markets in an optimal way, the DA needs to:

- Forecast the baseline consumption of the next day, which is the consumption that the consumers would have without any flexibility activation.
- Forecast the available flexibility from its portfolio, considering the possible rebound effect due to a flexibility activation.
- Optimize its bidding strategy in different electricity markets to maximize the value of the flexibility offered and reduce eventual penalizations for not providing the service offered.
- Manage in real time the flexibility activated to not incur in penalizations.
- Be able to communicate and manage distributed flexibility assets remotely.
- Have a deep knowledge of electricity market mechanisms.

2.3.2 The position of each actor in DA

The actors involved in DR through DA are classified in different levels through the electricity grid. In the upper level there are the actors that safeguard the state of the grid, that is, the transmission and the distribution system operators (TSO & DSO) and, in some cases, there are other entities such as the Balancing Responsible Parties (BRPs) that are specifically related to balancing. On the second level, there are companies which trade the flexibility of their costumers for grid balancing purposes (receiving a payoff from SO or BRPs) as one of the energy services offered to their clients e.g. energy retailers, monitoring or energy management companies. This is where the DA should be and, in some countries, the DA must stay under the umbrella of an energy retailer. On the third level is where the users (buildings, industry) are and, finally, the fourth level is where to find the assets that are within the buildings. Note that, in certain cases, such as with charging stations, assets and users might be considered as the same.

Depending on the interactions between the "commercial", "user" and "assets" levels, there are three different categorizations [30], which affect the communications between the elements in each level and the final configuration:

i. Flat: the retailer provides a flat rate with no additional incentive for the user, which eliminates in fact the willingness of the user to provide flexibility. This is the traditional use case.
ii. Stackelberg Game: the retailer decides unilaterally anticipating to the prosumer rational reaction giving a time-varying rate for the consumer. In this case, the aggregator or retailer is looking for an implicit demand response. The interaction between the aggregator and the consumers is just economical since the retailer does not manage the consumption of its clients. This scheme may be represented as a Stackelberg game and is the scheme applied nowadays in Europe by major electricity companies. In this case there is no need of an aggregator.
iii. Nash Bargaining Game: the aggregator or retailer cooperate with end users by dividing the benefits coming from DR. If the aggregator and the DR providers cooperate, the game governing the division of the benefits of this interaction may be represented as a Nash Bargaining Game, explicitly accounting for power relation between the aggregator and the DR providers. This is the case where

the figure of the DA appears to manage the consumption of consumers, allowing them to participate in implicit and explicit demand response programs.

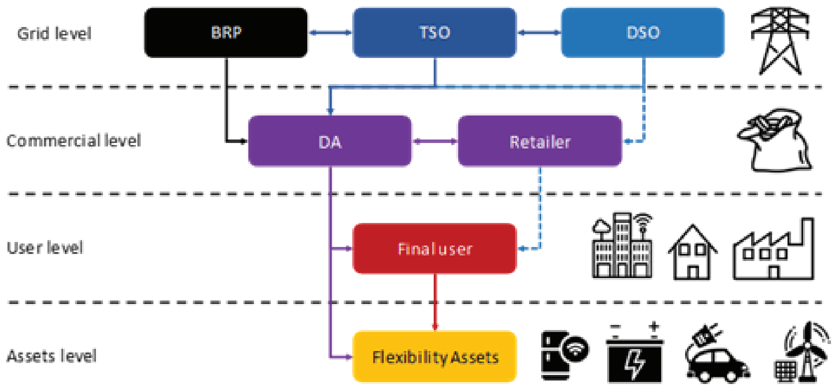


Fig. 2-4 Actors involved in DR through DA and their position in the system.

However, several crossovers might occur in-between these categorizations. It is true that the contracts between levels might affect the communications, but what really forces the communications is not just the element taking the decisions but also the one that activates the flexibility assets. For instance, in the work by Iria et al [14], the DA had a perfect knowledge of the reality of the flexibility assets, so the DA knew whom to ask for flexibility. However, the element deciding what to do once the activation was raised is the Energy Management System (EMS).

2.3.3 DR Business models in Europe

In order to define the mathematical programming models that enable the optimal management of a demand aggregation and its optimal bidding strategy it is essential to understand the business model behind its operation. As summarized by Hamwi et al. [31], the optimization problem deals with two branches, one for costs and the other for revenues, that should end up in positive value so the DR business model has sense. While literature is focused in finding new solutions for the bidding strategies and real time management of flexibility sources, revenues for DA and flexibility providers depend principally on the characteristics of the site, the business model adopted and on the national specific market requirements [32]. Costs can be divided in five main categories, and can be Capital expenditures (CAPEX) or Operating expenses (OPEX):

1. Communications (CAPEX): DR programs need a bi-directional channel between the flexibility provider and the DA to communicate the current consumption of the site and receive flexibility activations orders. The communication channel could also include further functionalities, e.g. provide predictable response or send flexibility bids. The cost varies depending on the starting point of the site and on the objective of the communications [33]. Notice that for the participation in some manual programs, such as interruptible program, a conventional smart meter is enough.

2. Computation (OPEX): variable cost that depends on the degree of automation desired and the amount of data needed to feed the algorithms used by the DA. The cost could be concentrated on one actor (the DA) in case of centralized control or distributed among different EMSs otherwise.

3. Transaction (CAPEX): includes the costs of collecting information regarding products and customers, managing contracts and procedures for external transactions [34].

4. Activations (OPEX): defined as the cost to activate flexibility in the site. In the case the flexibility activation in an industrial site implies a reduction in the industrial production, the activation cost can be very high [35]. On the contrary, if the flexibility activation reduces the HVAC consumption, the activation cost is null since it does not bring any economical lost to the building owner.

5. Penalizations (OPEX): whenever the flexibility provider (or its representative) does not provide the flexibility requested, it incurs in a penalization.

Although it is possible to treat the flexibility provider and the demand aggregator as the same entity, costs and revenues are distributed differently depending on how the service is provided. There are different possible ways flexibility can be provided by consumers; three extreme examples are presented below.

i. Manual activations without intermediary: this is the simplest case; the flexibility provider has a bi-lateral contract with the SO or BRP. The activation is manual, through e-mail or SMS. Here the computation effort is low and concentrated at the SO level and there are low communication costs. All revenues and eventual penalizations go to the final user.

ii. Aggregator as financial intermediary: the SO organizes a competitive flexibility market. If a minimum bid size is needed, small participants need to be aggregated and represented as one. In this case, the final users need to forecast their flexibility and make a bid to the DA, which sends the offer to the SO. Most of the effort is on the EMS level because the aggregator is just the financial representative. In this case, communications costs are higher since the EMS needs to communicate with the DA and computation costs fall into the user level. Penalizations for not accomplish with the offer should be charged to the final user too. A big share of revenues should go to the final user, since the DA has less risks being just the intermediary. In this case, the optimization is at the user level without coordination among final users, loosing potentially opportunities in contrast to coordinated optimizations.

iii. Aggregator as physical and economical intermediary: the SO organizes a competitive flexibility market as in 2). However, here the aggregator oversees the whole aggregation process, from market bidding optimization to real time flexibility management. Communications costs are still higher than in the previous case since the DA needs to control the physical assets. The computation effort resides on the DA side since it forecasts, optimizes, and manages a big number of installations. The DA optimizes all the assets together, since it knows the potentiality and the status of all the assets, maximizing the common benefit. In this case, penalization should fall into the aggregator and revenues should be higher for the aggregator than in previous models.

Whatever the DA is acting as financial intermediary (ii) or oversees the full aggregation process (iii), the DA business models consist in trading the flexibility of their clients to one or more actors through market mechanisms or through bilateral contracts. The DA can participate in frequency regulation services or help to solve grid congestions by selling flexibility to the TSO or DSO. Another option for the DA is to help balancing and optimize the electricity market position of the BRP and/or retailers' portfolio. The DA could also operate outside the conventional chain of energy supply i.e. is neither BRP nor retailer (Third-Party Aggregator) [36], or it can be the same BRP/retailer acting as DA [37], as shown in Fig. 2-5.

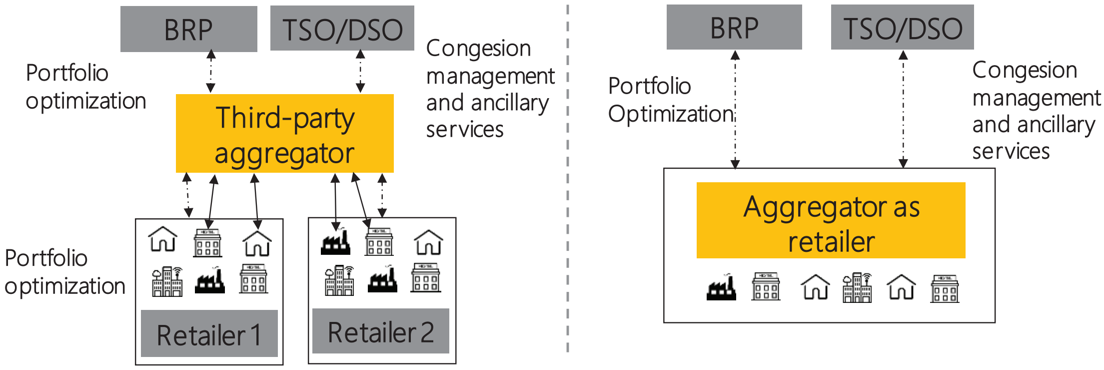


Fig. 2-5 Comparison between "Third party aggregator" and "aggregator as retailer" business model.

In the case of a Third-Party Aggregator, consumers contract the energy provision from different retailers and the DA takes advantage of the consumer's flexibility by selling the aggregated flexibility to different actors. In this case, consumers do not buy energy from the DA, its role is to trade and manage the consumer's flexibility. The DA can either provide frequency regulation services and congestion management to the TSO/DSO or balance external BRP/retailer's portfolio by trading the shifted energy in intraday markets. The main drawback of this business model is that the flexibility activation from part of the DA could create unbalances in the consumer's BRP/retailer/DSO portfolio. Without clear rules about the unbalances created by the DA, the consumer's BRP/retailer/DSO could be penalised unfairly [16] or the DA could be indebted for the unbalance created.

In the case in which the DA is the same as the retailer, its main business is to sell energy to its clients. However, in Europe, there are retailers that act as DA, since they offer special tariffs to consumers that are able to shift part of their consumption when it is necessary. Usually, they are retailers that own renewable generation assets and are able to take advantage from the flexibility of their clients to reduce the unbalances costs by balancing their own portfolio. Complementary, a competitive retailer will use DR in order to reduce the risk of being exposed to high prices in the spot market [38]. If retailers have enough flexibility, they could also provide frequency regulation services and congestion management to TSO/DSO or balance external BRP's portfolio. The main drawback of a retailer as DA is that it can raise some conflicts of interest.

Table 2-1 summarizes some of the current business models in Europe. France, UK, and Finland are the only countries where some residential consumers are aggregated in Europe. In general, the great majority of DA works with industrial or large energy consumers, Voltalis is the only DA that works exclusively with households. In UK, where consumers are charged depending on their consumption during the three peaks power of the country during the year, all DA analyzed try to reduce grid charges. In general, demand aggregators that are retailer uses the flexibility of their clients to provide services to the grid and to operate in the wholesale/intraday market. On the contrary, companies that are independent aggregators cannot operate in the energy markets, with the exception to French aggregators, where there is a special regulation that allow independent aggregators to offer demand reductions in the energy market. Some of this companies also license or sell their software solution to other companies.

Table 2-1 Analysis of the main European DA business model.

	Aggregator	Grid services	Energy market	Reduction of grid charges	Portfolio balancing	Client target	Independentaggregator	Is retailer	Software platform
Belgium	Centrica [39]	X			X	Industries, tertiary buildings	X		X
	Yuso [40]		X		X	Renewables, batteries, industries		X	
Finland	Fortum [41]	X	X		X	Households, batteries, EVs, renewables		X	
France	Smart Grid energy [42]	x		X		Industries, generators	X		
	Energy Pool [43]	X	X		X	Industries, DER	X		X
	Voltalis [44]	X	X	X	X	Households	X		
UK	Open Energi [45]	X		X	X	Industries, generators, batteries.	X		
	Kiwi Power [46]	X	X	X	X	Industries, tertiary buildings, batteries, and CHP	X		X
	Flexitricity [47]	X				CHP, consumers, batteries, back-up generators, renewables	X		
Spain	BambooEnergy [48]	X	X	X	X	Industries, tertiary buildings, batteries			X

2.4 Discussion

DR is a crucial piece in the energy transition puzzle. The uncontrollability of renewable energies creates new needs for flexibility from the demand side. SOs need DR to assure the stability of the grid and avoid investments for grid reinforcement.

At the same time, consumers are becoming more and more aware about their environmental impact due to their energy behaviors and want to be at the center of the energy system. DR potentially will be a fundamental tool to reduce their electricity bill, helping the transition toward a 100 % renewable energy system. As a consequence, traditional energy companies such as electricity retailers or Energy Service Companies (ESCO) also see an opportunity to differentiate from their competitors by offering the possibility to provide DR to their clients adopting an aggregation software.

However, the business model is not easy to draw. The aggregator needs specific knowledge about electricity markets to maximize the flexibility potential of their portfolio participating in multiple electricity markets, with a fast-changing regulation. Moreover, demand aggregators need to tackle with the constraints of the physical world, treating different type of assets in a coordinated manner, each one with its intrinsic characteristics and communication field interface. To build a scalable, replicable, and automated solution the demand aggregator also needs a strong expertise in machine learning algorithms to predict demand, generation, flexibility and electricity prices and optimization algorithms to optimize the bidding strategy in different markets and the schedule of flexible resources in real time.

Despite this, in the last years, different business models have risen in Europe. The two main categories of business models individuated are the independent aggregator and the aggregator as retailer. However, a wide range of business models have been identified depending on the grade of automation of the solution, the specific regulation of the country and the core business of the aggregator. Some companies have already participated in DR programs in Europe and in the future, there will be more and more interest on this topic.

Chapter 3 - Electricity Markets Analysis

This Chapter revisits the basics of deregulated electricity markets including energy, and balancing service markets. Based on a brief overview, the relevant markets for the scope of this thesis are summarized. Many electricity markets today are not fully liberalized. For instance, in North America, the markets are mainly driven by physical network and operational constraints and thus the TSOs and nominated electricity market operators (NEMOs) are combined in the joint role of Independent System Operators. An overview of markets in the USA is given in [49] for instance. This thesis narrows the focus on European markets, especially on the Iberian market. In Europe, the transmission system operation (TSO) is a natural monopoly, whereas other roles including the DA and electricity supplier allow for competition. Section 3.1 presents the general structure of European electricity markets, focusing on the Iberian market, that is the market that will be used as case study for the thesis. Section 3.2 explains the main barriers a DA can meet to participate in balancing markets. Section 3.3 gives a critical overview on five European electricity markets. Conclusion and final remarks are presented in the Section 3.4.

3.1 General structure electricity markets

In Europe, the structure of the electricity market is fruit of its complex nature and of the historical organization of the sector. Historically, electricity markets were regulated markets, with four main activities: generation, transportation (TSO), distribution (DSO), electricity commercialization. It is just from 1997, with the law 54/1997 [50] that in Spain the generation and commercialization of the electricity has been liberalized, while transportation and distribution are still regulated sectors.

In the Spanish Electricity Market OMIE (Operador del Mercado Ibérico de Energía - Polo Español) [51] is the designed NEMO, the entity in charge to manage all the energy day ahead and intraday markets. OMIE, is also in charge to communicate to the TSO the expected aggregated consumption and generation curve for the next days. On the other hand, the Spanish TSO, “Red Eléctrica de España” (REE) [52] guarantees that the electricity is supplied with quality, security and reliability and is independent from any agent that participates in the electricity market and, also, from the NEMO. REE is the owner of the high-voltage transmission network and is in charge of managing all the balancing markets in Spain. In this situation, the coordination between the NEMO and the TSO became essential in order to guarantee that the market transactions are physically feasible and fulfill the security criteria [53].

To complete the picture, the long-term markets like futures, forwards, swaps, and options are financial markets for price hedging and risk management, operated by (Operador del Mercado Ibérico – Polo Portugués) OMIP [54] and OMIClear in Spain, founded in 2003 . The technical constraints are not considered in these markets, and there is no physical delivery for financial contracts. Instead, the financial settlements are compensated throughout the trading period, acting as a sort of insurance for market participants. These long-term contracts are not in the scope of the thesis. Fig. 3-1 resumes the existing market mechanisms in Spain and the entity in charge.

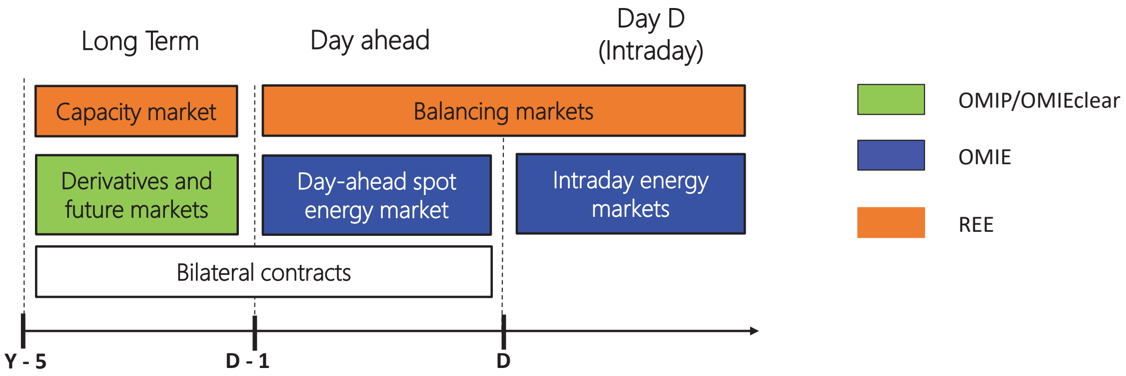


Fig. 3-1 Market organization and entity responsible.

3.1.1 Day-Ahead spot electricity market

The Day-Ahead spot energy market is the most important market with regard to physical exchanges. In Spain, during 2019, 74 % of the energy was traded in the spot electricity market. In this market it is decided the reference electricity price for each hour of the next day. The reference price is the one used to set the electricity price to all the consumers that have an indexed tariff. The good exchanged in this market are *MWhs* of electricity for each one of the 24 hours of the next day. Demand and supply present its offer in *€/MWh*, that represent the maximum price they are disposed to buy or sell and the amount of energy they want to buy or sell in *MWh*. Once the market closes, at 12:00, the OMIE's algorithm maximizes the social welfare of the participants, establishing a price in *€/MWh* for each hour of the next day. The clearing-price λ^{sp} is determined by the intersection of the aggregate supply and demand curve. All the sale (purchase) bids with a lower (greater) bid price Q are matched and will be remunerated at the same clearing price λ^{sp}, independently from the original bid price.

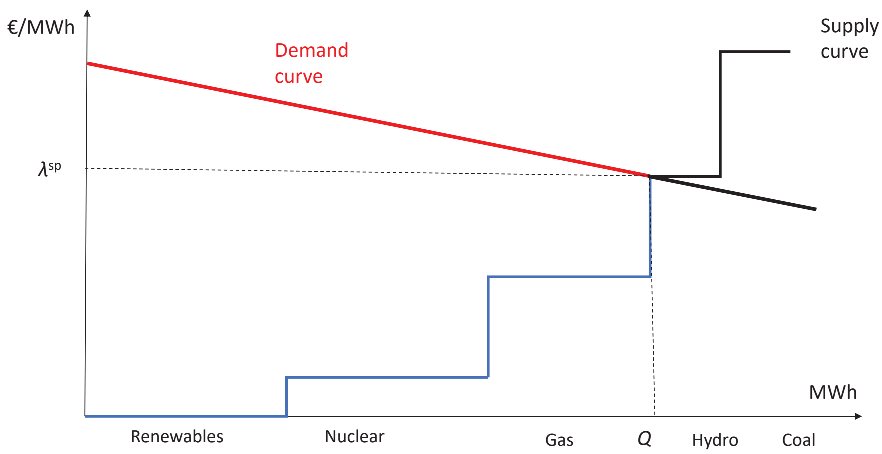


Fig. 3-2 Illustration of the market clearing process for a certain hour.

3.1.2 Intraday electricity market

The Intraday electricity market is an adjustment market. Here, as a difference with the Day-Ahead market, any entity can buy or sell energy. This market allows renewable generators and retailers to improve their operations by using better forecast with the aim to avoid penalization due to unbalances. In Spain, during 2019, about the 6 % of the electricity was traded in Intraday markets.

The Intraday market auction takes place before and during the delivery day; the traditional one is currently structured in six consecutive sessions, with the hourly distribution per session as in Fig. 3-3. These auctions work exactly as those of the Day-Ahead market, with a matching process that is also identical.

	SESSION 1º	SESSION 2ª	SESSION 3ª	SESSION 4ª	SESSION 5ª	SESSION 6ª
Auction Opening time	14:00	17:00	21:00	1:00	4:00	9:00
Auction Closing time	15:00	17:50	21:50	1:50	4:50	9:50
Matching Process	15:00	17:50	21:50	1:50	4:50	9:50
Results publication (PIBCA)	15:07	17:57	21:57	1:57	4:57	9:57
TSOs Publication (PHF)	16:20	18:20	22:20	2:20	5:20	10:20
Schedule Horizon (Timing periods included in the horizon)	24 hours (1-24 D+1)	28 hours (21-24 y 1-24 D+1)	24 hours (1-24 D+1)	20 hours (5-24)	17 hours (8-24)	12 hours (13-24)

Fig. 3-3 Auctions Spanish Intraday electricity market.

Since 2018, Spanish market participants also have the possibility to participate in the continuous European intraday market, also called Single Intra-Day Coupling (SIDC). This gives market agents the chance to manage their energy imbalances with two fundamental differences regarding the traditional intraday market:

- In addition to gaining access to market liquidity at the local level, agents can benefit from the liquidity available in markets in other areas of Europe, given that cross-border transportation capacity is available between the zones.
- The adjustment can be made up to one hour before the moment of delivery.

Fig. 3-4 shows by day, period, and time the contracts in negotiation.

DAY	OPENING	CLOSING	ROUND	ROUNDS "D" AND "D+1"																															SESSION
D-1	14:00	15:00	17	17	18	19	20	21	22	23	24																								MI1 14:00-15:00 (1-24)
D-1	15:00	15:10	18	18	19	20	21	22	23	24																									
D-1	15:10	16:00	18	18	19	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
D-1	16:00	17:00	19	19	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
D-1	17:00	17:50	20	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24			
D-1	17:50	18:00	20	20																															MI2 17:00-17:50 (21-24, 1-24)
D-1	18:00	19:00	21	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24				
D-1	19:00	20:00	22	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24					
D-1	20:00	21:00	23	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24						
D-1	21:00	21:50	24	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24							
D-1	21:50	22:00	24	24																															MI3 21:00-21:50 (1-24)
D-1	22:00	23:00	1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24								
D-1	23:00	0:00	2	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24									
D	0:00	1:00	3	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24										
D	1:00	1:50	4	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24											
D	1:50	2:00	4	4																															MI4 1:00-1:50 (5-24)
D	2:00	3:00	5	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24												
D	3:00	4:00	6	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24													
D	4:00	4:50	7	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24														
D	4:50	5:00	7	7																															MI5 4:00-4:50 (8-24)
D	5:00	6:00	8	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24															
D	6:00	7:00	9	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24																
D	7:00	8:00	10	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24																	
D	8:00	9:00	11	11	12	13	14	15	16	17	18	19	20	21	22	23	24																		
D	9:00	9:50	12	12	13	14	15	16	17	18	19	20	21	22	23	24																			
D	9:00	10:00	12	12																															MI6 9:00-9:50 (13-24)
D	10:00	11:00	13	13	14	15	16	17	18	19	20	21	22	23	24																				
D	11:00	12:00	14	14	15	16	17	18	19	20	21	22	23	24																					
D	12:00	13:00	15	15	16	17	18	19	20	21	22	23	24																						
D	13:00	14:00	16	16	17	18	19	20	21	22	23	24																							

Fig. 3-4 Auctions Continuous European Intraday Market.

The sum of the energy bought or sold for a certain hour *t* in the day ahead e_t^{da} and intraday markets e_t^{id} defines the energy contracted by a market unit.

This is important for the settlement period, since the unbalance e_t^{Δ} is calculated as the difference between the measured consumption e_t^m and the energy traded:

$$e_t^{\Delta} = e_t^m - (e_t^{da} - e_t^{id})$$

In Spain the unbalance created at hour *t* has to be purchased or sold at a price λ_t^{un}, that depends on the λ_t^{sp}, the costs of the system for the balancing markets during the hour *t* and on the direction of the unbalance in comparison to the unbalance of all the system. This unbalance settlement is designed in a way that no market participant can profit from its unbalance.

3.1.3 Balancing markets

Balancing markets are a series of mechanisms that are needed to maintain the balance between generation and demand at every timestep. These mechanisms ensure system balance and nominal frequency, e.g., 50 Hz in Europe. In Spain, these markets are managed by REE, and they are four: primary reserve, secondary reserve, tertiary reserve and replacement reserve. Since February 2021, in Spain, demand units through the figure of the DA can participate in these markets [55], a part from primary reserve that is not a market mechanism and is an obligation for generation units.

The reserves can be composed of demand and generation units and have upward and downward capacity. The upward reserve consists of generation units (or demand) able to increase their generation levels (or decrease their consumption levels). The downward reserve consists of generation units (or demand) able to decrease their generation levels (or increase or start consuming). The nomenclature and technical characteristics of reserve services are different across Europe and will be analyzed in Section 3.2 and 3.3. These Balancing markets are different from energy markets for the following reasons:

- There are multiple sellers, called flexibility service providers (FSP), and just one buyer, the TSO.
- Indeed, there is not a supply a demand curve. The TSO every day publish its needs for balancing reserves, which need to be satisfied to guarantee the security of supply, whatever is the price.
- Whilst in Europe the price in the energy markets is settled by the marginal price, in balancing markets the price-making mechanism could be either the marginal price or a pay-as-bid method.
- There are two phases in balancing markets: availability and use. During the first phase the FSP offer their availability to provide upward or/and downward reserve to the TSO, who selects the most economical offers. During the second phase, if necessary, the TSO activates the needed reserves.
- To participate in these markets, the FSP need to be prequalified by the TSO. This means that the FSP need to pass some tests to demonstrate to be able to correctly deliver the service

3.1.4 Toward an integrated European Market

The European Union (EU) aims to develop an integrated electricity market to foster security, efficiency, and sustainability. From 1996, different directives and energy packages were approved to build a single European electricity market, with the objectives to improve the share of renewable energies and to incentives the participation of consumers. The first electricity directive (96/92/EC) in 1996 and the second in 2003, aimed to liberalize the energy sector establishing competitive markets. In April 2009, the Third Energy Package was approved, and the European Agency for the Cooperation of Energy Regulators (ACER) (Regulation (EC) No 713/2009) and the European Network of Transmission System Operators for Electricity

(ENTSO-E) were created to promote cooperation between national regulatory authorities at regional and European level. With the Fourth Energy Package in 2019, the EU revises rules and principles of the internal electricity market to ensure proper functioning and competitiveness and to support decarbonization of the energy sector.

This process has led, slowly but steadily, to a higher integration of EU electricity markets and has built the basis for the design of the internal electricity market. EU strongly incentives the active participation of consumers through the figure of the independent aggregator. To support this shift to variable and distributed generation, short term markets and scarcity prices are considered essential. In this sense, intraday markets will take even more importance, allowing market participants to balance themselves as close as possible to real time. The elimination of price caps assures to reflect the real value of the energy during each period and should be a sufficient economic signal to assure enough production capacity in the system. In addition, EU sets emissions limit for the participation of generation power plant in capacity mechanisms, which must be the last resort for the countries to assure the security of supply.

Many milestones have already been reached, as the implementation of a European platform for day ahead markets. In this case, different nominated NEMOs and SOs converged to harmonized market rules, capacity allocation systems and energy price formation using the common EUPHEMIA algorithm. OMIE participates in the European Single Day-Ahead Coupling (SDAC) since 2014. However, due to the low interconnection with France, an effective market coupling between the Iberian peninsula and the rest of Europe was reached just during the 28.2 % of the hours during the last five years [56]. Another important milestone was reached in 2018 with the Cross-Border Intraday Market Project (XBID), where NEMOs participate in a continuous energy market with implicit allocation of cross-zonal transmission capacity, which currently allows intraday coupling for 21 countries. Also in this case, energy exchanges are allowed just in case of having enough interconnections available, for this reason the old regional intraday market organized and managed by OMIE is still active.

Despite the need to reinforce interconnections, Day Ahead and Intraday markets have already reached a good level of harmonization. However, Balancing markets are still away from that harmonization, and they still differ in several important aspects that should be addressed before of the Balancing market integration. This is mainly due to the different needs that single countries may have to assure the security of supply to their citizens. Countries such as Spain or Denmark which have a high share of intermittent renewable energy, will be mainly worried to maintain the stability of the grid in the very short term. In contrast, other countries such as Belgium or Finland, that have a lower share of intermittent renewables but have a low production capacity in respect to their annual demand peak, are mainly worried to assure the long-term security of the system.

To start the targeted harmonization, the first step is to have a common definition of balancing products, which is provided by ENTSO-E [57]:

- Replacement Reserves (RR): this reserve is activated manually in the case other reserves are exhausted and is characterized by the slowest activation time.
- Frequency Restoration Reserves (FRR): this reserve can be activated automatically (aFRR) or manually (mFRR) to restore the system frequency at the desired level. These services are also known as secondary and tertiary reserve.
- Frequency Containment Reserves (FCR): this is the first reserve activated for reestablishing grid frequency at an acceptable level. This reserve is also known as primary reserve.

Spain in March 2020 was integrated in the European platform for RR services (TERRE) with other eight countries, while in 2023 it is expected the integration in the m-FRR platform (MARI) and in 2024 in the a-FRR platform (PICASSO).

3.2 Barriers for Demand Response participation

To improve energy processes and use, the Energy Efficiency Directive 2012/27/EU states that barriers for DR participation have to be removed and that DR has to be encouraged, including the participation of aggregators [15]. Moreover, the EU winter package "Clean Energy for All Europeans" previews faster markets, where the energy is traded close to real-time and intraday and balancing markets gain even more importance. The package suggests to incentivize the use of Demand Side Flexibility and storage resources, strengthening the role of the aggregator [26]. Although some countries have already opened the market to DA, they still maintain several technical requirements strongly oriented to classical centralized generation sources, reducing potential participation of consumers in the system [58]. A recent study [59], which analyzed balancing markets in Austria, Germany and Netherlands, found key differences among the countries of study and presented some examples of how the markets' design is not yet aligned with the EU policy objectives. Moreover, various countries, such as Portugal, have not yet transposed European Directives having their balancing markets closed to prosumers [60].
Different type of barriers have been analyzed for DR in balancing markets [61]. This section follows the structure presented in [62], which grouped possible barriers for DA to entry in balancing markets in three types: regulatory, technical and economic barriers.

3.2.1 Regulatory Barriers

Regulatory barriers refer to all those barriers that can appear due to the market regulated and not-regulated framework, that are:

- Restriction on demand aggregation: although Demand aggregation is allowed, there can be still restrictions on the type, the size or the voltage connection of the load [62].
- Inappropriate or incomplete regulation defining roles and responsibilities between market's participants [63]: TSOs should clearly define the balance responsibility in case of flexibility activation from part of a DA. If the TSO does not exclude the activated flexibility from the retailer/BRP's balancing area, a DA can cause unfair purchasing and balancing risks to retailers, BRPs and DSOs [16].
- Number of contracts needed for DR [38]: the need for DA to sign a contract also with the consumer's BRP/retailer/DSO can be a strong barrier as they are potential competitors. In case of incomplete regulation on balancing responsibility's BRP, retailers and DSOs are not incentivized to allow any DA trade their consumer's flexibility since DA can create additional costs to them.
- Independent aggregation not allowed: in some countries such as Spain, independent aggregators are not allowed to participate in balancing markets because only retailers are allowed to aggregate demand. This creates an unfair competition in the country.

Regulatory barriers can forbid or limit the participation of DA in the markets. If the regulatory framework is organized to exclude DAs, aggregators' revenues will be null [62].

3.2.2 Technical barriers

Technical barriers are imposed by functional requirements needed to participate in balancing markets that have been historically defined for generation units and should be updated for allowing the participation of DA [64]. Tertiary or residential buildings participating in DR programs have characteristics completely different from generators and their major constraint is to assure their occupants' comfort. It is worth to remember that a market agent can deliver balancing services to the TSO only if it is prequalified [65], demonstrating the capability to respect all technical requirements. For this reason, it is very important that prequalification is made at the DA portfolio level. If prequalification is made at an asset level, each consumer has to be able to respect all the market's technical requirements on their own [63]. The requirements are:

- Minimum bid size: indicates the MW necessary to participate in the market. If this requirement is lower, than the DA needs fewer customers to participate [66].
- Maximum number of activations: indicates the maximum number of time that a flexibility resource can be activated during a certain period. Consumers use to have restrictions about the maximum number of activations during a period to respect comfort or process constraints.
- Symmetricity of the offer: flexibility can be in two directions, upward or downward. If the offer needs to be symmetric, the number of consumers that can participate in DR is lower, given that some consumers can offer flexibility just in one direction [66].
- Notification time: indicates the maximum reaction time of the flexibility source. Short notification time can give raise to problems due to the communication delay between the DA and the consumers' reaction time, apart from increasing automation costs [66].
- Duration of delivery: shorter the maximum duration of the flexibility activation, more consumers are able to participate in the service, since most of consumers can activate flexibility as maximum during 1 or 2 hours [67].
- Product resolution: indicates the minimum time during which a unit has to offer its flexibility. If it is very long, e.g. one day, it can limit DR participation, since different consumers could offer their flexibility just during some hours a day [67].
- Tender period: indicates how often the market opens. If there is not a daily auction it could be difficult for the DA to predict the flexibility of its clients [67].
- Telemetry requirements: some TSO asks for high-demanding equipment to participate in balancing markets, the same used by big generation plants. Their cost can be prohibitive to allow small consumers to participate in the market.

Technical requirements can limit the available reserve of DAs in the market and can limit the type of consumers that can participate in the DA portfolio, reducing their profitability.

3.2.3 Economical barriers

Economic barriers occur when the DA business model is not viable due to costs exceeding benefits from participation of DR in balancing markets [68]. These barriers are:

- Low prices in balancing markets.
- High technical costs: smart meter installation, communication and control technologies, automation, etc... can reach high costs if very high performances are demanded to participate in the markets [69].
- High penalization costs: market costs such as penalization for not dispatching the committed energy should be reduced to incentivize demand side participation [70].
- Subsidies to peak power plants: they can create an unfair competition; peak power plants are the direct competitors in provide balancing services to the grid. The absence of direct incentives to DR technologies could decrease revenues for DA.

Economic barriers due to the market design affect the way in which the same reserve will be remunerated. A good market design should assure a fair remuneration to DA and give incentives to provide services to the network.

3.2.4 Link among barriers

The barriers presented have different links among them, as represented in Fig. 3-5, which should be considered to improve the balancing market design. At first, regulatory barriers should be avoided to allow DA participation. Then, technical requirements need to assure participation to the largest pool of flexible loads to maximize their availability. Finally, a good market design is necessary to allow a sufficient remuneration to DA and reduce their financial risks.

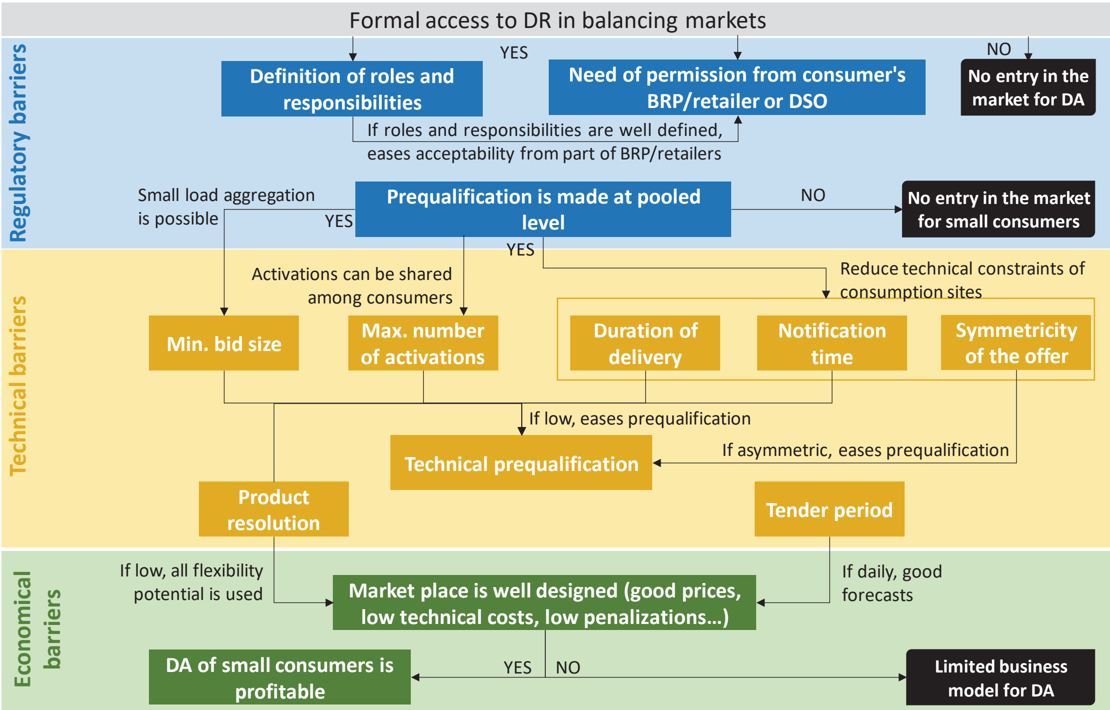


Fig. 3-5 Links between barriers for DA in balancing markets in hierarchical order of importance.

3.3 Critical analysis European electricity markets

The Spanish market is under development and one objective of this Thesis is to offer an assessment of the barriers and enablers for DA operation. For covering that objective, this Section presents an overview on frequency markets opened to DA in Belgium, Finland, France, and UK. The objectives are to understand how far the harmonization of balancing markets in EU is and to understand how different the necessities of these countries are, to assure the security and reliability of their electricity system and understand the market accessibility for DA in these markets. The choice of these countries is not random: France and Germany represent nearly 40 % of the EU-28 total energy generation and they also play a central role in the process of European electricity market integration because they are interconnected with 13 other European electricity markets. Finland has been selected as an example of Nordic countries because is the country where aggregators and DR is more developed. Belgium is facing problems to assure enough production capacity in the system and is interesting to analyze how they are facing these problems. UK has a great variety of balancing services defined by the national SO and the market is the most liberalized in Europe. Prices come from the ENTSOE's transparency platform [71].

3.3.1 Belgium

Belgium increased DR programs after important capacity shortages due to technical issues of some nuclear power plants in the country in the last years. Moreover, the planned closure of some conventional power plants and nuclear power plants and the increase of renewable capacity [72] makes DR a vital source for the system.

- Principal enablers:
  - Third-party aggregators can participate in the market.
  - Offers do not need to be symmetrical in FRR and RR.
  - The minimum time between two successive activations is 8 hours in the mFRR market.
  - Prequalification takes place at pool level.
  - For FCR and FRR penalties are proportional to the payments, with a multiplication factor of 1.3.
- Principal barriers:
  - DSOs can block the consumer participation in DR programs without taking responsibility for the costs incurred by the consumer, DA and TSO.
  - Contracts are made on yearly basis for RR.

Table 3-1 illustrates technical requirements described by Elia, the Belgian TSO [73].

Table 3-1. Summary of balancing markets open to demand aggregators in Belgium.

1 Market open to DA	Min. bid size [MW]	Not. time	Max. number of activations	Product resolution	Symm.	Duration of delivery	Tender period	Energy payment €/MWh	Capacity payment€/MW/h
Symmetric FCR 200 mHz ENTSO-E	1	15 s (50 %) 30 s (100 %)	Continuous activation	4 hours	YES	10 minutes maximum	1 day	NO	8.6 on average
R3 (mFRR)	1	15 min	Minimum 8 hours from the last activation	4 hours	NO	2 hours	1 day	145 on average	11.2 on average
Strategic reserve (RR)	1	Several hours before activation	40 times/y 20 times/y	1 winter	NO (+)	4 hours 12 hours	1 year	At least 10,500	N/A

[1] Dark cells represent that the requirement should be improved to increase DR participation

3.3.2 Finland

Finland has the necessity to add flexibility in its grid as currently the major part of the Finnish reserves are bought from its neighboring countries such as Estonia, Sweden, Norway and Russia [74]. DA can help Finland to be more independent from these countries.

- Principal enablers:
  - Unbalances created by the DA in a BRP area does not increase costs for the BRP, as the TSO corrects the BRP curve after the DA flexibility activation.
  - Prequalification takes place at portfolio level.
  - Smart meters are widely used.
  - The minimum bid size is 0.1 MW for FCR-N.
  - Product resolution is 1 hour for all services.
- Principal barriers:
  - DA needs the agreement of the consumer's retailer/BRP.
  - Aggregating sources from different BRP's areas is only allowed in FCR market.
  - The minimum bid size is 5 MW for FRR and 10 MW for RR services.

Table 3-2 illustrates technical requirements described by Fingrid, the Finnish TSO [75].

Table 3-2. Summary of balancing markets open to demand aggregators in Finland.

Market open to DA	Min. bid size [MW]	Not. time	Max. number of activations	Product resolution	Symm.	Duration of delivery	Tender period	Utilization payment [€/MWh]	Capacity payment [€/MW/h]
FCR-N	0.1	3 min	Continuous activation	1 hour	YES	No stop	Yearly or daily	Yes if yearly reserved	13.5
FCR-D	1	Piece-wise linear regulation or 5 s if f*<=49.7 3 s if f<=49.6 1 s if f<=49.5	Several times per day		NO (+)	Until the freq. has been 49.9 Hz for 3 minutes		50 on average	2.4
aFRR	5	30 sec - 5 min (100%)	Several times per day	1 hour	NO	No stop	daily	50 on average	0
mFRR	5	15 min	Depends on the bids, several times per day/per year	1 hour	NO	15 minutes	No later than 45 minutes before the hour of use, or weekly	50 on average	3.3
Strategic reserve (RR)	10	15 min	Rarely	1 hour	NO (+)	NA	Every 2-3 years	NO	Pay as bid

3.3.3 France

France is possibly the European country with the longest tradition in DA, along with the UK. The massive presence of nuclear power plants and the wish to increase renewable generation resulted in a great interest of the country in DR programs. However, prices of balancing markets are dropping in last years, making more difficult the business for DA.

- Principal enablers:
    - DA can access consumers directly without the permission of the BRP/retailer.
    - The "*appel d'offres Effacement*" (RR) is appositively thought for consumers [76].
    - Prequalification takes place at pool level.
    - The duration of delivery is well suited for consumers for all services.
- Principal barriers:
    - Aggregation of DR and generation in the same bid is not allowed.
    - Generators are obligated to deliver a-FRR services, however they can subcontract DR services through secondary markets.
    - Participation in aFRR market is limited to those consumers connected at the TSO level.

- The minimum bid size for mFRR services is 10 MW.
- FRR and RR are tendered on yearly basis.

Table 3-3 illustrates technical requirements described by RTE, the French TSO [77].

Table 3-3. Summary of balancing markets open to demand aggregators in France.

<table>
<tr><th>Market open to DA</th><th>Min. bid size [MW]</th><th>Not. time</th><th>Max. number of activations</th><th>Product resolution</th><th>Symm.</th><th>Duration of delivery</th><th>Tender period</th><th>Utilization payment [€/MWh]</th><th>Capacity payment</th></tr>
<tr><td>Symmetric FCR 200 mHz (ENTSO-E)</td><td>1</td><td>15 s (50%)
30 s (100%)</td><td>Continuous activation</td><td>4 hours</td><td>YES</td><td>15 min</td><td>2 days</td><td>NO</td><td>8.6 €/MW/h on average</td></tr>
<tr><td>Réglage secondaire de fréquence (aFRR)</td><td>1</td><td>400 s</td><td>Unlimited</td><td>Depending on the plant's scheduling</td><td>YES</td><td>No limit</td><td>Obligation for generator</td><td>NO</td><td>18 €/MW/h</td></tr>
<tr><td>Réserves rapidez (mFRR)</td><td rowspan="2">10</td><td>15 min</td><td rowspan="2">2/day</td><td rowspan="2">1 week (labor days and week-end)</td><td rowspan="2">NO (+)</td><td>2 hour</td><td rowspan="2">Year</td><td rowspan="2">41 on average (Balancing market price)</td><td>0.6 €/MW/h</td></tr>
<tr><td>Réserve compléme-ntaire (mFRR)</td><td>30 min</td><td>1.5 hour</td><td>0.4 €/MW/h</td></tr>
<tr><td>Appel d'offres Effacement</td><td>0.1</td><td>2 hours</td><td>20 days/year</td><td>1 hour</td><td>NO (+)</td><td>2 hours</td><td>Year</td><td>Spot price</td><td>30000 €/MW/y max</td></tr>
</table>

3.3.4 UK

Although UK was one of the first countries to incorporate DR solutions in Europe, the market is yet immature and the capacity of DR is decreasing each year [16].

- Principal enablers:
  - DA can access consumers directly without the permission of the BRP/retailer.
  - Prequalification takes place at pool level.
  - The maximum RR (STOR for the national TSO) activations per day is agreed with the TSO.
  - The system used for counting grid charges to consumers can help DA business model (TRIAD system).
  - Apart from utilization and capacity payment, balancing service providers get also the nomination payment, which consist in a holding fee for each hour (£/h) used within nominated windows.
  - In 2018, UKPN presented their Flexibility Roadmap, an ambitious plan to develop market-based solutions to procure flexibility for its network where DA can participate [78].
- Principal barriers:
  - Tender period can be a barrier in all markets.
  - The minimum bid size in the aFRR market is 25 MW.
  - Demand Turn Up service did not take place since 2019

Table 3-4 illustrates technical requirements described by NationalGrid, the UK TSO [79].

Table 3-4. Summary of balancing markets open to demand aggregators in UK.

Market open to DA	Min. bid size [MW]	Not. time	Max. number of activations	Product resolution	Symm.	Duration of delivery	Tender period	Utilization payment [£/MWh]	Capacity payment [£/MW/h]
Primary response (FCR)	1	2 s (5 %) 10 s (100%)	Continuous	4 h	NO	20 s	Month	NO	8.6 On average
Secondary response (FCR)		30 s	Continuous / Discrete			30 min			
High frequency response (FCR)		10 s	Continuous			Indefinite			
Enhanced frequency response (FCR)		1 s	Continuous	4 years	YES	Minimum 15 min	Sporadic-ally	NO	9.4 on average
Fast reserve (aFRR)	25	2 min	10/day on average	1 month	NO (+)	15 min	Month	102 on average	N/A
STOR (RR)	3	As max. 240 min	Indicated by the service provider	1 h	NO (+)	2 h	Tendered 3 times a year	167 on average	1.8 on average
Demand Turn Up (RR)	1	6 h on average	Several times per week	Some hours	NO (-)	On average 4 h and 36 min in 2018		67 on average	1.5 on average

3.3.5 Spain

In Spain, 55 % of power installed in the country comes from renewable sources, being the 38 % from solar and wind [80]. The high share of stochastic sources in the generation mix means high needs for flexibility in the grid. Today, to assure that the generation can cover all the demand, there are 111 GW installed of power plants against the historical maximum demand registered of 45 MW. The addition of DR sources in the system is a necessity for the country to hold a transition toward a 100 % renewable electricity system.

- Principal enablers:
  - Prequalification takes place at pool level.
  - Short tender period in m-FRR and RR facilitates participation of DA
  - The SO previews to open flexibility markets during 2023 to independent aggregators
  - In 2022, REE presented a new capacity mechanism in Spain
- Principal barriers:
  - Only retailers can participate in electricity markets as DA
  - Energy payments are positive for up regulation and negative for down regulation
  - m-FRR and RR are not paid on for the flexibility capacity provided

- The participation in secondary reserve markets is limited to portfolio with minimum 200 MW of power contracted.
- Secondary reserve bids need to be symmetric
- Market price volatility is still low to facilitate a DA business model

Table 3-5 illustrates technical requirements described by REE, the Spanish TSO.

Table 3-5. Summary of balancing markets open to demand aggregators in Spain.

Market open to DA	Min. bid size [MW]	Not. time	Max. number of activations	Product resolution	Symm.	Duration of delivery	Tender period	Utilization payment [€/MWh]	Capacity payment
Secondary Reserve (aFRR)	1 up and down	100 - 300 s	Unlimited	1 hour	YES	No limit	1 day	Tertiary reserve price	13.23 €/MW/h
Tertiary Reserve (mFRR)	NO	15 min	Depends on the bids	1 hour	NO	2 hours	No later than 25 minutes before the hour of use	Marginal price	NO
Replacement Reserve (RR)	1	30 min	Depends on the bids	1 hour	NO	1 hour	No later than 1 hour before the hour of use	Marginal price	NO

3.4 Discussion

According to the qualitative analysis of best practices, enablers, and barriers from existing markets in Europe, this Section resumes the current state of balancing markets from a DA perspective and proposes some improvements. To allow participation of small consumers in balancing markets, it would be desirable that the prequalification takes place at pool level, as in Finland, UK, France, and Spain. Otherwise, just large energy consumers will be able to be prequalified and DA would not increase the number of consumers that could participate in frequency markets. Taking Belgium, France, and UK as example, it would be better if DA does not sign any contract with BRP/retailers and DSOs but directly with prosumers. In addition, the TSO should automatically adjust the BRP/retailer's curve when flexibility is activated from part of the DA, as it is done in Finland, to avoid increasing BRP/retailer unbalances costs due to the DA action.

FCR, due to the nature of the service, is the most similar market among countries. It is a very rapid regulation, for this reason the notification time is between 2 and 15 seconds and it is activated continuously. Capacity payments are necessary for this type of service and should be higher than in other markets, as it is a more sophisticated service. Fig. 3-6 represents qualitatively the FCR market proposed in respect to the five markets analyzed. Spain has no score since it has not yet a market for FCR.

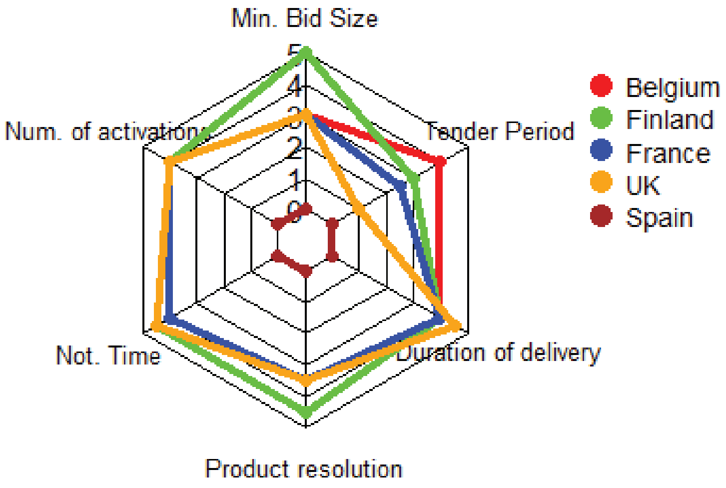


Fig. 3-6 Comparison among countries for FCR balancing services.

Regarding aFRR, this is probably the market where there are more technical barriers in all the countries analyzed. Like the FCR, this is a rapid service, so the notification time is between 100 and 400 seconds. The service is continuously activated, apart from UK where there is a limit of activations per day, probably because there are more FCRs services which are continuously activated. The minimum bid size is a big barrier in almost all the countries, varying from 1 MW of France to 25 MW in UK, which is prohibitive to allow DR participation. An hourly product resolution like in Spain is desirable, higher product resolutions would tap a lot of flexibility potential. Regarding payments, capacity payments are necessary for this type of service, as it is a very sophisticated service. Fig. 3-7 represents qualitatively the aFRR market proposed in respect to the five markets analyzed. Belgium has no score since it has not yet a market for aFRR.

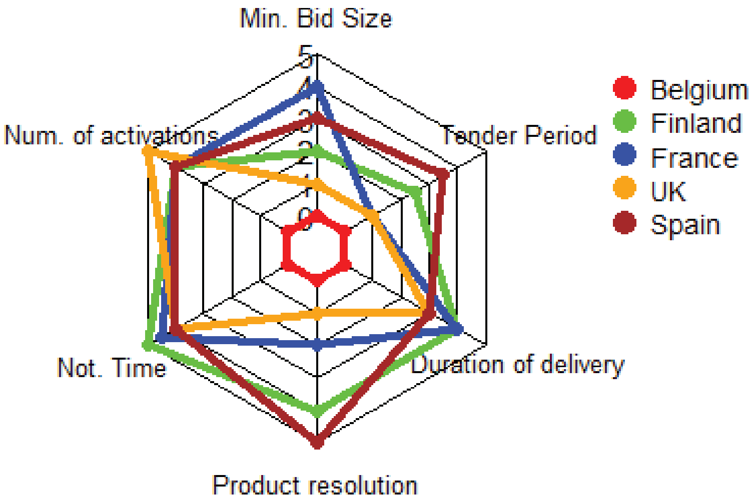


Fig. 3-7 Comparison among countries for aFRR balancing services.

Regarding mFRR, the notification time recommended is 15 minutes, in line with all markets analyzed. Taking the Belgian and the Spanish example, it is proposed a minimum bid size of 1 MW. To allow DR participation, the average number of activations per day recommended is two, as in France. 30 minutes product resolution is suggested, as a longer product resolution would reduce the number of clients able to deliver the service using thermal devices or batteries. In all countries analyzed, mFRR is not a symmetrical service and the duration of the service is between 15 minutes and 2 hours. Duration of delivery between 15 minutes and 1 hour are well suited for DR, although the ideal is a duration of delivery lower than 30 minutes. Regarding the tender period, in all countries apart from Finland and Spain, where it is contracted until some minutes before the hour of use, FRR is tendered monthly or yearly. The Finnish and Spanish case demonstrate that shorter tender time is possible. Marginal price for capacity payments and bid price for utilization payments should reflect costs and ensure revenues to all market participants, as already happens in France and Finland. Having just utilization payments like in Spain strongly limits cost effectiveness of DR. Fig. 3-8 represents qualitatively the five m-FRR markets analyzed.

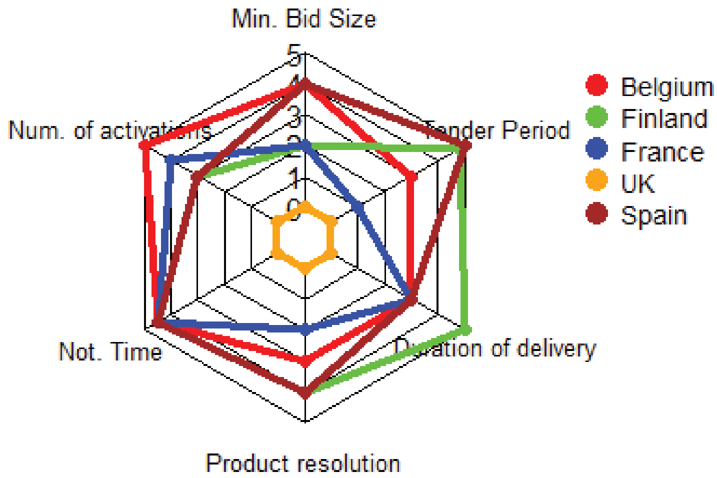


Fig. 3-8 Comparison among countries for m-FRR balancing services.

Regarding RR, the notification time varies significantly among countries; it goes from 15 minutes to 8 hours. DR sources usually can react relatively fast, a minimum notification time of 2 hours as in France or less can be enough for the DA. The minimum bid size should be fixed to 1 MW as in Belgium, UK, and Spain to boost DA participation. UK is a great example of how the maximum number of activations can be agreed with the DR source. The maximum duration of delivery should be fixed to 1 hours, as in Spain. Finally, in the market proposed there should be both capacity and utilization payments as in UK, France, and Belgium. Fig. 3-9 represents qualitatively the RR market proposed in respect to the five markets analyzed.

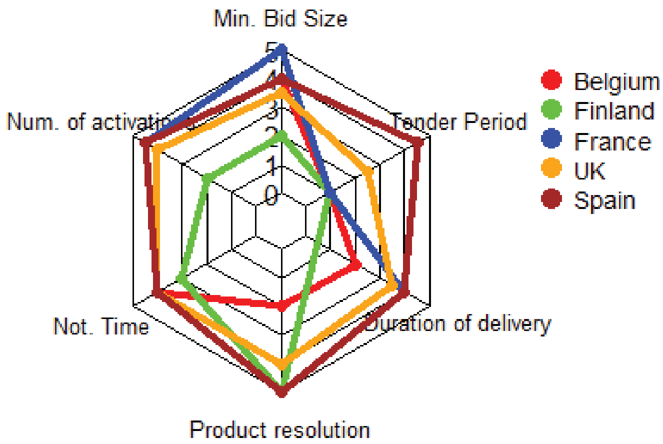


Fig. 3-9 Comparison among countries for RR balancing services.

3.5 Conclusions

This Chapter firstly describes the general structure of electricity markets and identifies the main barriers a DA can find to participate in balancing markets. Regulatory, technical, and economic barriers are identified in hierarchical order. These barriers are reinforced when prequalification is made at the asset level and when there is a lack of regulation for determining the effect of DA on the Balance Responsible Party or retailer's portfolio balancing.

On the regulatory side, huge work is still needed to harmonize technical requirements for consumers' participation in balancing markets. It is important to recognize the role of the independent aggregator to allow raise new business models and unlock the flexibility potential of consumers. At the same time, prequalification should be facilitated to the DA portfolio, not only by allowing prequalification at the portfolio level, but also by simplifying the telemetry and communication requirements that are still designed for large generation plants, implying a too high upfront cost to allow the real participation of distributed energy resources.

Technical requirements represent a barrier for DA in some of the markets analyzed. Regulators should focus in decreasing the minimum size needed to participate in balancing markets to incentive a more competitive environment, where also small assets can participate. Another important barrier is the product resolution of the market, which must be harmonized with the product resolution of energy markets to unlock the flexibility potential of distributed flexibility assets.

From an economic point of view, capacity payments assure a long-term income to flexibility providers making the investment less risky and helps the entrance of first consumers in flexibility markets, such as it happened in France years ago. However, European Regulation goes towards short term energy-only markets making high price volatility and the presence of spike prices paramount to assure reliable participation in electricity markets. In addition, the obligation to install costly hardware such as the ones installed in a big power plant can seriously jeopardize the economic reliability of consumer's participation in balancing markets.

With the aim to highlight good and bad practices and stand out the huge differences that still exist in the balancing market structure between European countries, this Chapter critically compared five European

Countries. From the comparison, any market is ideal to enable demand side participation. Although France and UK are the most mature markets, there is still room for improvements, especially improving the product resolution. Spain, despite having recently opened its markets to demand response (not FCR), has implemented acceptable market requirements. However, especially the prequalification process should be revised to facilitate consumers' participation in flexibility markets.

Further research should focus in updating and extending the electricity market's analysis to other European and non-European countries to enlarge the scope of the work. In addition, the analysis of the balancing market design itself is far from completed, considering its complexity, the effect of other design variables, such as unbalance price formation, connectivity and hardware requirements, and aspects related to the market operation should be further analyzed to understand the reliability for a demand aggregator to participate in these markets. Finally, the analysis could be extended to include non-balancing markets such as voltage control markets, local markets, energy markets, capacity mechanisms, network tariffs and direct incentives for demand response.

Chapter 4 - Load Forecast

4.1 Introduction

Short-term load forecast is taking ever more importance in the electricity sector. An understanding on how energy is consumed helps SOs to assure the balance between consumption and generation. Moreover, accurate predictions are necessary for DA to optimize their bidding strategy in energy markets and for consumers to implement DR strategies and to evaluate energy savings measures [81].

Focusing on the building sector, the classical approach to predict electricity consumption is based on thermodynamic properties of the building's envelope, on the heating and cooling system characteristics and on the building's schedule [82]. This type of approach is defined as "white box model" and needs a detailed knowledge of the building, which usually is not available. In recent years, due to the combination of the difficulty on the detailed modelling of the buildings and the wide spread of smart meters and appliances, data-driven models, also called "black box models", are getting ever more attention [83]. These models are useful to forecast consumption of existing buildings when data are measured and available. Black box models can be described as mathematical models combining the information of one or more independent variables (e.g. weather variables and time variables) to understand and forecast the building behavior [84].

In [85], the authors review 99 works which objective is to predict building energy consumption through statistical methods. From this review, it is evident that most of the state of the art in this field is based on Neural Networks (NN) and Support Vector Machine methods, which represent respectively the 47 % and 25 % of the works analyzed. Performing meta-analysis on these studies is challenging as they adopted different granularity on the response, as well as different number of available variables and error metrics. In addition, the type of consumption analyzed varies among households, tertiary buildings, and industries. For these reasons, it is necessary to build a dedicated study to compare different proposed methods on the same data sets, to establish the best one depending on the type of building analyzed, controlling all the other bias sources.

This Chapter aims to present and compare three statistical prediction models over four different real data sets and buildings to evaluate the performance of each model for each type of representative electricity consumption. The models analyzed are k-Nearest Neighbors (k-NN), Kernel Regression (KR) and Time Series Factor Analysis (TSFA). Data are gathered from a tertiary building, a residential building, a cogeneration plant used for district heating and an industry.

k-NN was introduced by Fix and Hodges in [86] and later formalized by Cover and Hart in [87] for classification problems, but it can be easily adapted to time series forecasts. The main advantage of k-NN is its simplicity and intuitiveness. It was mostly used in finance, text mining, agriculture and medicine [88], while for load forecasts it has not yet been deeply studied. Al-Qahtani and Crone in [89] proposed a multivariate k-NN regression method to forecast UK electricity demand and Fan et al. in [90] proposed a weighted k-NN algorithm for short term predictions of the Australian national power load. However, techniques developed for aggregated load forecast cannot be applied for disaggregated load forecast without any modification, because they fail to reflect the volatility of individual consumers [91]. Valgaev et al. in [92] used a k-NN approach to forecast disaggregated demand. All these works demonstrated that k-NN is a promising technique for electricity load forecasts.

KR is a non-parametric regression method that uses Kernel estimators to predict a certain variable [93]. From the state of the art analysis, we cannot conclude on the usability of this methodology for load forecast given that contradictory conclusions were found. Brown et. Al. in [94] developed a KR method to forecast real-time building consumption that outperformed a classical NN. The method proposed includes different external factors as ambient temperature and solar radiation. With other hypothesis, in [95] the authors used KR to predict daily consumption of a building for the next 30 days using historical consumption data; results show that KR has worst results in terms of accuracy than classical time series models. However, the KR was able to provide more information on the building than the NN. Wu et al. [96] proposes a multiple kernel learning for short-term residential load forecasting applying transfer learning to deal with very limited amount of data and reduce the computational time of the algorithm. Despite this state of the art conclusions, this methodology is considered appropriated and included in this work because the parameters of the KR can provide useful information on the building analyzed that could be used also to predict buildings with a similar behavior, unlike other machine learning techniques.

TSFA is a Time Series Analysis technique used for the first time by Gilbert and Meijer in [97] for macroeconomics predictions. TSFA is an alternative to static and dynamic factor models, already widely used in many fields [98]. In the energy sector it was applied by Muñoz et. al. in [99] to predict electricity prices in the energy market, but it has never been used to forecast energy consumption up to authors knowledge. The correlation existing between energy consumption and energy prices [100] foresees the adequacy of these methods for forecasting energy consumption using advanced time series analysis.

In the literature, there are some works that compare different methodology on electric loads. Chou and Bui [101] compared different Artificial Intelligence techniques to predict cooling and heating loads in households, including Support Vector Regression (SVR), NN, classification and regression tree, chi-squared automatic interaction detector and general linear regression. The consumptions are compared with a white-box model and the model that best fitted the building's consumption was an ensemble between SVR and NN. Yun et al. in [102] compared the hourly consumption predictions for a small office building, a medium office building, a mid-rise apartment and a high-rise apartment of an Auto Regressive model with exogenous variables (ARX), an Auto Regressive model, a NN and a Multiple Linear Regression. The study demonstrates that the ARX has results comparable to the NN but adds information on the variables that most affect the consumption. In this case, results are compared with the simulated consumption and the prediction are done 1 hour ahead. In [103] 12 data-driven models (7 shallow learning, 2 deep learning, and 3 heuristic methods) were developed to predict thermal load in a university campus building in California. They concluded that for the specific building analyzed Long Short-Term Memory algorithm is recommended for short-term predictions, while Extreme Gradient Boosting (XGBoost) is recommended for long-term predictions.

The main contributions of this Chapter are:

- The methodology proposed allows to determine the best model for each consumption type and user's objective.
- k-NN, TSFA and KR are compared to assess pros and cons of each method in predicting hourly consumption during the day ahead using four different real data set.
- For the first time TSFA analysis is assessed for energy consumption's prediction of buildings.

The remaining part of the Chapter is organized as follows: Section 4.2 describes the methodology and evaluation methods adopted. Section 4.3 describes the buildings treated and the data used in this study. Section 4.4 shows and discuss the results obtained in the consumption prediction. Concluding remarks and suggestions for further research are given in the final Section.

4.2 Methodology

This Section introduces the theoretical background of the forecasting techniques evaluated in this study and the metrics adopted for predictions comparison. The objective of the forecasting techniques presented is, given a training data set $D = \{(x_{1,1}, \dots, x_{1,m}, y_1), \dots, (x_{n,1}, \dots, x_{n,m}, y_n)\}$ of *n* hourly observations, each observation being an *m+1*-dimensional vector composed of a vector of input variables $X_i = (x_{i,1}, \dots, x_{i,m})$, and one output variable y_i , to forecast the unseen output value $\hat{y}$ associated to the new vector of input variables $\hat{X} = (\hat{x}_1, \dots, \hat{x}_m)$.

Note: this Section nomenclature is used for the basic illustration of the theoretical background of the different methods presented. This nomenclature is the classical one that can be found in the literature and is not used for the specific DA mathematical models presented in Section 5 and Section 6. This decision is made for the sake of simplicity when introducing the following methodologies.

4.2.1 K-Nearest Neighbors

The idea behind k-NN is quite simple but effective: data with similar input variables have similar output [104]. The algorithm selects *k* historical data, compares the value of the input variables of these data with the value of the new set of input variables $\hat{X}$ and makes a weighted average of the outputs at those points to predict the new output value $\hat{y}$ [105].

The dataset is divided in *N* subsets depending on the average consumption of the day and hour. Let $\bar{y}_1$ be the mean value of the energy consumption grouped by day of week D1 and hour h1, and $\bar{y}_2$ be the mean value of the energy consumption grouped by day of the week D2 and hour h2. Then, the pairs (D1, h1) and (D2, h2) belong in the same subset if and only if (1):

$$0 < \left| \frac{\min(\bar{y}_1, \bar{y}_2)}{\max(\bar{y}_1, \bar{y}_2)} \right| < \alpha , \tag{1}$$

where α is a parameter in (0,1]. Then, the algorithm optimizes the *k* parameter for each one of the *N* subsets. The selection of the *k* parameter at each cluster and the value of α is done through a *Grid Search* using the scikit-learn library from Python [106]. It is also necessary to decide how to evaluate distance among values. The Euclidean distance (2) is the most frequently used [107] for *m-dimensional* case.

$$d_i = \sqrt{\sum_{j=1}^{m} \left(x'_{i,j} - \hat{x}'_j\right)^2}, \qquad i = 1, .., n \tag{2}$$

Where $\hat{x}_j$ is the *j*-th component of the new vector of input variables $\hat{X}$, $x_{i,j}$ is the *j*-th component of the vector of input variables X_i, and *m* is the total number of variables. All data $x_{i,j}$, $\hat{x}_j$ is scaled between 0 and 1 before computing the Euclidean distance (3)

$$x'_{i,j} = \frac{x_{i,j} - min(x_j)}{max(x_j) - min(x_j)} , \tag{3}$$

Where $x_{i,j}$ is the original value, $x'_{i,j}$ is the new scaled value and $min(x_j)$ and $max(x_j)$ are respectively the minimum and the maximum value of the variable *j* in the training set.

The final step is to compute the weighted average of the k selected historical consumptions, with weighting factors $w_i = (1/d_i)/\sum_{i=1}^{k}\frac{1}{d_i}$ for every $i = 1, \dots, k$, depending on the distances d_i calculated, where $\hat{y}$ is the predicted energy consumption, y_i is the $i-th$ historical consumption considered (4).

$$\hat{y} = \sum_{i=1}^{k} w_i \cdot y_i \tag{4}$$

4.2.2 Kernel Regression

Kernel density estimation, indicated as $K(X)$, is a non-parametric technique used to estimate the conditional expectation of a random variable. The objective is to find a non-linear relation between a pair of random variables. This technique is also used as a method for smoothing data [108]. A Kernel function could be defined by $K: \mathbb{R}^m \to \mathbb{R}$, where K is a symmetric probability density function (p.d.f) with finite variance.

The Kernel can be used to approximate the best p.d.f. estimator $\hat{f}$ in an $m-$dimensional spaces [109], through (5). Here, $h \in \mathbb{R}^m$ is a vector of unknown Kernel bandwidths, one for each input variable, and it is the parameter to optimize when constructing a Kernel function [110].

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_1 \cdot h_2 \cdot \dots \cdot h_m}\mathrm{K}\left(\frac{\hat{x}_1 - x_{i,1}}{h_1}, \dots, \frac{\hat{x}_m - x_{i,m}}{h_m}\right) \tag{5}$$

Where $\hat{x}_j$, again, represents the value of the j-th variable of the new observation $\hat{X}$, $x_{i,j}$ is the value of variable *j* for the $i-th$ historical consumption considered, $i = 1, 2, \dots, n$ and *m* is the total number of variables.

This study uses a multivariate Gaussian Kernel in *m* dimensions with diagonal covariance, as in [111]. The output $\hat{y}$ can be computed using the Nadaraya-Watson Kernel estimator [112], defined as (6).

$$\hat{y} = \sum_{i=1}^{n}\mathrm{K}\left(\frac{\hat{x}_1 - x_{i,1}}{h_1}, \dots, \frac{\hat{x}_m - x_{i,m}}{h_m}\right) \cdot y_i \Bigg/ \sum_{i=1}^{n}\mathrm{K}\left(\frac{\hat{x}_1 - x_{i,1}}{h_1}, \dots, \frac{\hat{x}_m - x_{i,m}}{h_m}\right) \tag{6}$$

The bandwidth vector of the Kernel smoother is optimized with the Kullback-Leibler cross validation [113] over the training set (by means of function *npregbw* from package *np* in R [114]). All input data are previously scaled using (3).

4.2.3 Time Series Factor Analysis

The idea of TSFA is that observed data can be explained by some latent variables (factors). TSFA has few assumptions in respect to static and dynamic factor analysis, for example, it does not assume covariance stationarity [115]. The model is represented as (7).

$$y_i = B\xi_i + \varepsilon_i \tag{7}$$

Where the n observed processes are denoted by y_i, $i=1,..,n$, the k unobserved factors are collected in the k-vector ξ_i, B is an $n \times k$ matrix parameter of loadings and is assumed to be independent on time, ε_i represents the residuals.

It is possible that y_i has a stationary first difference, defining D as the difference operator, (8) becomes:

$$Dy_i \equiv y_i - y_{i-1} = \tau_i + BD\xi_i + D\varepsilon_i \tag{8}$$

Which is still an equation with factor structure and the same loadings, so the model can be estimated with differenced data. It is assumed that τ_i is a constant vector. The sufficient conditions (assumptions) such that this leads to consistent estimators of relevant parameters and further details on the technique are described in [116].

The loading matrix B is estimated using the function *estTSF.ML* from the R package *tsfa* [116]. Once estimated the loading matrix, the factors' score can be estimated as well. To estimate the factors it is used the Bartlett predictor, described in [117], which becomes (9):

$$\xi_i = (B'\Omega^{-1}B)^{-1}B'\Omega^{-1}\gamma_i \tag{9}$$

Where:

$$\Omega \equiv \operatorname*{plim}_{n\to\infty} \sum_{t=1}^{n} D\,\varepsilon_t\, D\,\varepsilon_t' \;/n \tag{10}$$

The number of factors can be fixed depending on the Comparative Fit Index (CFI) and on the Root Mean Square Error of Approximation (RMSEA) [118]. In this study, the number of factors that assure a CFI higher than 0.95 and a RMSEA minor than 0.05 are selected.

Once estimated the loading matrix B, and the factors until i, ξ_{i+1} can be predicted. In this study, each series factor is predicted using an Auto Regressive Integrated Moving Average with exogenous variables (ARIMAX) model.

Finally, the predicted factors ξ_{i+1} are multiplied by the loading matrix B to obtain the predicted vector γ_{i+1} of the power output for the next day, as represented in (6).

4.2.4 Accuracy Measures

After testing the statistical methods proposed, it is necessary to evaluate the accuracy of the results to compare the different methods. The most used evaluation measure in consumption's prediction is the Coefficient of Variation of the Normalized Root Mean Square Error (CV(RMSE)) [119], it is the error metric proposed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) guideline to measure how well a mathematical model describes the variability in measured data [120]. It gives the same weight at the forecast independently from the measured data, without affect excessively the model when errors occur in low consumption periods. The CV(RMSE) is defined as (11).

$$CV(RMSE) = \frac{\sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}}{\bar{y}}, \tag{11}$$

Where y_i is the real energy consumption, $\hat{y}_i$ is the forecasted energy consumption, $\bar{y}$ is the average energy consumption over the period considered and n is the total number of data available.

To enable a wider assessment on the three methodologies, in this study it is also included another evaluation metric, the Mean Absolute Percentage Error (MAPE), which is also widely used in literature [121] and is defined as (12).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} 100 \cdot \left|\frac{\hat{y}_i - y_i}{y_i}\right|, \qquad (12)$$

The MAPE gives a quite direct understanding on the forecast error, being the mean value of the forecast errors' percentage. However, to use the MAPE as the unique error metric evaluation is not recommended, since a forecast error in low energy consumption periods, e.g., during nighttime, can have a great impact on the final metric result.

To evaluate the forecasting algorithms, this study also examines the computational time used to train the model on a machine with an Intel(R) Xeon(R) CPU E5430 clocked at 2.67 GHz and 8 GB RAM using one core of the CPU. Having low computational time can be decisive in the selection of the forecasting algorithm.

To not to limit the evaluation to the accuracy and the computational time, the study also evaluates the goodness of the algorithms when less data is available. To do so, the algorithms are trained firstly with the full data set available and then using just half of the data set available. Results are compared on the same test set to understand if and how errors increased.

Finally, to have a full understanding on the quality of the algorithms proposed, an increasing number of variables are used to train the models. Doing so, it is possible to assess if the models could be used with confidence when a limited number of variables is available.

4.3 Case Study

This Section describes the characteristics of the consumption analyzed and the data available in the study. The dataset used consists of hourly energy consumption from four data set.

4.3.1 Consumption A – Small tertiary building

Consumption A comes from a public library situated in Montgat (Barcelona, Spain). The building was built in 2003 and has two floors, with a total of 1596 m^2 surface. The building is primarily made from concrete, and it has an extended transparent surface. A HVAC system with 39 kW of electric power output assures the thermal comfort of the users. Power consumption data are available from 17/09/2018 to 29/11/2018. Fig. 4-1 shows the library and its electrical consumption during two consecutive weeks.

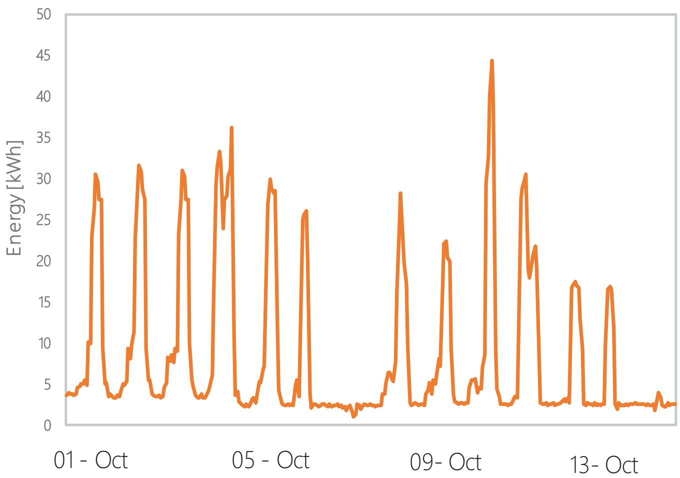


Fig. 4-1 Montgat library with consumption from 1 October to 14 October 2018.

The weather variables available are the temperature (*T*), the irradiation (*I*) and the humidity (*H*).

4.3.2 Consumption B – Residential building

Consumption B comes from a forty years old, 90 m^2 single family flat situated in Barcelona, Spain. The electric appliances in the building are a washing machine, a dishwasher, a cloth dryer, an electric oven and the cooling and heating system. In the building, there are living two people with regular working schedule. Power consumption data are available from 21/01/2018 until 17/11/2018. Fig. 4-2 shows the flat and its electrical consumption during two consecutive weeks.

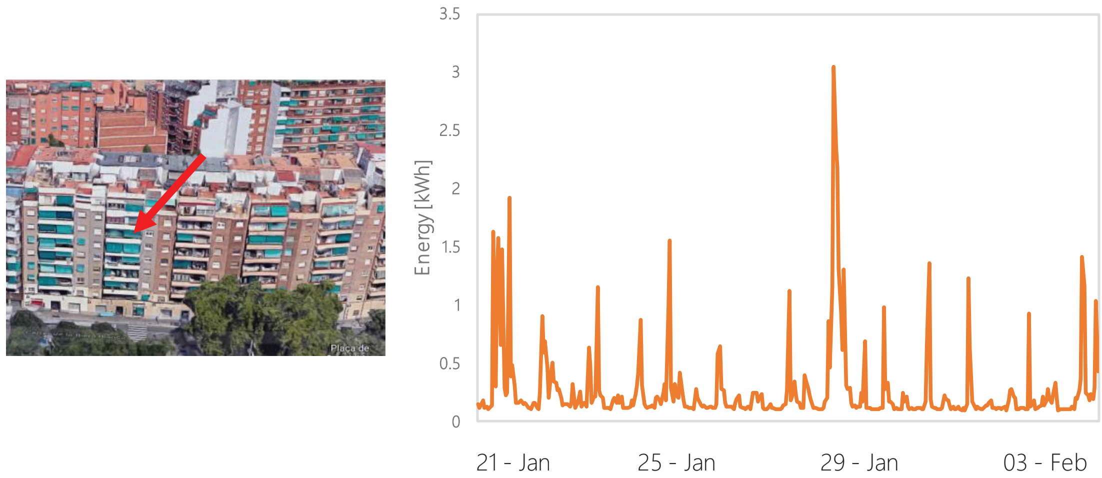


Fig. 4-2 Flat with consumption from 21 January to 4 February 2018.

The only weather variable available for Consumption B is the temperature (*T*).

4.3.3 Consumption C – Cogeneration plant

Consumption C comes from a small cogeneration plant close to Barcelona, Spain. The power plant supplies the thermal and electrical demand of an entire neighborhood, where there are also two fast electric vehicles chargers. Data are available from 21/03/2018 to 25/11/2018. Fig. 4-3 shows the electric production of the cogeneration plant for two consecutive weeks.

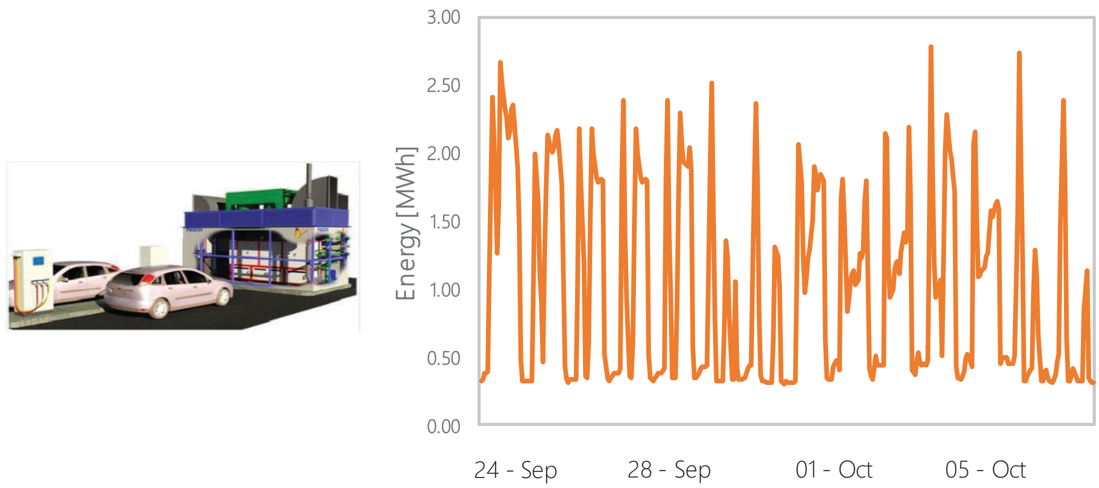


Fig. 4-3 Representation of the site [122] with consumption from 24 September to 7 October 2018.

The weather variable available are the temperature (*T)* and the irradiation (*I*).

4.3.4 Consumption D - Industry

Consumption D comes from a small factory located in Barcelona, Spain. Data from power consumption are available from 1/01/2018 to 20/12/2018. Fig. 4-4 shows the power consumption of the site during two consecutive weeks.

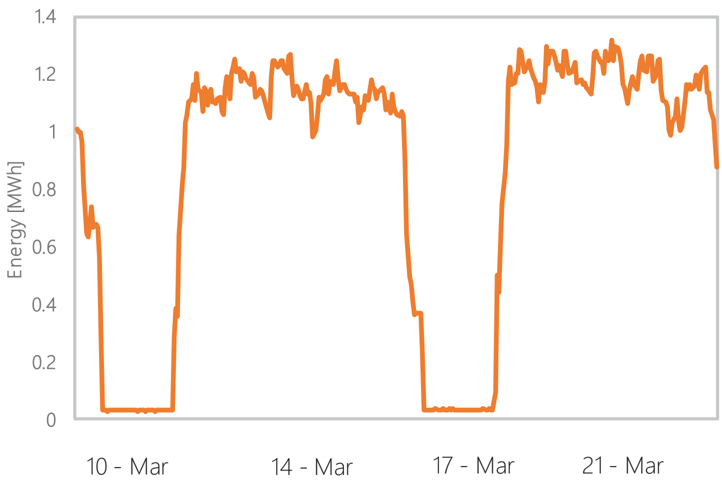


Fig. 4-4 Building D consumption from 10 March to 24 March 2018.

The weather variables available are the temperature (*T*) and the irradiation (*I*).

4.3.5 Variables included in the forecast models

In conjunction with variables available from the weather station, that are the outdoor temperature (*T)* and the irradiation (*I),* other physical variables are considered:

- Temperature with a lag of 24 hours (*T_24*);
- Consumption during the same hour of the previous week (*C-7*).
- "Temperature sun-air" (*Tsun_air),* used to combine the irradiation and the ambient temperature and it is calculated as *Tsun_air = T +*βI, where β= 0.026 [m^2*C/W] [123]. This variable indicates the effect of the solar radiation incident *I* [W/m^2] on the building. In some cases, it is useful to include it because the irradiation can reduce or increase the power consumption depending on the ambient temperature.

In addition, both k-NN and KR algorithms use temporal variables such as the month (*m*), the type of day (*D*) and the hour (*h*) considered. Regarding the hour, this study proposes the variable *h' = sin(h**π*)/24*, which allows to avoid the jump between hour 23 and 0 from one day to the other, improving forecasting results. In both k-NN and KR models, the variables used among the available are selected empirically by making different tests to find the best combination to minimize forecast errors.

It was found that the best option for the TSFA algorithm in Consumption A, B and C is to use the degrees' day (*DD*) as the only exogenous variable to predict the factors. *DD* is a physical variable used to calculate the heating degree day (*DDH*) or the cooling degree days (*DDC*) of a day. In this study the *DD* were calculated as the difference between *DDH* and *DDC* (13).

$$DD = |DDH - DDC| = |\max\{0{,}15 - \bar{T}\} - \max\{0, \bar{T} - 18\}| \tag{13}$$

Where $\bar{T} = \sum_{i=1}^{24} T_i/24$ is the mean temperature. Table 4-1 shows the variables used for each method and consumption that reached the best error metric.

Table 4-1 Variables used for each model and consumption.

Consumption	Model	Variables used
A – Small tertiary	k-NN	*D, h', T, T_24, I, C-7, Tsun_air*
	KR	*D, h', T, Tsun_air, T_24, H, I*
	TSFA	*DD*
B - Residential	k-NN	*D, h', C-7*
	KR	*D, h', m, C-7*
	TSFA	*DD*
C – Cogeneration Plant	k-NN	*D, h', C-7, I, T_24, T*
	KR	*D, h', T_24, T*
	TSFA	*DD*
D - Industry	k-NN	*D, h', T_24, C-7, I, T*
	KR	*D, h', m*
	TSFA	No exogenous variable

4.4 Results

This Section shows and discuss the performance of the models proposed on the different type of energy consumptions analyzed. For all the consumptions, predictions are evaluated during the last week of available data, while the rest of data is used to train the model. Table 4-2 represents main results, which are discussed in next Section.

Table 4-2 Comparison for the proposed techniques.

Consumption	Model	CV(RMSE)	MAPE	Computacional time [s]
A – Small tertiary	k-NN	0.30	0.19	**2**
	KR	**0.23**	**0.15**	237
	TSFA	0.35	0.21	15
B - Residential	k-NN	**0.81**	0.51	**1**
	KR	0.82	**0.47**	2152
	TSFA	0.95	0.49	70
C – Cogeneration Plant	k-NN	0.23	0.15	**5**
	KR	**0.17**	**0.12**	932
	TSFA	0.31	0.28	104
D - Industry	**k-NN**	0.12	**0.14**	**2**
	KR	**0.06**	**0.14**	208
	TSFA	0.17	0.24	88

4.4.1 Consumption A – Small tertiary

Fig. 4-5 represents the evolution of the KR and k-NN errors depending on the number of variables used to predict the consumption of tertiary building analyzed, described in Table 4-1. The number of factors used by the TSFA model is 10.

On the one hand, the k-NN shows different behavior for the MAPE and CV(RMSE) metrics. The MAPE has a slight increase of 11% when including weather variables, but a decrease of 18% when considering the CV(RMSE). This means that using weather variables decrease errors when consumption is higher but increases the forecast when consumption is low, e.g. night time. On the other hand, KR reduces the error when including weather variables, reducing by 38% and 29% the CV(RMSE) and MAPE errors, respectively, when more variables are considered.

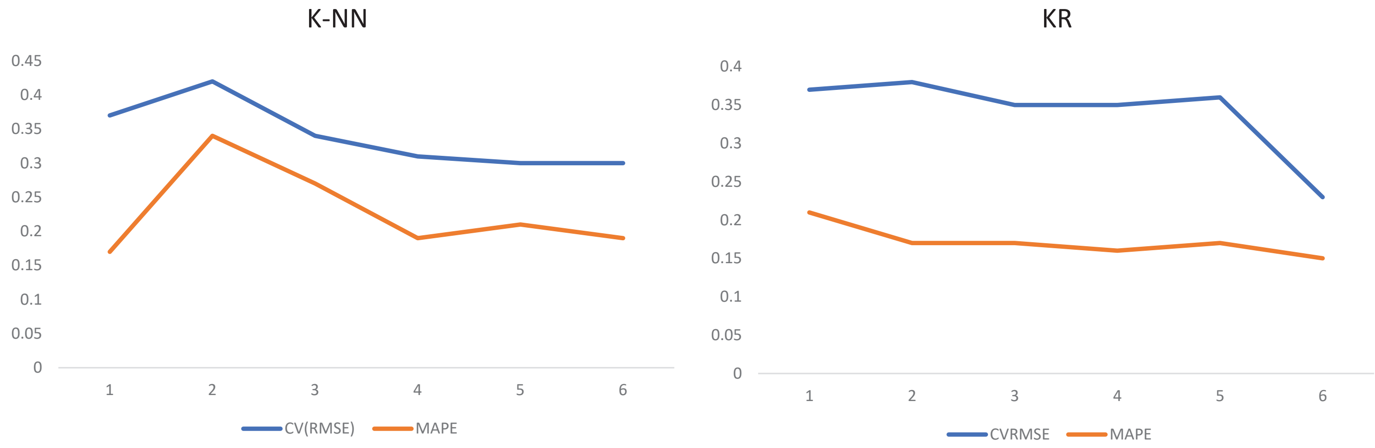


Fig. 4-5 Errors depending on the number of variables used for consumption A - Small tertiary building.

Here, the KR performs better in respect to the k-NN, while the TSFA is the one with worst predictions, as represented in Table 4-2.

As shown in Fig. 4-6, consumption's prediction from k-NN (dashed red line) and KR (green continuous line) are lower than the real consumption (black line) almost during the whole week. On the contrary, the TSFA predictions (dashed blue line) are higher than the real consumption on Saturday, Monday, and Thursday (day 24-26 and 29 November).

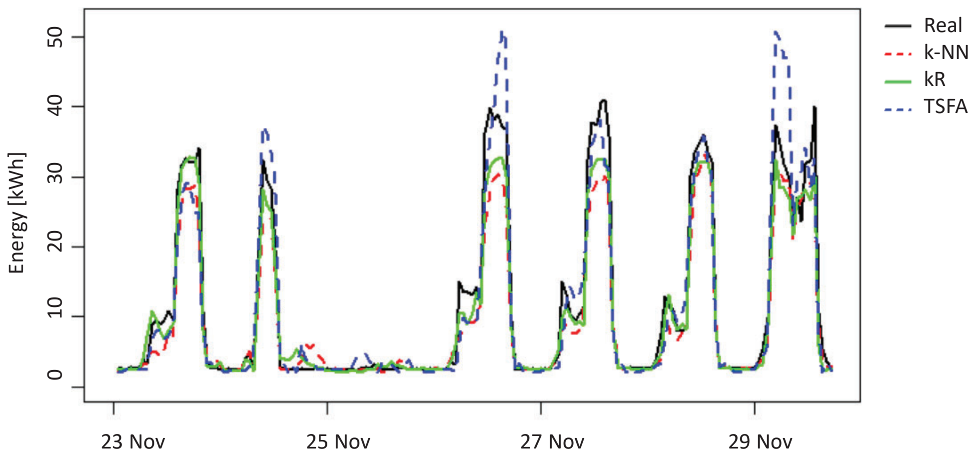


Fig. 4-6 Real and predicted consumption using K-NN, KR and TSFA for consumption A – Small tertiary building.

In general, it is possible to conclude that KR and K-NN can correctly predict the consumption of a small tertiary building, while the TSFA algorithm has some problem in predicting the consumption during peak periods, as showed in Fig. 4-6.

Even when using half of the available data set, the KR does not increase its error forecast, while k-NN and TSFA in this case performs worse with less data available. Table 4-3 shows the error metrics using half of the data set and the percentage increase in the error.

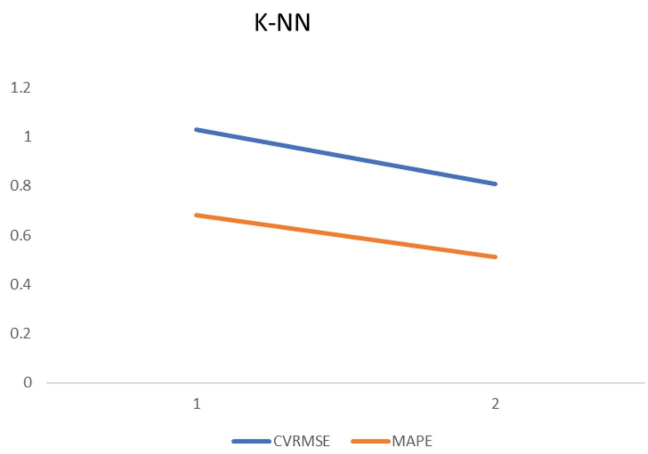
Table 4-3 Error forecast with half data set for consumption A – Small tertiary building

	CV(RMSE)	MAPE	% Increase errors CV(RMSE)	% Increase errors MAPE
k-NN	0.43	0.27	43	42
KR	**0.24**	**0.15**	**4**	**0**
TSFA	0.44	0.43	25	104

The computational time to train the best models is 2, 237 and 15 seconds for k-NN, KR and TSFA respectively.

4.4.2 Consumption B – Residential Building

Fig. 4-7 represents the evolution of the k-NN and KR errors depending on the number of variables used to predict the consumption of the residential building analyzed, as described in Table 4-1. In this case, both algorithms improve significantly the predictions increasing the number of variables considered. k-NN has a decrease of 21 % and 25 % on the CV(RMSE) and the MAPE, respectively, while the KR reduces the CV(RMSE) and MAPE metrics by 5% and 28%, respectively. Note that for both algorithms the most significative variable, apart from calendar variable, is *C-7.* The number of factors used by the TSFA model is 11.



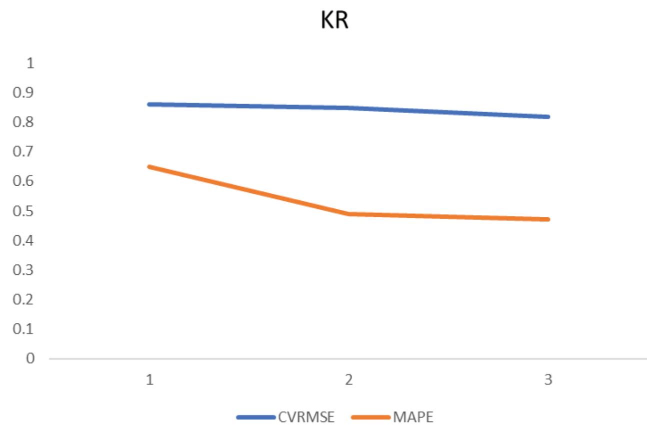


Fig. 4-7 Errors depending on the number of variables used for consumption B - Residential building.

The KR is the one that best performs considering the MAPE as metric, while k-NN takes the lead when we are considering the CV(RMSE), as represented in Table 4-2.

Fig. 4-8 shows that no model adequately fits the consumption. However, during the week, all the models can predict the hour of the daily peak. During the first day considered (11/11/2018) which is Sunday, errors are very high, with CV(RMSE) errors of 1.39, 1.51 and 1.25 respectively for KR, k-NN and TSFA. The reason is that Sunday is the day in which the flat's occupants are at home and different type of consumption's curves are possible. From errors represented in Table 4-2, it is possible to conclude that real residential loads are the most difficult to predict using whatever method due to their high stochasticity.

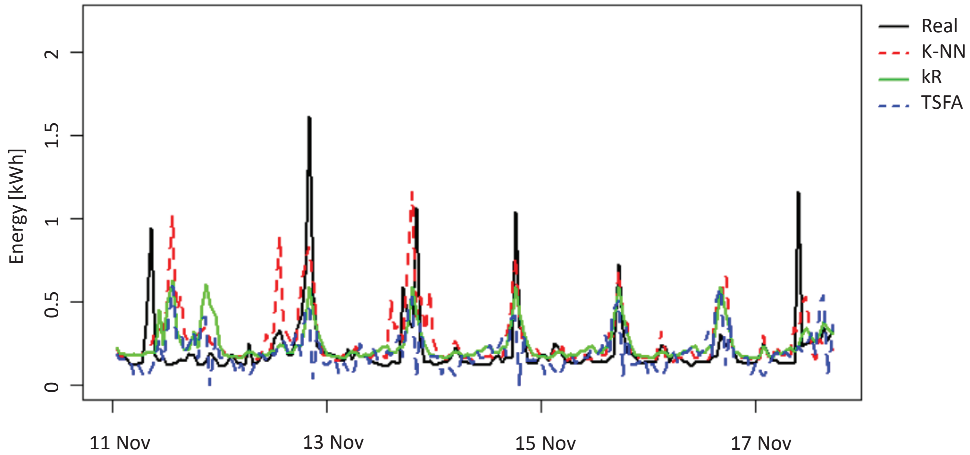


Fig. 4-8 Real and predicted curves using k-NN, KR and TSFA for consumption B – Residential building.

Table 4-4 represents the errors and the percentage error increase using just half of the data set. Also, for the residential building, having less data does not influence the KR, while the influence is higher for the k-NN. The TSFA algorithm improves its CV(RMSE), but significantly deteriorate the MAPE.

Table 4-4 Error forecast with half data set for consumption B – Residential building.

	CV(RMSE)	MAPE	% Increase errors CV(RMSE)	% Increase errors MAPE
k-NN	0.94	0.55	16	8
KR	**0.85**	**0.48**	**3**	**2**
TSFA	0.93	0.61	-2	24

The computational time to train the best models is 1, 2152 and 70 seconds for k-NN, KR and TSFA respectively.

4.4.3 Consumption C – Cogeneration plant

Fig. 4-9 represents the evolution of the k-NN and KR errors depending on the number of variables used to predict the consumption of the cogeneration plant analyzed, as described in Table 4-1. For KR the *T* and the *T_24* are important explanatory features, bringing significant improvements to the forecasts. KR reduces by 88 % and 81% the CV(RMSE) and MAPE errors when including more variables, while the k-NN by 88 % and 91%. The number of factors used by the TSFA model is 12.

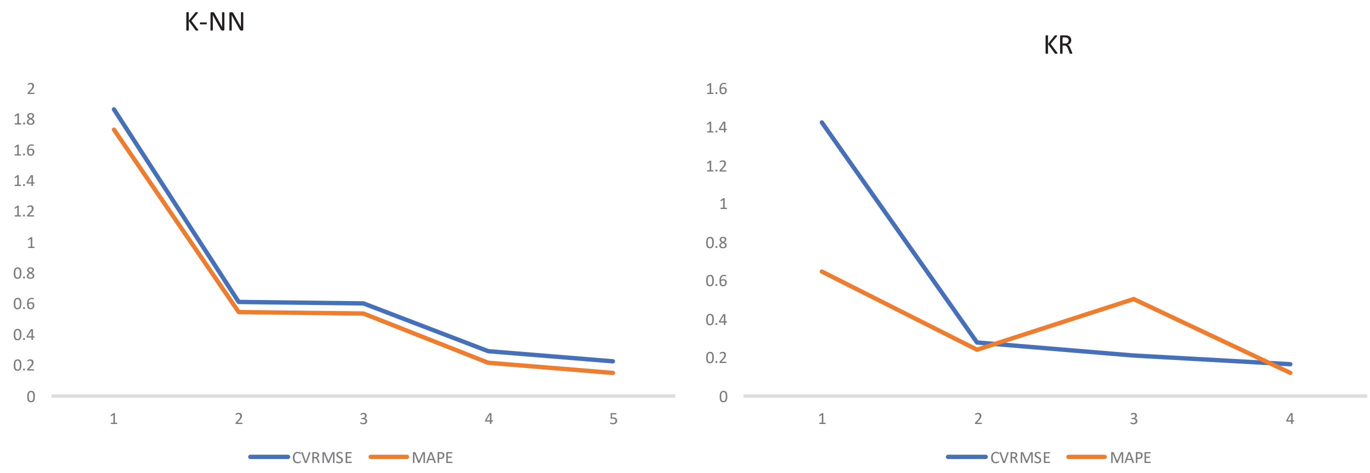


Fig. 4-9 Errors depending on the number of variables used for consumption C – Cogeneration plant.

Fig. 4-10 represents the consumption forecast during the week from 19/11/2018 to 25/11/2018. Also in this case, the KR is the one that best fits this data set. Regarding the KR, most of the error comes from Saturday 24th, with a partial CV(RMSE) and MAPE error of respectively 0.46 and 0.26. During this day the real consumption is lower than the predicted, although the shape predicted is very similar to the real one. During the rest of days, the KR prediction is almost perfect. The same happens with the k-NN.

The TSFA model can predict the consumption during the peaks, while is during the base load when most of the error is concentered. The reason could be that this model consider just the lasts days for the predictions. During the last month, there were different profiles in base hours and the TSFA used these data for the prediction, while the KR and k-NN use the whole data set. For this reason, the KR and k-NN can predict satisfactory the base loads.

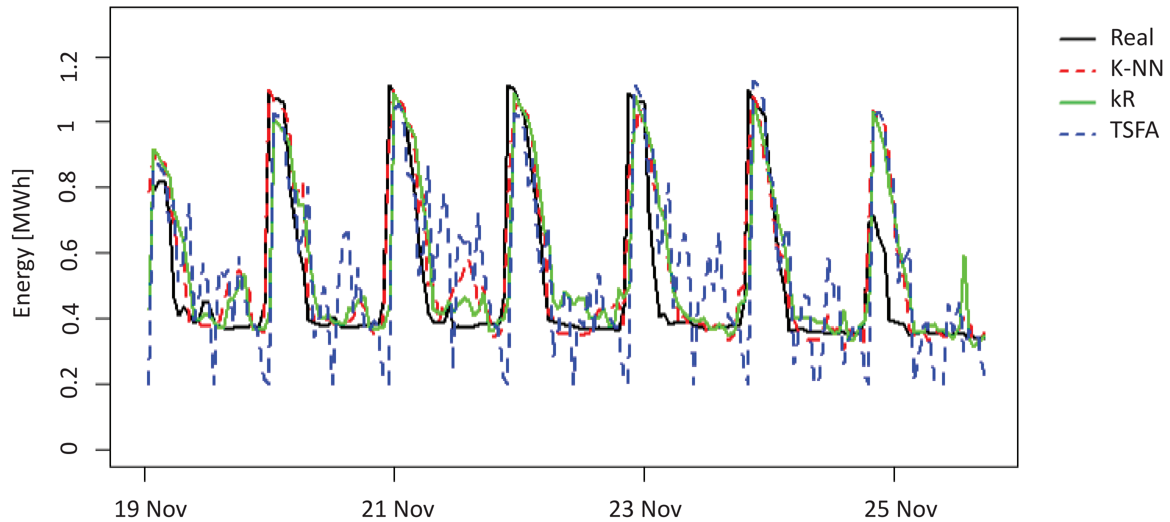


Fig. 4-10 Real and predicted curves using k-NN, KR and TSFA for consumption C – Cogeneration plant.

Table 4-5 represents forecast errors and percentage error increase of the three methods analyzed using just half of the data set. The k-NN does not show great implications in its performance, mismatching the behavior of the KR and TSFA in this case, which dramatically increase their errors.

Table 4-5 Error forecast with half data set for consumption C – Cogeneration plant

	CV(RMSE)	MAPE	% Increase errors CV(RMSE)	% Increase errors MAPE
k-NN	**0.25**	**0.17**	**8**	**13**
KR	0.38	0.15	123	25
TSFA	0.49	0.37	58	32

The computational time to train the best models is 5, 932 and 104 seconds for k-NN, KR and TSFA respectively.

4.4.4 Consumption D – Industry

Fig. 4-11 represents the evolution of the k-NN and KR errors depending on the number of variables used to predict the consumption of the industry analyzed, as described in Table 4-1. In this case, to use more weather variables does not improve consistently the prediction, because the industry's consumption does not change depending on the weather conditions. However, the k-NN reduced the CV(RMSE) and MAPE error by 4 % and 22 % when considering some weather variables and the consumption of the last week, while the KR reduces by 50 % and 18 % the CV(RMSE) and MAPE errors when considering the month. In the case of TSFA, results show an improvement in the forecast without using any exogenous variables. The number of factors used by the TSFA model is 7.

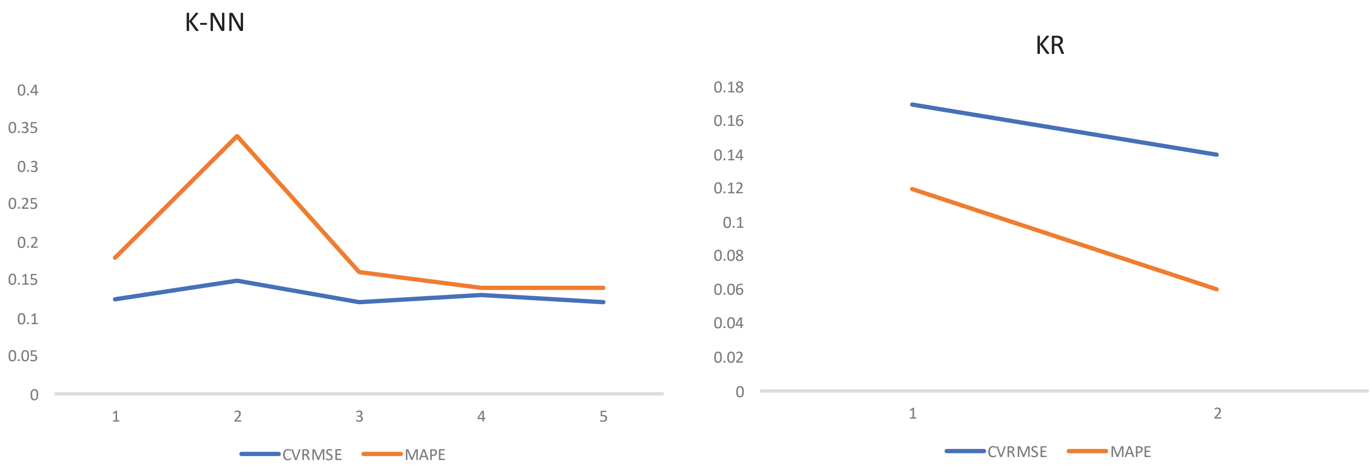


Fig. 4-11 Errors depending on the number of variables used for consumption D – Industry

Consumption D is the most constant consumption among the analyzed and, as represented in Table 4-2, it is the consumption best predicted by the models proposed. Also in this case, the KR is the one that best performs considering CV(RMSE) and reaches the same MAPE metric as the k-NN.

Fig. 4-12 represents consumption forecast for the week from 14/12/2018 to 20/12/2018. KR's and k-NN's predictions, are very good, having a CV(RMSE) equal to 0.06 and 0.12 respectively. The TSFA model does not fit well data during the first day considered. During this day its corresponding CV(RMSE) is 0.24, while the forecasts are accurate during the rest of days.

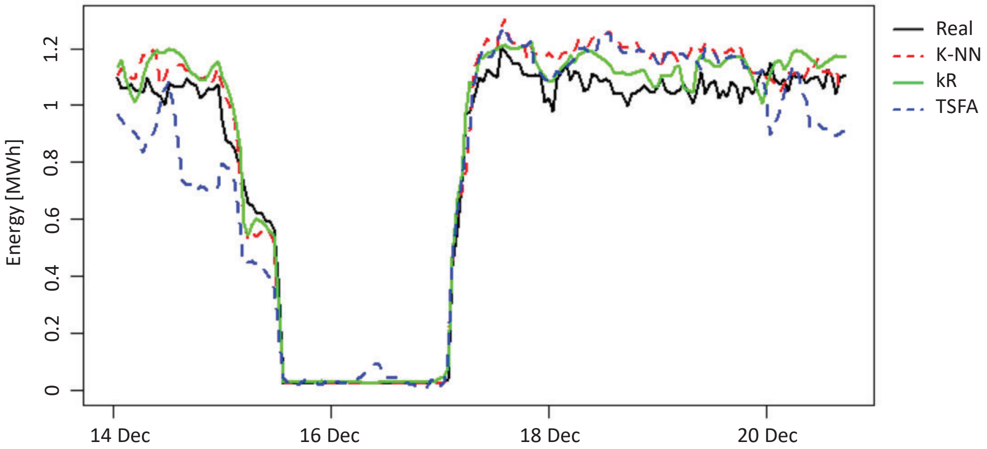


Fig. 4-12 Real and predicted curves using TSFA, KR and k-NN for consumption D - Industry

Table 4-6 represents forecast errors and percentage error increase of the three methods analyzed using just half of the data set. In this case the KR increases the CV(RMSE) error but reduces the MAPE, meaning that makes more error when the real consumption is higher. On the contrary, the TSFA algorithm keeps the same CV(RMSE) error but substantially increases the MAPE. Finally, the k-NN slightly increases both errors.

Table 4-6 Error forecast with half data set for consumption D - Industry

	CV(RMSE)	MAPE	% Increase errors CV(RMSE)	% Increase errors MAPE
k-NN	0.17	0.15	41	7
KR	**0.10**	**0.08**	**67**	**-42**
TSFA	0.17	0.57	0	135

The computational time to train the best models is 2, 208 and 88 seconds for k-NN, KR and TSFA respectively.

4.4.5 Kernel Regression interpretation

As mentioned above, one important feature of the KR approach in comparison to other black box models is the possibility to interpret the parameters estimated. While using a statistical approach, it is possible to make a physical interpretation on the consumption's behavior. In the case in which the TSFA uses exogenous variables, although it is possible to give some interpretation to the weight of external variables in the factor's prediction, it is of much more difficult interpretation. In the case of the k-NN presented in the study, the only information provided by the algorithm is if a variable is worth or not.

Fig. 4-13 shows optimal parameters setting for the four data sets analyzed in this work. The score on the *y-axis* represents the reciprocal of the logarithm of the KR's *h* parameter, as this quantity gives some idea about the importance attached to that parameter. In all the data set considered, apart from the cogeneration plant, the most important parameters are *D* and *h*. This result confirms the well-known stationary component of the energy data series, specifically weekly and daily stationarity. However, including weather features substantially increases the forecast's prediction, as highlighted in the previous Section.

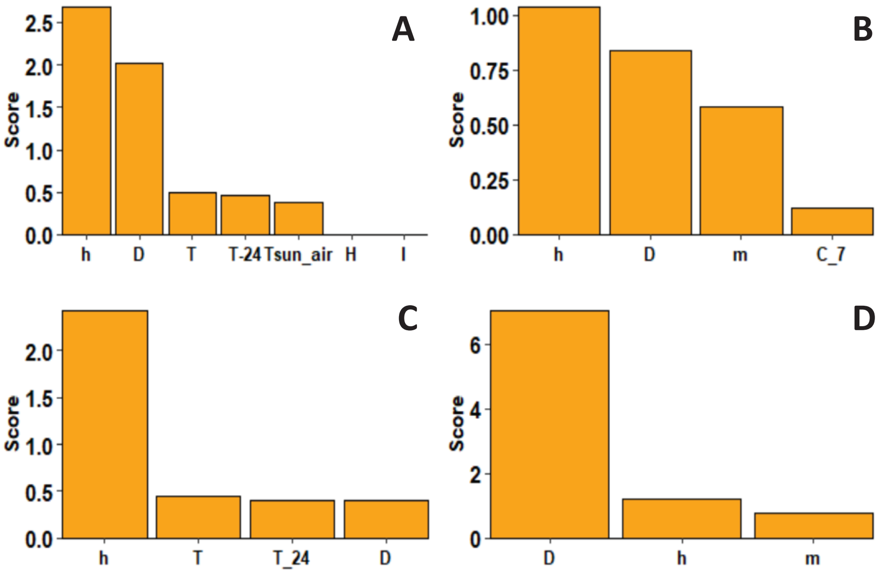


Fig. 4-13 KR parameters used to generate the predictions. Predictions target are (top right to down left): Consumption A, Consumption B, Consumption C, Consumption D.

Regarding Consumption A, which is a concrete library with extended glass surface, the most important variables are the *h* and *D* because the weekly opening schedule has a strong influence on the library's consumption. However, weather parameters such as the *T*, the *T_24* and the *Tsun_air* are very important in the consumption's prediction. The *Tsun_air,* which includes the solar radiation, takes importance due to the extended transparent surface of the building, while the importance of the variable *T_24 is* due to the concrete's wall inertia.

In Consumption B, which is a residential building, weather variables do not have any influence on the final consumption, probably due to the low usage of the cooling system installed. Temporal variables, especially *h* and *D* are the ones that better explain the consumption as the building's occupants follow the same occupational pattern during the week.

In Consumption C, which is the cogeneration plant, *h* is the most important variable. Also, the *T* and the *T_24* have some influence on the consumption, probably due to the increase of the cooling/heating requirement in the neighborhood depending on the weather condition of the previous day.

Finally, regarding Consumption D, which is an industry, it is possible to observe that weather parameters does not strongly affect the energy demand, as the weather does not affect the site's production. Weekly and daily cycles of production are the most important factors on the consumption.

4.5 Discussion

The energy industry clearly recognizes the importance of predicting the energy consumption of buildings, communities, and industries. In literature, it is widely accepted to consider the accuracy of the model as the only metric to evaluate a forecast algorithm, at most with the computational time [124]. However, if a method must be reproducible on different buildings, it should not need a big data set to be trained nor a big number of variables, and it needs to be fast enough to handle with a big amount of data. For this reason, Fig. 4-14 summarizes the rating of the evaluation metrics kept into account to evaluate the techniques proposed: accuracy, computational time, number of variables needed, and size of the data set available. The rating of the three techniques analyzed considers a value of 0 as a complete failure and a 5 as the optimal solution.

Considering accuracy (Table 4-2), KR presents the better behavior in the four data sets analyzed, followed by the k-NN and the TSFA

Regarding computational time, KR is the method that requires more computational time to be trained by far, as represented in Table 4-2. The total computational time needed by the k-NN is between 25 and 90 times lower in respect to the KR, while the TSFA is slower than k-NN but faster than KR. It is important to remark that the KR model needs to optimize the bandwidths, which brings complexity from a computational point of view. However, once these parameters have been computed, the same model can be used to forecast the consumption from that moment on, making it reliable for real time applications.

The three methods can work properly with a small number of weather variables available, which in certain situations can be determinant for the selection of the model to use. For TSFA algorithm it is not possible to include much external variables because they decrease the prediction's accuracy. Both KR and k-NN include weather parameters just in 2 of the data set considered. KR is the most sensitive to the number of variables included; it improves significantly its predictions when including weather variables in Consumption A and C, as represented in Table 4-3 and in Table 4-5 . On the contrary, when k-NN includes weather variables in Consumption C, it does not significantly improve its performance.

Regarding the data size needed, the KR regression has demonstrated to perform similar in terms of accuracy with a small training set, even improving its performances in the case of Consumption D. k-NN is the method that decreased in a more constant way its performances with half data sets, having between 7 and 42 % accuracy reduction. TSFA is the method that most decreased its performances with half data sets, having between 24 and 135 % accuracy reduction. Results show that with more data available, probably k-NN and TSFA results would have performed better in terms of accuracy.

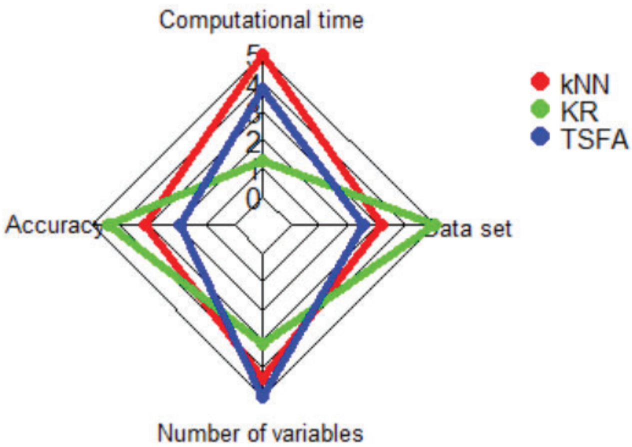


Fig. 4-14 Graphical comparison among methods.

4.6 Conclusions

This Chapter compares k-Nearest Neighbors, Kernel Regression and Time Series Factor Analysis to predict the 24-hour ahead consumption of four different real data set: a small library, a flat apartment, a cogeneration plant, and a small factory.

The comparison shows that the residential building is the most complicated consumption to predict, due to the stochasticity of the occupation and of the occupant's behavior. In fact, none of the algorithms presented in the study can correctly predict this consumption, especially during the weekend. For the rest of data set analyzed results are good; the MAPE calculated is between 0.12 and 0.15 using real data sets.

Kernel Regression is the method with the best accuracy in all data set analyzed, with errors that varies between 0.06 and 0.82 of CV(RMSE). In addition, Kernel Regression can provide physical information on the variables that most affect the consumption. However, the method needs up to 2000 times more computational time compared to the k-Nearest Neighbors model. In the case in which the objective is to forecast the consumption of many buildings or a scarce computational power is available, authors suggest opting for the k-Nearest Neighbors algorithm proposed. On the contrary, if the objective is to reach a high accuracy, the best method is the Kernel Regression.

It was also found that the number of features available differently affects the methods tested: Kernel Regression significantly improve the prediction accuracy when more variables are available, while k-Nearest Neighbors improves moderately and the TFSA proposed does not include any weather variable apart from the temperature. The study also evaluates the influence of the data size available, and it finds that Kernel Regression performs almost the same when less data is available, while k-Nearest Neighbors and Time Series Factor Analysis clearly reduce their performances when less data is available. In the case of a small training set available, authors suggest using the Kernel Regression for its adaptability on smaller data sets.

The work also evaluates for the first time the Time Series Factor Analysis method for consumption prediction, which could likely be improved by having wider data set available, since when tested on half data set the performances dropped in all the cases. Further research will focus in improve the Time Series Factor Analysis algorithm; use a non-parametric model, e.g. NN, for the factor's prediction could help to include more weather variables in the model and to improve accuracy.

In addition, this work highlights the importance to compare different methods over different real data sets. It has found that using the same forecast model predictions, results can be very different depending on the site's characteristics. For an energy consumption with low variability, such as the industry site analyzed, it would be preferable to use the k-Nearest Neighbors instead of the Kernel regression, since accuracy is very similar, but the k-Nearest Neighbors is much faster to be trained. Regarding the other data set analyzed, if a good accuracy in the prediction is needed it is preferable the Kernel Regression, if there are no constrains regarding the computational time. In the case in which no weather data are available, the Time Series Factor Analysis could be the best option.

It has been demonstrated that k-Nearest Neighbors can be used to predict different type of consumers' behavior, especially residential and industrial consumers. The work also confirms in a real case that Kernel Regression is a valid alternative to more classical machine learning methods, e.g., NN when external features are included in the model. Kernel Regression has shown to be the most robust method among all the presented although its larger training time.

Chapter 5 - Flexible assets modeling

5.1 Introduction

This Chapter objective is to model flexible assets keeping into account the rebound effect (Section 2.2). The purpose of the modelling is to find a set of equations that can be used for the participation of these assets in different electricity markets. The differences between the traditional modelling of these assets and the proposed one is highlighted.

This Chapter is organized as follows. Section 5.2 contains a literature review about the flexibility asset modelling and flexibility prediction. Section 5.3 presents the modeling of the flexibility assets analyzed to allow their market participation, used in the optimization problems presented in Chapter 6, and proposes a forecasting algorithm for each type of assets. Section 5.4 presents the physical characteristics of the flexibility assets used to validate the methodology proposed. Section 5.5 presents the results of the flexibility forecasting method proposed on real devices and compare their flexibility potential for balancing market participation. Finally, Section 5.6 discusses the main contributions of the Chapter.

5.2 State of the art

As introduced in Chapter 2, the latest advances in smart grid and building technologies promise to unlock the participation in DR programs and to transform passive consumers into active consumers, also called "prosumers". Prosumers are able to modify their energy consumption depending on external signals, i.e. economic or environmental among others. Smart buildings having to manage their energy flows of generation from renewable power sources and consumption may include solutions to manage their flexible loads. The main challenge is to transform these functionalities into products that consumers can trade in electricity markets [14] to reduce their electricity bill while helping the energy transition toward a 100% renewable energy system.

To participate in DR programs, the first step for end-users is to identify flexibility asset potential and be aware about the characteristics of the different elements within the building, which can be classified as deferrable or thermal, shiftable, interruptible loads and storage devices (Section 2.2).

Once consumers are aware about the potential of their energy assets, the next step is to quantify the flexibility available in the site, and finally to be able to manage all the flexibility assets within the building to reach the pursued result. Since the flexibility capacity of the assets is not constant through the day (or season of the year), an estimation of the overall flexibility capacity along hours needs to be accurate to participate in DR programs.

It is important to mention that flexibility forecast is a novel research topic and there are few works specifically focused on it. The approach used in this thesis is, based on existing models for other management objectives, build models that allow to forecast the flexibility, trade it on the energy and flexibility markets always taking into consideration the rebound effect of the flexibility potential activation. In [125] Han et al. reviewed more than 80 articles about residential flexibility. They found that that surprisingly, there is not a common definition about what is flexibility, and they conclude that the main research gap is the lack of a standard representation of characteristics of energy flexibility technologies. Just recently some studies analysed the characterization of flexible loads. In [126] Kara et al. discuss the concept of flexibility by characterizing it in terms of time and risk profile. The time dimension indicates during how much time the flexibility is available, the ramp rate of the resources and the predictability horizon, while the risk profile includes the uncertainty of the resource to not be delivered correctly and the rebound effect of the resource. in [127] Degefa et al. provide a clearest idea on how many parameters should be taken into account to characterize a flexible resources. They classify a flexible resource based on 28 parameters that considers quantitative, qualitative, technical, and economical characteristics. However, none of these studied performed a quantitative or qualitative evaluation of the characterization proposed using a relevant case study.

As when forecasting the load, the state of art on asset modeling can be divided in three principal groups: white box, grey box and black box models [128]. White box models refer to all that models based on physical methods to model energy the behavior of an asset. In this case, a very detailed knowledge of the physical characteristics of the asset is necessary to perform an accurate modeling. Grey box models combine some physical characteristics with statistical methods to simulate the assets' behavior. However, most of gray box models presented in literature still need a time-consuming modeling of the asset, since simpler models usually do to not provide a satisfactory result [129].

To model and forecast the flexibility of thermal loads, the first step is to model the thermal behaviour. In [130] Madsen et al. nicely provide guidelines on how to build different time-series methods to model the thermal behaviour of a building. They start with simple steady state models, next the study considers autoregressive model and finally they analyse static and dynamic grey box models. In [131] Harb et al. developed four different models to forecast the thermal behaviour of a building, using also the *Tsun_air* as input variable. They conclude that the most precise model to predict the building thermal behaviour is a double lumped network, although the increase in the accuracy is very low in comparison to the simplest model. Other studies, such as [132] or [133], propose very detailed grey-box models, which could be considered almost white-box models. Although results are good, the objective of this work is to find easy and adaptable to whatever type of thermal load models. For example, in [134] Ding et al. proposed a simplified model for aggregated thermal loads focused in calculate the reliability of the reserve to be activated, and not on the bidding strategy. The model proposed in this thesis is inspired by the work done by Iría et al. in [135], where a model for thermal load aggregation in energy markets is proposed. The main difference is that the formulation proposed by Iría et al. is designed for energy markets, while the one proposed in this thesis is designed for energy and flexibility markets and implicitly calculates the rebound effect due to the activation, which has not been considered in these previous works.

Storage system modelling, and in particular stationary battery modeling, is an older and more developed topic. In [136] Wu at al. present a review of the modeling and optimization for optimally control and size grid-connected energy storage systems. Also, in the case of batteries, exist white and grey box models. White box models keep into account the deep design of each battery cell, like in [137] where Li et al. proposed a modeling to provide FCR services to the grid using a battery. In [138] Huang et al. proposed a method for the stationary battery management in buildings equipped with renewable sources based on Lyapunov optimization technique. In this case, they are not considering any balancing market participation but just self-consumption applications. In [139] Fang et al. proposes a method to cooperatively manage a large number of batteries to stabilize the electricity grid, using MPC (Model Predictive Control). The approach proposed in this work is based on this approach but with another scope since the objective is not demonstrate that the battery si able to follow a certain signal from the grid but to model it to build an offer in balancing markets considering its rebound effect.

Regarding shiftable load modeling, in literature there are just few references and generally they are more focused on small household devices such as washing machines. For example, in [140] Bajda et al. proposed a bottom-up approach that uses a non-homogeneous Markov chain to model each appliance within the household. In [14] Iría et. al present a method to model domestic shiftable load appliances to bid in energy markets, but in none of its studies include them for balancing market participation. However, it is in the industrial sector where there is more potential for DR [27]. Industries have historically provided some DR to the SO, but usually in capacity mechanisms with just few flexibility activations per year. The objective of this work is to model industrial shiftable loads to be able to participate in short-term balancing and energy markets without affecting their normal operations. In [141] Zhang et al. proposed a method for an optimal control of industrial loads providing balancing services to the grid. The model proposed in this study is designed for a bidding optimization strategy and adds to this previous approaches more limitations that could affect an industrial process while keeping into account the rebound effect.

Therefore, this Chapter presents how to identify flexibility assets within a site, how to quantify the flexibility available during the day ahead depending on weather forecast, historical data, and appliances characteristic and how to model flexible assets to allow their participation in energy and balancing markets. Finally, the Chapter discuss about the intrinsic characteristics of the flexible loads analyzed quantifying and comparing them.

5.3 Modelling

This Section presents the flexibility asset's models for thermal loads, stationary batteries, shiftable and curtailable loads used to allow their participation in energy and flexibility markets. This Section also describes the models used to predict the flexibility available from a site that can be useful in case of manual construction of the offer, to know the current and future demand side flexibility potential for grid operators or estimate the flexibility available from an asset.

The following sections are encrypted for confidential reasons.

CONFIDENTIAL

5.4 Case study

This Section describes the characteristics of the flexibility assets analyzed and the data used in the study. The dataset used consists of quarter hour data about energy consumption and critical variables needed for the asset flexibility estimation.

5.4.1 Thermal loads – Tertiary building with HVAC system

Data comes from an automotive dealer building located near to Barcelona in Catalonia, Spain. The building is composed by a basement and three floors, separated by two symmetrical wings with 8145 m^2 of total area. In the central body of the building there is a hole like a patio. The wings are separated from this central courtyard by glasses. Fig. 5-8 shows the building analyzed and its electrical consumption due to the air conditioning system from July 15th to 22nd.

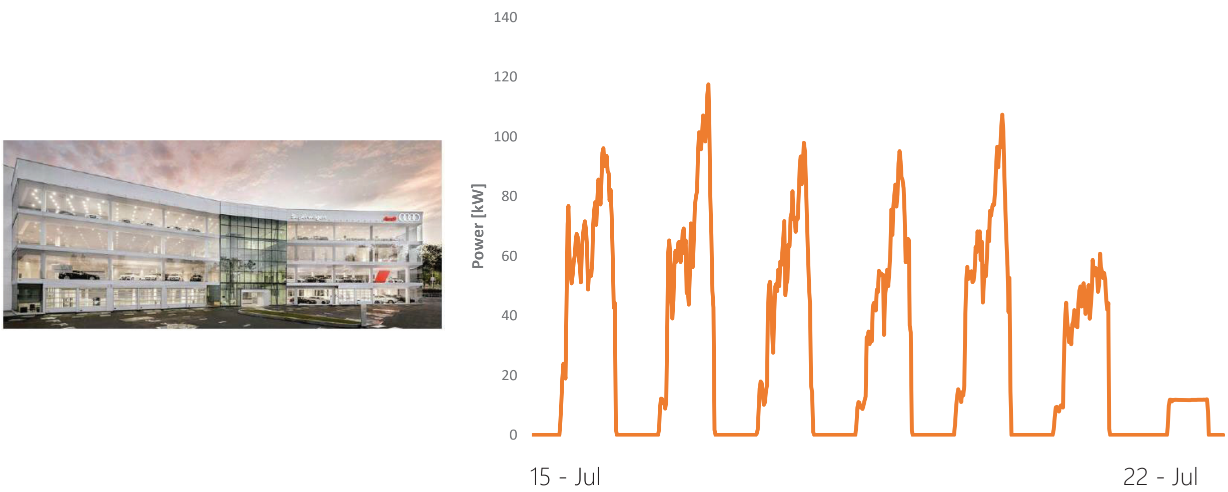


Fig. 5-8 Car dealer with electric thermal consumption from 15 to 22 July 2019

The building is used at 100 % of its capacity from Monday to Friday, while on Saturday just the repair shop is open. The usage of the building per floor is:

- Basement: repair shop, parts warehouse, and offices.
- Floor 1: Sales and dispatches.
- Floor 2: Sales and restaurant.
- Floor 3: Sales occasion, rooms, and museum.

The historical data tested is from May to October 2019. Consumption and internal temperature data are gathered from the sensors installed in the building, while weather data comes from a weather station close to the site.

The thermal comfort in the building is assured by 10 Panasonic variable fan speed condensers, consisting of 10 outdoor machines with nominal power equal to 19.1 kW each, which serves the indoor HVAC systems with a COP of 3.5. The electrical consumption from the thermal loads represents the 25 % of the total building consumption.

For the flexibility estimation, the basement and the 3rd floor are not considered. The basement's cooling system is used rarely, and the desired comfort is not maintained since during most of the time the big doors of the repair shop are open. In the same way, the management of the 3rd floor thermal loads is limited because this floor is used just for special events some days per year. Floors 1 and 2 are divided in four different thermal zones because there is an outdoor HVAC system feeding each one of the wings of each floor. The interval of acceptable indoor temperature was fixed by the building owner to be between 26 and 29 °C and the set-point temperature is fixed to 27.5 °C.

It is possible to modify the power consumption of the HVAC system by modifying the set point temperature of the zone or by modifying the total air flow of the system.

5.4.2 Shiftable load – Industry

The shiftable load analyzed comes from a fragment industry. The total power of the industry is about 2.5 MW, 1.6 MW of those come from a process that consists in fragment residuals from cars. The process duration is about 4 hours per day and the machine can be controlled by sending an on or off signal without any reaction time restriction and without any additional cost. The major restriction is that the process' machine, due to the noise created, can work just from 7 am to 8 pm and the scheduled fragmentation must be respected by the end of the day.

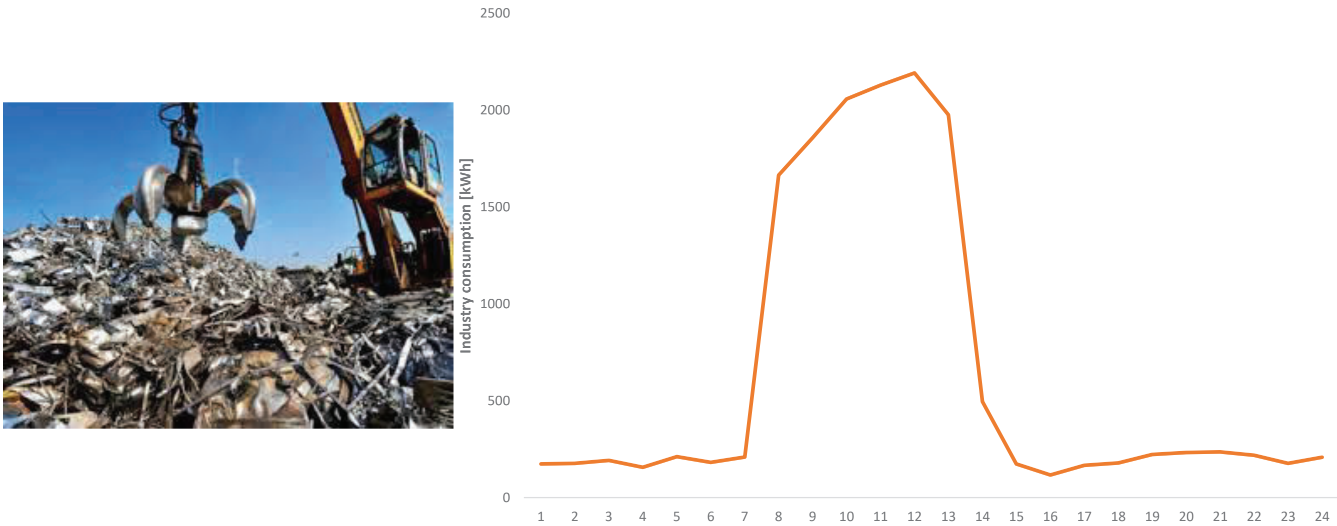


Fig. 5-9 Typical industry consumption (17 November 2021)

5.4.3 Battery – Tertiary building with stationary battery

The battery analyzed belongs to the Montgat library presented in Section 4.3.1. The battery flexibility estimation is based on a 2nd life Electric Vehicle battery. The current capacity is 18.4 kWh and in its current configuration the maximum power that the battery can provide is limited to 10 kW by the inverter.

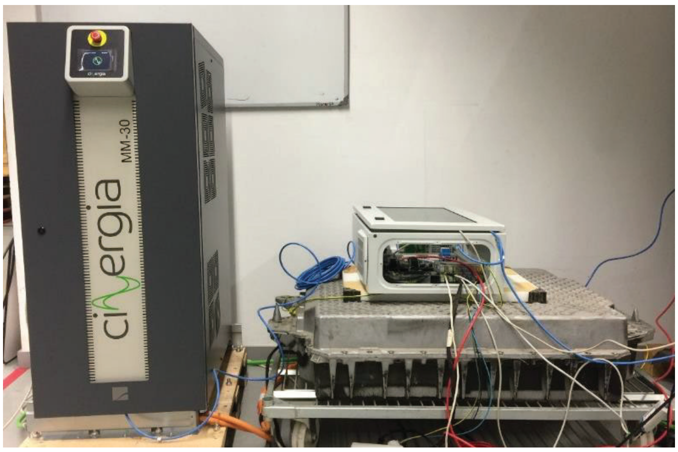


Fig. 5-10 Second life EV Battery (right) and regulator from Cinergia (left) in the testing facilities.

The battery is expected to work following two objectives: to store the excess of energy produced by the PV panels on the rooftop of the library, and to take advantage of the price differences in the electricity tariff, consuming energy at night, when fares are lower, and delivering it whenever prices increase according to the hourly discrimination tariff contracted by the library.

Fig. 5-11 shows the battery power charge and discharge (orange line) and the SOC (red line) in the building from 4th to 11th October 2020. During the first hours of the night, when the electricity price is lower, the battery charges, reaching its maximum SOC of 95 %. Then, from 8 a.m. on, when the electricity is cheaper, the battery discharges until its minimum SOC of 17 %. The power peaks of charge during the day are due to PV excess absorbed by the battery.

In this case, it is possible to control the battery behavior by modulating the power injected or absorbed by the inverter.

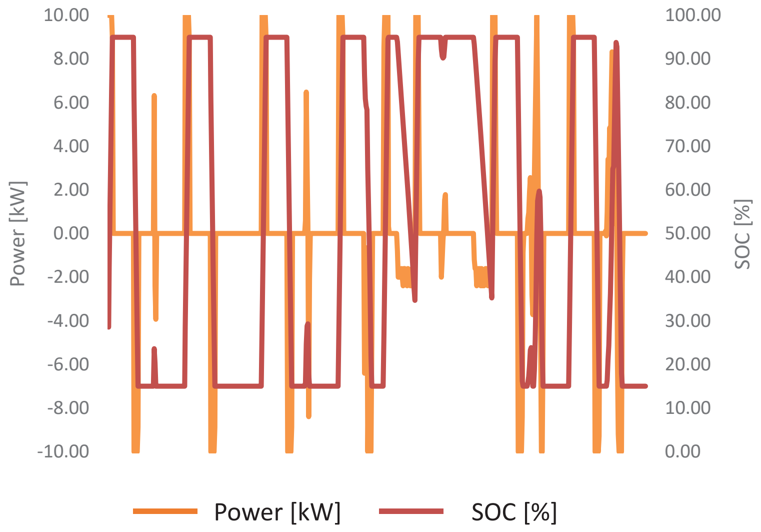


Fig. 5-11 Battery behavior in terms of power and SOC from 4th to 11th October 2020

5.4.4 Curtailable load – PV

The PV analyzed belongs to the Montgat library presented in Section 4.3.1. The PV panels installed have a maximum generation power of 19.8 kW. The PV is used for self-consumption purpose and when there is not enough consumption from the building to absorb the generation, the energy is injected into the grid. Fig. 5-12 shows the electricity generation of the PV panels installed from August 2nd to 5th.

In this case, the PV generation can be controlled modifying the power output of the system's inverter.

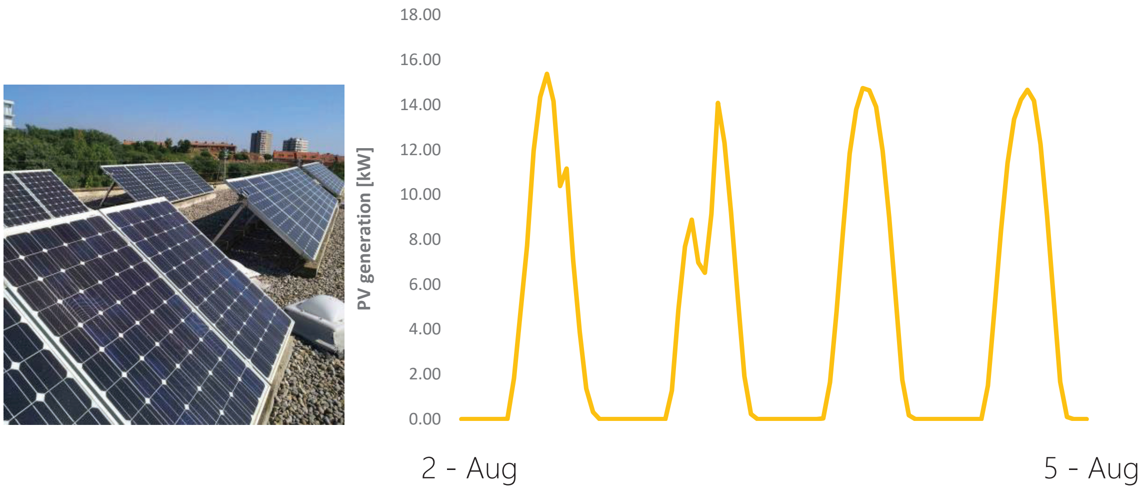


Fig. 5-12 PV generators and generation from August 2nd to 5th

5.5 Methodology application and Discussion

This Section presents the main results from the methodology presented in Section 5.3 and briefly compare the assets analyzed.

5.5.1 Thermal loads – Tertiary building with HVAC system

Table 5-1 shows the trained parameters obtained from May to October 2019 for the thermal zone corresponding to the 2nd floor of the building. The *C* and *R* parameters are quite constant during the months analyzed. Small differences between months are expected due to the different working condition and efficiencies of the thermal loads depending on the weather conditions and different building usage. The equivalent window area Aw is higher during the sunniest months since the sun radiation has a stronger effect during summer when the sun rays are perpendicular to the windows.

Table 5-1 Trained parameter from May to October

	Thermal resistance R $[°C/kW]$	Thermal capacitance C $[kWh/°C]$	Equivalent Window Area Aw $[m2]$
May	11.8	21.7	7.2
June	6.9	35.8	9.3
July	5.6	44.5	11
August	5.3	46.9	10.6
September	5.0	49.5	10
October	3.7	54.5	7

It is not possible to evaluate directly the flexibility forecast performance because the flexibility itself is not measurable. For this reason, to evaluate the accuracy of the building modelling, the internal temperature prediction $\widehat{T_{i,t}}$ is compared to the measured internal temperature T_t^i, such as in (Eq. 5-2).
The accuracy of the algorithm is acceptable, with a RMSE ranging between 0.12 $°C$ and 0.19 $°C$ calculated using the parameters obtained with the data of the previous month (e.g., May) over the next month (e.g., June in this case).

Table 5-2 Temperature prediction error over the different months

	RMSE $[°C]$
May	-
June	0.18
July	0.19

August	0.16
September	0.12
October	0.15

Fig. 5-13 shows the comparison between the predicted (blue line) and the measured (orange line) internal temperature of the building. The temperature prediction is quite accurate and some bigger temperature fluctuations are captured by the model, meaning that the model is reliable for the aggregator purpose.

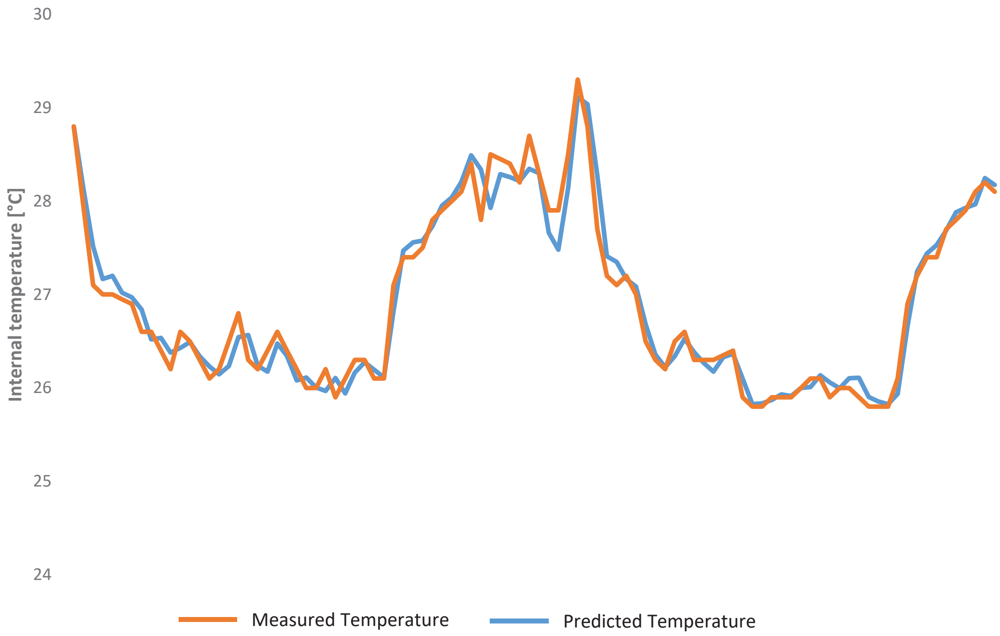


Fig. 5-13 24-hour comparison between the predicted and the measured internal temperature

Finally, Fig. 5-14 shows the available flexibility estimated during the day-ahead compared with the building's Baseline consumption, considering that just 2 of the 4 building's floors can provide flexibility from the thermal loads due to the building owner preference.

At 17:00 h, although it is not the hour of maximum consumption, it is the hour where more flexibility is available (35 kW). This is because most of the building's consumption is not controllable. This means that the building is potentially able to reduce up to 23 % of its power consumption during some hours of the day. It is important to remark that the estimated flexibility from the HVAC system during the day ahead is just an estimation about the real flexibility that will be available. This happens because it is not possible to correctly forecast the internal temperature of the thermal zones during the day head, so the set point temperature (27.5 °C) is considered as the internal temperature of the building. However, if during a certain time step the measured temperature is higher than the set-point, the flexibility available would be lower than the estimated. On the contrary, the building's flexibility is underestimated in the case the current temperature is higher than the set point temperature.

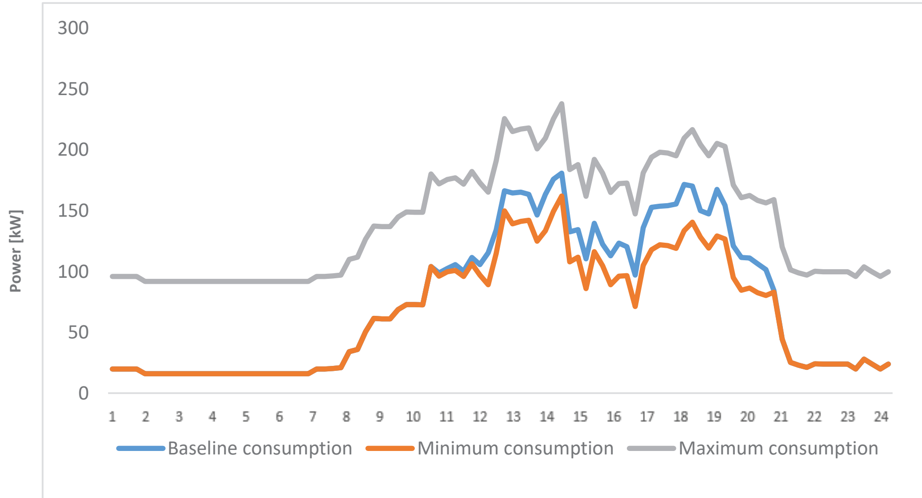


Fig. 5-14 Minimum and maximum possible consumption of the building thanks to the HVAC's flexibility

5.5.2 Battery – Tertiary building with stationary battery

Differently from thermal zones, a battery does not need any training to estimate the parameters, since they are known from the manufacturer. The forecasted load and PV generation, and the strategy adopted by the battery define the baseline charge and discharge power. For this reason, an aggregator should be able to forecast the baseline battery behavior under different strategies to include in its portfolio all type of batteries.

Once the forecasted baseline is defined it is possible to predict the available flexibility from the battery using (Eq. 5-30) and (Eq. 5-31). Fig. 5-15 shows the battery flexibility behavior without flexibility activation, which is the expected baseline power (blue line) and SOC (violet line) associated to that baseline, and the maximum (grey line) and minimum (orange) possible battery consumption with a flexibility activation. Notice that the maximum and minimum possible consumption is limited by the power inverter to be 10 kW. When the battery's SOC is not at its maximum or minimum, the battery has both up and down flexibility, meaning that it could charge or discharge. As expected, the downward (upward) flexibility available is higher (lower) when the battery is discharging and lower (higher) when the battery is charging.

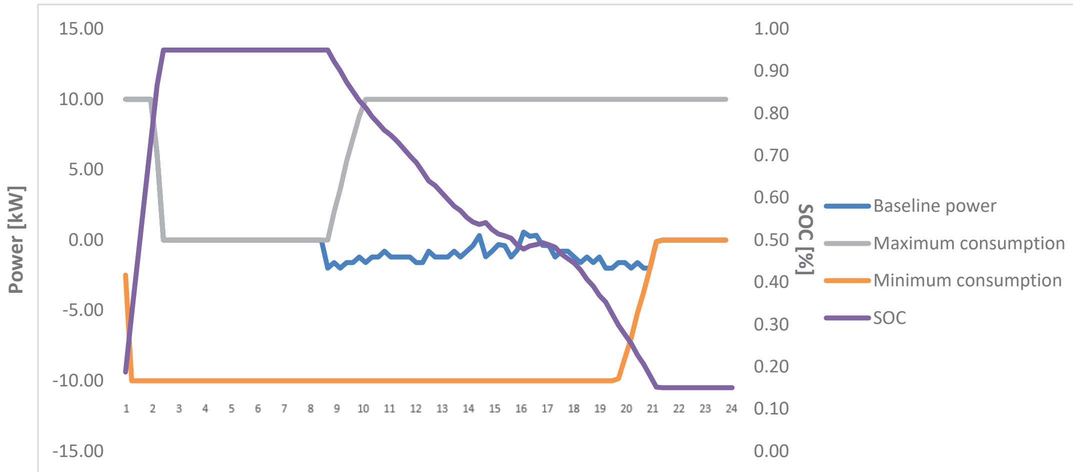


Fig. 5-15 Battery's SOC and minimum and maximum possible consumption of the battery

5.5.3 Shiftable load – Industry

Similarly, the shiftable load does not need any training to estimate their parameters. These parameters are given by the asset owner and the task of the aggregator is to maximize the profits from the assets respecting the given conditions.

Once the shiftable load power profile is estimated, it is possible to calculate the downward and upward flexibility available using the logic showed in Fig. 5-5 and Fig. 5-6 respectively. Due to the characteristics of the shiftable load analyzed, when it is available from 7 a.m. to 20 p.m., it is always possible to modify its consumption, meaning that it could be potentially turned off when it is expected to work and turned on when it is not working.

It is important to remark that on the contrary of the thermal load and battery previously analyzed, it is not possible to modulate the consumption between the baseline and the maximum or minimum possible consumption because the asset can work at 100 % of its power or it can be turned off. For this reason, the load has or upward flexibility available or downward flexibility available, but not at the same time.

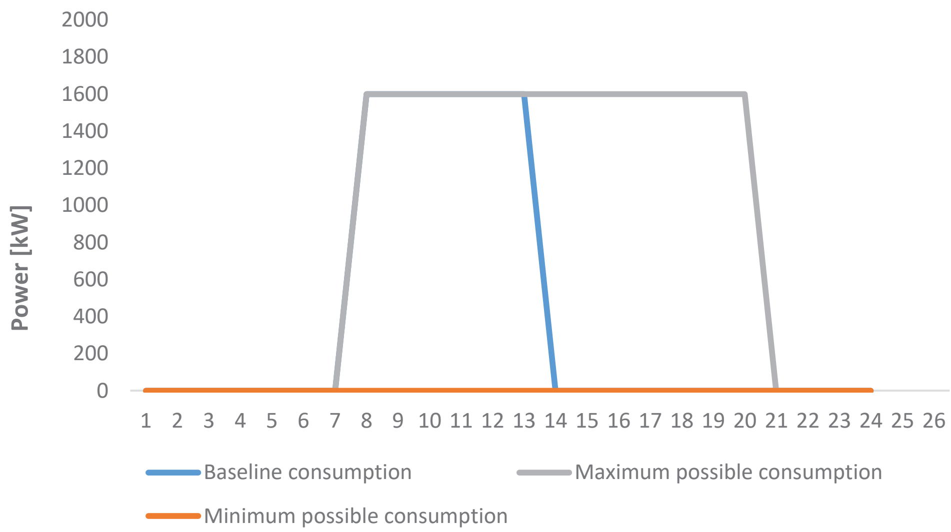


Fig. 5-16 Minimum and maximum possible consumption of the shiftable load

5.5.4 Curtailable asset – PV generator

Similarly, the curtailable asset does not need any training to estimate their parameters. Once the PV power profile is estimated, it is possible to calculate the downward flexibility available using (Eq. 5-41(Eq. 5-42). In this case, the downward flexibility available is the same as the estimated baseline, meaning that the PV could produce in the range between 0 and the expected production modulating the power output of the inverter. In this case, no upward flexibility is available since it not possible to generate more.

5.5.5 Discussion

The scientific community and energy industry clearly recognizes the gap for a general flexibility asset modelling and characterization. This Section, based on the proposal of [126] and [127] compares the four flexible assets using 4 dimensions that affects directly the asset participation in balancing markets and their economic profitability:

- Activation time: the time between the flexibility activation is sent to the asset and the time the asset changes its behavior. If the activation time is too slow it prevents the asset to participate in faster balancing markets.
- Maximum duration of the activation: during how many time the asset can modify its consumption
- Rebound effect: if there is a rebound effect and how the rebound effect is managed.
- Cost of the flexibility activation: cost for a loss in the production of the industry or missed energy generation.
- Symmetricity: if the asset has flexibility available in both directions and how symmetric is the flexibility available.

Considering the activation time of the four assets analyzed, the faster are the ones using power electronics such as an inverter, which is the case of the battery and of the PV generator. In this case, an activation signal instantly modifies the power output of the asset, allowing its participation in whatever type of market. In the case of the HVAC system, when the control is done over the air flow, the activation time is about five minutes, while in the case to modify the air flow the activation time is about 1 minute. This means that HVAC that have a direct air flow control can participate in faster balancing markets than the ones where the only possible control is the set point temperature. Finally, shiftable loads, like the industrial process analyzed, have the slowest activation time, since the large engine is quite slow and it can be completely turned off or on in about 15 minutes, preventing its participation in fast balancing markets.

Regarding the maximum duration of the activation, generally, the longer the time the asset can provide flexibility, the better it is for its balancing markets participation. The maximum duration of the activation depends on several variables that affect the process, such as the capacity of the battery or the thermal comfort range of a thermal zone. For the specific assets analyzed, the PV generator is the asset with the highest duration of the activation, because it could be curtailed during all day without affect any process. The shiftable load has a quite long maximum duration of the activation too, equal to 5 hours for that specific day, which is the time the machine is on. The maximum duration of the activation of the thermal zone depends on the equivalent thermal capacitance of the zone, the allowed temperature range and the nominal power of the HVAC installed. For the specific case of the thermal zone analyzed, the 19 kW HVAC should be turned on at maximum power during almost 1 hour to decrease the internal building temperature by 1.5 degrees during summer. The battery's parameters that affect the maximum duration of the activation is the relation between the useful battery capacity and the battery's power. The battery presented in this Chapter has a ratio of 1.43, meaning that at most the battery could charge or discharge at maximum power during about 1 hour and 25 minutes.

Regarding the rebound effect, the ideal case is to not have rebound effect while the worst scenario is that the rebound effect is not manageable and happens right after the flexibility activation. The ideal case is the curtailable PV generator, that does not present any rebound effect. Neither the battery has a direct rebound effect but, due to the flexibility activation, there is a rebound at the building level due to the different usage of the battery in the hours after the activation. The industrial shiftable load has a rebound effect in case of flexibility activation that can be managed over the day when the asset is available to modify its consumption. The strongest rebound effect comes from the thermal loads, that recovers immediately after the flexibility activation the consumption decrease or increase when the set-point is returned at its normal level. This means that contrary to all other type of assets, the rebound effect of a thermal load is not manageable by the aggregator and it is essential to be considered on the optimal bidding strategy.

Looking at costs incurred due to a flexibility activation, the thermal load is the one with the lowest cost associated. This is because an HVAC does not have associated costs for the loss of comfort in the building. Neither the shiftable load analyzed has no cost associated due to a flexibility activation if all the production is respected. However, in case of having an energy debt by the end of the day, there would be costs associated to the missed production. The battery has some indirect costs due to the efficiency of charge and discharge of the battery; whenever the battery is used, part of the energy is lost through the inverter, representing a cost. The most expensive type of asset is the PV generator because a flexibility activation would reduce the quantity of electricity generated and consequently reducing the self-consumption rate or the energy injected to the grid, which is paid at a certain price.

Finally, regarding the symmetricity of the flexibility available, the battery is the asset that always presents the highest symmetricity between up and down flexibility available. Also, the HVAC analyzed, having a modulable power output, has up and down flexibility available when the HVAC is working. However, when the HVAC is not working or it is working at a low rate, the building has just downward flexibility available. On the contrary, the shiftable load analyzed, having an on/off control, has just up or downward flexibility available, but never at the same time. However, the asset with the lowest symmetricity is the curtailable load because it can provide flexibility in just one direction.

Fig. 5-17 graphically quantifies the comparison among the four assets analyzed. No one of them is ideal for flexibility market participation and this highlights the importance for the aggregator to be able to manage many different assets to balance their characteristics and treat them as one virtual asset. The battery is the one with the best results considering all the parameters. This means that it is well adapted to all type of markets since its only functionality is to provide some flexibility to the building and does not affect any critical process. The curtailable load is the best looking at the activation time, the maximum time of duration and the rebound effect management. However, due to the high cost of the flexibility activation, and its intrinsic unidirectionality it does not fit well for different balancing markets and could be not economically profitable. Shiftable loads flexibility activations are more or less expensive depending on the process, but the rebound effect can be managed by the aggregator avoiding direct costs. However, the longer activation time of the asset impossibilities its participation in fast markets. Finally, modulable thermal loads are good candidates for balancing market participation thanks to its null activation costs and acceptable symmetricity. However, the rebound effect is more difficult to manage, and the flexibility activation cannot be immediate, hindering its participation in continuous-fast balancing markets. Furthermore, if the control over the thermal load would have been on/off, its score would have been lower regarding the symmetricity and rebound effect.

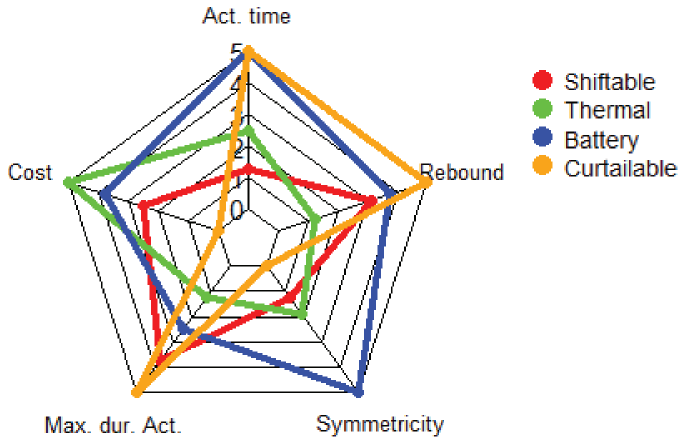


Fig. 5-17 Asset comparisons among the five parameters analyzed

5.6 Conclusions

This Chapter has reported in detail the different methodologies used to model the flexibility assets managed by the aggregator considering its rebound effect and has presented some practical case studies to compare their characteristics. The method presented responds to the specific objective of the thesis to develop a new modeling for different type of flexibility assets able to keep into account their rebound effect, filling the gap found in the literature. Although it is not possible to measure flexibility itself and therefore to validate the methodology in a classical way, the modeling presented allow the aggregator to optimize the flexibility offer of different type of assets in multiple energy and flexibility markets.

To keep into account the rebound effect of the assets and the flexibility effectively delivered, this study proposes three novel concepts:

- The concept of T^{flex}, representing the difference in the internal temperature of the thermal zone between the temperature that would have been in the zone without any flexibility activation and the real temperature of the zone after the flexibility activation allows to estimate the consequence of a flexibility activation on the thermal zone. In addition, a specific modeling for on/off thermal loads and its relative rebound effect improves classical studies that consider thermal loads as completely modulable assets.
- The variables D_t^{aux} and U_t^{aux} used in the battery modelling allow to correctly manage the upward and downward flexibility delivered keeping into account the charging and discharging efficiency of the battery.
- The energetic debt of the shiftable load allows to track the flexibility delivered by the shiftable load and to dynamically manage the rebound effect of the asset, assuring to respect the scheduled consumption. In addition, for the first time a shiftable load is modeled keeping into account parameters such as the minimum time between activations or the total number of switches during a day.

After the literature review, the characteristics and modeling of thermal loads, storage system, shiftable loads and curtailable assets have been described, and they are practically applied on four use cases and results show the available flexibility of the assets analyzed. Flexible assets are compared depending on their characteristics to evaluate their fit in balancing markets. The comparison shows that none of the asset is ideal and each of them presents some barrier. The activation time of shiftable assets is the major barrier for their participation in fast balancing services. At the same time, the rebound effect management of thermal loads need an accurate bidding strategy of the aggregator to respect the limitations of these assets. Also, the activation cost of curtailable assets limits their economic potential, although their physical characteristics position them as precious resource for the SOs. Finally, electric batteries appear as the best assets to provide flexibility since they do not directly affect any critical process and can respond very fast to a flexibility activation.

The aggregator must be able to manage the intrinsic characteristics of all the assets in its portfolio and to make them fit into the economic and technical characteristics of the energy and flexibility market where it is bidding. Chapter 6 show how the aggregator can manage these difficulties while maximizing the economic value of its portfolio.

Chapter 6 - Optimal Demand Aggregator Market Strategy

6.1 State of the Art

The literature proposes different mathematical models to optimize the participation of demand aggregators in electricity markets. They can be categorized depending on:

1) Objective function: minimization of the consumer cost, maximization of the DA profits, environmental benefits.
2) Type of optimization: deterministic Mixed Integer Linear Programming (MILP), stochastic optimization, model predictive control (MPC), risk-aversion, cooperative optimization.
3) Type of users: industries, storage systems, EV, thermal loads, etc…
4) Type of market: day-ahead, primary reserve, secondary reserve, tertiary reserve, real-time portfolio balancing, etc…
5) Type of control on the consumers: direct control, price signal, etc…

Table 6-1 summarize the strategy adopted by the studies analyzed to optimize the DA participation in electricity markets. On the following sub-sections the main works and their contributions are summarize organized by type of optimization approach.

Table 6-1 Resume optimization techniques used by DA

Reference	Objective function	Type of methodology	Type of users	Type of market	Type of control
A. Agnetis et al. (2011)	Maximize DA's profits	MILP	Clustered residential consumers	Day-ahead market	Price signal
D.T. Nguyen et al. (2014)	Minimize costs/maximize profits	Two-stage stochastic problem	Microgrid	Day-ahead and real time market	Direct Control
M. Heleno et al. (2016)	Maximize DA's profits	Heuristic model	Air conditioning	Tertiary reserve market	Controlled by the HEMS
R. Henriquez et al. (2016)	Maximize profits	Stochastic bi-level program	Load curtailment and differentiable loads	Day ahead and intra-day market	Direct control
S. Behboodi et al. (2017)	Minimize individual consumer's costs	MPC	Thermostats	Real time electricity market	Price signal
M. Diekerhof et al. (2017)	Optimize consumers' individual objective	MPC	Generators and consumers	Day ahead and intra-day market	Price signals
P. Olivell-Rosell et al. (2017)	Minimize DA's cost of meeting DSO's request	MILP	Batteries, DER, shiftable loads	Local electricity market	Direct control

Reference	Objective function	Type of methodology	Type of users	Type of market	Type of control
J. Iria et al. (2018)	Minimize costs for the DA	Two-stage stochastic optimization model for day ahead and MPC for real time operations	Air conditioning, EV, PV	Day ahead with real-time balancing	Direct control
X. Zhang et al. (2018)	Maximize revenues for the DA	MPC for real time operations, and MILP for day-ahead	Industrial loads and battery	Day ahead and regulation market	Direct Control
Y. Tang et al. (2018)	Assure grid stability	Mixed-integer nonlinear programming	EV and thermal loads	Real time balancing	Direct Control
Malik et al. (2018)	Assure grid stability	Rule - based	Residential refrigerators	Real time balancing	Direct control
S. Ottensen et al. (2018)	Maximize profits	Multi-stage stochastic problem	4 industrial loads	Day ahead and reserve markets	Direct control
K. Liu et al. (2018)	Maximize profits	Stochastic problem	Batteries	Day-ahead and regulation market	Direct Control
J. Iria et al. (2019)	Minimize costs for the DA	Two-stage stochastic optimization model for day ahead bid and MPC for real time operations	Air conditioning, EV, PV	Day ahead and tertiary reserve with real-time balancing	Direct control
F. Lezama et al. (2020)	Maximize DA's profits	Evolutionary algorithm	Residential shiftable loads	Real time balancing	Direct Control
L. Xiaoxing et al. (2021)	Maximize DA’s profits	MILP	Residential shiftable, thermal loads and batteries	Day ahead energy and regulation market	Direct control
T. Rawat et al. (2022)	Maximaze DSO and customer profits minimizing voltage deviations	Non-linear multi-objective bi-level optimization model	Distributed generation, batteries, flexible load	Local flexibility market	No control
R. Herding et al. (2023)	Minimize costs	two-stage stochastic MILP model	Generation, inflexible loads and storage	Day ahead and real time energy market	Direct control

On the following subsections, the state of the art is presented grouped by the type of model presented in the reviewed works.

6.1.1 Deterministic Mixed Integer Linear Programming models

In [144] Agnetis et al. proposed a model where the DA knows exactly the baseline consumption, the flexibility available and the price at which the consumers, categorized in clusters, are inclined to accept a flexibility activation offer. The objective function maximizes the DA's profits, defined as the profits in the market minus the consumer's remuneration for participating in the program and results show good revenue margins for the DA and its clients.

Olivella-Rosel et al. in [145] designs a local energy market, where a DA is able to manage generators and flexumer's to meet the DSO need. The study assumes that the consumers can propose a price for its flexibility activation and make an offer to the DA. The objective function consists in reducing costs for the flexibility activation. It includes costs for switching on/off units and energy costs. Two strong assumptions were made: the DSO communicates to the DA during the day-ahead the flexibility needed, and the DA makes perfect baseline and flexibility predictions.

Xiaoxing et al. in [146] modeled the day ahead bidding strategies of a DA in the north-american day ahead energy and regulation market to enable the participation of residential consumers with thermal and shiftable loads and batteries. In study the aggregator sends a consumption level to the household's EMS according to its economical and comfort preferences. The authors ignore all the uncertainties since they assume that both energy and flexibility prices are known before of the bids, such as the time of flexibility activations.Stochastic optimization models

Nguyen in [147] proposes a method to optimize the bidding strategy of a microgrid that has the possibility to operate in the day-ahead and real-time energy market to avoid renewable curtailments. The microgrid is formed by controllable conventional generation units and not-controllable renewables, batteries, HVACs, and non-controllable loads. The DA directly controls the HVACs respecting the temperature constrains imposed. Uncertainties comes from renewable energy generation, total uncontrollable load, ambient temperature, and energy prices. A Monte-Carlo simulation creates scenarios used for the optimization solved by a two-stage stochastic program. In this study, the microgrid does not provide any flexibility service to the main grid.

Henriquez in [148] takes into account uncertainties about energy prices and proposed a stochastic bi-level program transformed in MILP for the US day ahead and real time markets. In this case DA's clients are clustered as fixed loads, curtailable loads, and shiftable loads. The study shows that there exists a gain in the deployment of DR contracts by DA, which depends on the needs of the SO and electricity prices.

Liu [149] proposes a stochastic problem to manage a DA of batteries that provides ancillary services to the grid and participates in the day-ahead market. The author includes capacity payments and degradation costs to establish the optimal bidding strategy. The model keeps into account different scenarios with its correspondent probability about energy prices. However, for the simulation, the author uses the average price of the last thirty days in PJM, thus the effect to keep into account the stochasticity of the price cannot be analyzed.

Iria et al. in [14] face the problem to optimize the energy day-ahead bidding strategy and to set the operation of flexible loads in real-time to avoid penalization. The DA controls 1000 flexible consumers, each one equipped with a thermostat (with certain comfort temperature range), an electric vehicle and one shiftable load. The model considers different consumption scenarios in the first stage of the stochastic problem; each scenario has a different positive or negative imbalance in respect to the energy bought in the day-ahead market. The author creates 20 scenarios with equal probability used to find the optimal strategy for the day ahead bids based on physical parameters. Stochastic optimization reduces up to 14 % of the costs in comparison to business-as-usual inflexible strategy.

This study was expanded by Iria et al. in [150] considering the aggregator participation also in tertiary markets. In this case the quantity of flexibility activated, and the direction of the activation are stochastic variables. The authors consider the participation in the Iberian market. The main limitation of this work is to consider just one market session for the tertiary reserve although in the reality it exists one market session per hour. Nevertheless, working with uncertainty adds computational complexity in the bidding process, making the problem unable to solve for a big number of flexibility sources. However, clustering or scenario reduction strategies reduce the size of the problem without compromise the solution, as proposed by the same author in [151].

In [152] Ottesen et al. analysed a generalized market design that includes an options market for flexibility reservation, a spot market for day-ahead or shorter and a flexibility market for near real-time dispatch. The aggregated assets are four shiftable industrial loads. Since the bidding decisions are made sequentially and xºthe price information is gradually revealed, they formulated the decision models as multi-stage stochastic programs, generating scenarios for the possible realizations of prices. The use of stochasticity in this case is reinforced by the fact that the northern reserve market is a pay as bid market. This means that in those markets it is fundamental to anticipate spike prices to maximize the aggregator benefits. This is not the case for the Spanish market.

In [153] Herding et al. propose a MILP stochastic approach for optimal day-ahead market bids and real time operations of a microgrid with inflexible demand, generation, and storage systems. Uncertainty is considered in the electricity price and PV generation. The novelty of the work is to optimize sumultanously bid prices and quantities. In the proposed approach, the aggregator reaches higher profits. However, computational times are not reliable for real time markets, and a time limit computation time of one hour was set, reaching a gap from the optimal solution of 1.56 %.

6.1.2 Model Predictive Control

MPC is a technique that solves an optimal control over a finite future horizon. It implies the ability of predicting the change in dependent variables caused by changes of the independent variables and the possibility to control these independent variables. The main advantage of MPC is the possibility to optimize the current time slot keeping into account the effect of the current decision in future time slots. This process is repeated different times, e.g. each 15 minutes, optimizing the current time slot.

Iria et al. in [14] uses MPC to minimize costs in real-time operations controlling flexible loads. The MPC receives forecasts about power profiles, electric vehicle SOC, ambient temperature, energy prices and solves a deterministic optimization model with the new information retrieved. Finally, power and temperature set-points are communicated by the DA to all the thermostats. The optimization is executed with 1 step forward. The technique used allows 4% savings in comparison to another algorithm which objective is simply to reduce imbalances.

Behboodi et al. in [154] uses MPC to optimize real-time operations for thermostat control to minimize costs in a real-time retail market. The author assumes that the retailer broadcast to all the thermostats the estimated mean price and standard deviation price over the future time window (5 min). In this way, depending on the internal temperature of the building and the comfort zone decided by the users, the thermostat decides if activate the heating system or not. One of the assumptions of the study is a great intelligence from part of the building's energy management system.

In [155] Zhang et al. optimize the day-ahead bidding strategy and real-time control strategy of an industrial plant through MILP and MPC. MILP is used to establish the day ahead bids in the wholesale and regulation day-ahead market. For the day-ahead optimization, the author supposes that the regulation power price and energy prices in the wholesale market for each hour are known. MPC is used to optimize real-time operations, depending on an ARIMA prediction to predict the activations for the next hour.

6.1.3 Other Approaches

In [156] Lezama et al. propose the DA participation in a local market to resolve DSO congestions using residential shiftable loads. Here the authors propose an evolutionary algorithm to deal with the complexity of the formulation. In this study, the aggregator receives plenty of information from the user to optimize its strategies, including the reward that the consumer wants to receive for each specific flexibility activation. In addition, the aggregator's strategy is based on the DSO flexibility request received during the day ahead, making the model not suited for current market design and EMSs. With the same objective, Rawat et al. in [157] use a multi objective bi-level optimization approach. The upper level of the optimization determines the flexibility activation price to maximize profits for the DSO while minimizing the voltage deviation. At the lower level, depending on the price, decides the energy consumption profile of its customers. The bi-level problem is then converted to a single level problem and assessed on a 33-bus distribution system. In this study, the DSO and the DA are collaborating to find the best solution, although due to current market rules this would not be legal.

In [158] Tang et al. propose a hierarchical model for real time control to deliver balancing services to the low voltage grid. The aggregator communicates with the flexibility assets directly, controlling EV charging and thermal loads of the building. The model proposed is a mixed-integer nonlinear programming problem due to the complexity of the algorithm to keep into account grid and user constraints. This study is based on Chinese market rules, where the DSO can directly control appliances without any market intermediary. For this reason, market participation is out of the scope of the paper.

In [159] Malik et al. present a decentralized strategy by applying cooperative game theory model to allow flexumers to provide flexibility from domestic refrigerators to the grid, which has no information about the state of the flexumers. In this case, the home appliances act independently to follow the frequency deviation from the grid. Here the aggregator, described as cooperative home energy management system has no role in the decision-making process of the different home energy management systems. The aggregator is in charge to centralize the information from the different buildings and share it among all the participants.

An heuristic approach is proposed by Heleno et al. in [160] to optimize the bidding strategy of a DA of residential loads in the Portuguese day-ahead tertiary market. A bottom-up approach is presented: each Home Energy Management System (HEMS) calculates the day-ahead flexibility profile of each household and communicates it to the DA that presents flexibility bids in the day-ahead market to maximize its profits. However, the model proposed threats flexibility in a discussible way: the consumption of each house is established the day before and the HEMS is not able to change its consumptions during the same day, as there is not intra-day communication between DA and HEMS. In this way, when the tertiary reserve is not dispatched, the DA must pay a penalization to the system operator. Disregarding the business model used by the DA, the study presents a heuristic method for DA to optimize its profits considering energy prices and the probabilities of tertiary reserve dispatch.Final remarks on optimization models for DA participation in electricity markets

From the literature review performed, the type of market defines the market participation rules for the DA, which need to fit with the characteristics of the asset managed. Typically, the bidding optimization models consider only one type of flexible resource, market session and time horizon, i.e. they do not consider the joint optimization of different types of load and generation resources for multiple market sessions and time horizon. Most of the studies analyzes the participation of residential loads and batteries in electricity markets, while few studies analyze industrial sites or tertiary buildings.

In energy markets' participation, the objective function is usually the minimization of consumer costs, while the aggregator objective in flexibility markets is to maximize its benefits. Environmental or degradation costs usually are not considered.

The level of control of the aggregator varies from sending a price signal to the consumer to direct control of the appliances. This depends on the automation level of the appliance to control and on the type of market. For example, for an energy market a price signal to the consumer can be enough to expect a change in the consumer's behaviour, while in a flexibility market where penalizations exist in case of not delivery a direct control on the appliance is necessary, even more considering that the aggregator should manage hundreds of assets at the same time.

The type of optimization adopted depends on the characteristics of assets to control and their modelling, on the number of stochastic variables kept into account and on the timeline of markets where the aggregator participates. It is important to find the right trade-off between complexity and accuracy of the model.

This review show that while several approaches have been proposed for the usage of different customer-side resources for selected market-based services, there is still a need for the consideration of heterogeneous resource groups for cascaded services, as highlighted also in [161].

This Chapter proposes two different strategies for combined participation of different types of flexible assets in the secondary and tertiary reserve markets. The first strategy consists in a MILP bidding optimization algorithm used to construct the bidding strategy of the aggregator in secondary reserve market followed by an MPC to control in real time the flexible assets and maximize DA's revenues. The second strategy consists in a cascade MPC for participation in continuous energy and tertiary reserve considering real time control to allow the participation of shiftable and thermal loads, and stationary batteries in those markets.

6.2 Optimal Demand Aggregator Participation in Secondary Market

6.2.1 Secondary Market description

6.2.1.1 Spanish secondary market

The secondary reserve in Spain is regulated in the Operating Procedure (P.O.) 7.2, approved the 24 December 2020 [162] and consists of loads and generators under the direct control of the TSO, via an Automatic Generation Control (AGC), for increasing or decreasing generation or consumption to balance in real time the electricity grid. The response time for the participants is very fast, between 100 and 300 seconds. In Spain, aggregated demand needs to have at least 200 MW of contracted power, while the minimum bid size of the offer is 1 MW.

In Spain, the TSO is in charge to publish the proportion of the bid between up and down reserve (*r* parameter) every day for all the hours of the next days. The band availability is the sum of the upward and downward band accepted by the TSO and all the participants must offer up and down band respecting the proportion published by REE.

The secondary reserve is remunerated under two concepts: band availability and utilization. The band availability is traded under the form of bids (in MW), which are selected by an economic merit order and remunerated by a common marginal price (€/MW). The band utilization (MWh) is valued at the marginal price (€/MWh) of the tertiary reserve market of MIBEL.

6.2.1.2 Aggregator's timeline in the secondary reserve market

The participation of the aggregator in the secondary reserve requires the submission of band bids during the day ahead market session. The band bids are submitted between the 14:45 and 16:00 hours. During the operating day, the aggregator sets the operation of the flexible resources considering the set-points communicated by the AGC. Fig. 6-1 shows the timeline of the secondary reserve market.

The day ahead actions are the following:

1. REE communicates the proportion between Up and Down band.
2. The aggregator submits the secondary reserve bids (MW and €/MW).
3. REE communicates to the aggregator the accepted bids and the marginal band price.

The real-time actions executed in a continuous mode are:

4. Exchange of data between the aggregator and the consumers. The data includes state of operation of the appliances, availability, consumption, etc.…
5. Communication of the AGC signal (MW) of the secondary band to be activated.
6. Communication of the aggregator of unavailable distributed resources to the AGC to eventually reduce the available band.
7. Communication of the set-points to the consumers by the aggregator.

Days after the delivery of the energy and reserve services, REE settles the following market transactions:

8. Secondary reserve band availability and utilization, reserve not supplied and energy unbalances (€).

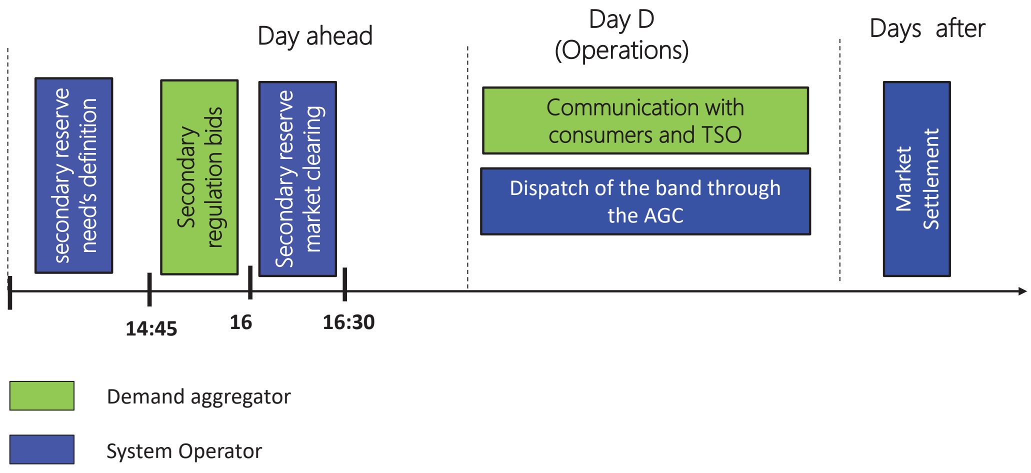


Fig. 6-1 Aggregator's tasks and market sessions based on the timeline of the Spanish secondary reserve.

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6.2.3.2 Data

The case study data includes information of the consumers and the electricity market. The consumer's information comprises battery's parameters, thermal load's parameters, and PV generation. The electricity market information includes secondary band prices, energy utilization prices, forecast and current ratios of utilization of the offered band, gathered from the ESIOS web page [165]. The flexumers' data and electricity market information are described in Annex A.

6.2.3.3 Implementation

The optimization models are implemented in Python using the Pyomo library [166] and solved by the SCIP solver [167] on a server machine with 7.41 GB usable RAM and an Intel Core i5-1135G7 clocked at 2.40GHz. No initial condition is fixed on models' variables.

6.2.4 Results

The results are divided into three main sections. Section 6.2.4.1 describes the day-ahead bidding results. Section 6.2.4.1 discusses the real-time control results. Finally, Section 6.2.4.3 resumes the financial benefits of the aggregator participating in the secondary reserve market.

6.2.4.1 Day-ahead Bidding Results

Cumulative Bidding Results

Table 6-3 shows the bidding results summary. The total band offer and the number of hours where the aggregator participates in the secondary reserve market vary slightly among the different days analyzed, since the aggregator uses the same input data regarding expected band price, flexible asset's parameters and expected hourly volume ratio activated. The only input difference among days, at this stage, is the expected activation up and down price, which is directly correlated to the energy spot price, already published by the OMIE at this stage.

The table compares the expected band benefits from the aggregator after having sent the offer and the real band benefit once the capacity prices are published. Here there is a huge difference among days. For example, on 2021-07-09 the aggregator received almost ¼ of the capacity payment expected, while on 2022-01-09, the real band benefits were more than the double than the expected. This is not an issue for the aggregator because its objective is to maximize the expected market benefits while assuring the reliability of the portfolio during real time operations.

Finally, the table shows the expected activation benefits from the secondary reserve and the expected unbalance benefits from the hours where the aggregator is not participating in the secondary reserve market, charged or paid at the expected unbalance price. The expected activation benefits are negative during all days analyzed. This is because the forecasted direction of the activation is downward during most of the time and the aggregator in this case is charged at the downward activation price. These expected economic losses are compensated by the unbalance benefits coming from the hours in which the aggregator does not participate in the secondary reserve market and its final portfolio position is paid or charged at the expected unbalance energy price. Note that higher spot market prices bring to higher expected activation costs and higher expected unbalance price. At this point, during the day ahead and before operations, the aggregator cannot know the real energy benefits coming from the real time operations.

Table 6-3 Cumulative bidding results

Day	Total Band offered [kW]	Expected band benefits [€]	Real band benefits [€]	Expected activation benefits [€]	Expected unbalance benefits [€]	Number of hours participating in the secondary market [h]
2021-06-09	12059	415	167	-30	84	21
2021-07-09	11793	410	99	-41	108	20
2021-08-09	11702	408	278	-46	139	20
2021-09-09	11815	411	171.6	-68	164	20
2021-10-09	11815	411	382	-102	254	21
2021-11-09	11803	411	528	-92	216	20
2021-12-09	11714	407	367	-112	248	21
2022-01-09	10953	375	855	-58	254	20
2022-02-09	12133	419	111	-101	250	21
2022-03-09	10725	361	528	-219	634	18
2022-04-09	11753	408	573	-123	319	20
2022-05-09	11781	409	255	-93	244	20

Placement of the Secondary Reserve Bids

Fig. 6-3 and Fig. 6-4 illustrate the available market data and consequent bidding strategy during the 9th July and 9th November respectively. The only reason why these two days have been selected to show the results, is because they are representatives of a day in which expected benefits are higher than the real ones and the opposite. The upper left graph in the figures shows the expected (blue line) and the real capacity price from the two days analyzed. During the 9th of July 2021, the capacity price was lower than the expected, explaining why in

Table 6-3 the expected capacity band benefits from that day were lower than the real ones. On the contrary, on 9th November 2021, the capacity band prices were higher than the expected during the first hours of the day, explaining why the real benefits from the secondary band were higher than the expected. The upper right graph in the figures shows the energy price from the day ahead spot market (green line), and the expected up (blue line) and down (orange line) activation energy prices. During the 9th of July 2021, the energy price curve is quite flat, reaching a minimum of 82.5 €/MWh at 17:00 h and a maximum of 107 €/MWh at 9:00 of the morning. Differently, on 9th November, there was higher volatility on the market, with a minimum price of 145 €/MWh at 4:00 h and a maximum price of 220 €/MWh at 20:00 hours.

The lower graph in Fig. 6-4 shows the up (blue bar) and down (orange band) bid placed by the aggregator in kW with the expected band activation used in the bid construction, in percentage. First, it is worth notice that the ratio between the up and down offer is not constant, because it depends on the TSO needs and vary on an hourly basis. On the 9th of July, the aggregator decides to not provide any bid at hour 8, 20, 21 and during the last hour of the day. The decision to not offer during the last hour of day is common in all the days analyzed, because in this way the aggregator is free from eventual penalizations and flexible assets can recover the up or down energy used during the day and be ready to operate in the secondary reserve market the next day. Hours 8, 20 and 21 are the ones with the lowest expected capacity price and, being the energy price quite flat, this is the main driver for the aggregator decision. Similarly, on 9th November, the aggregator decides to not place any bid at hour 8, 20 and 21 (this is not the same in other days analyzed). These hours, apart from being the hours with the expected lowest capacity price, they are also the hours with among the highest prices of the day in the morning and evening peak. Considering that the expected direction of the activation in that hours is downward, the aggregator decides not to bid in the secondary reserve market, expecting to activate upward flexibility paid at the unbalance prices of that hour.

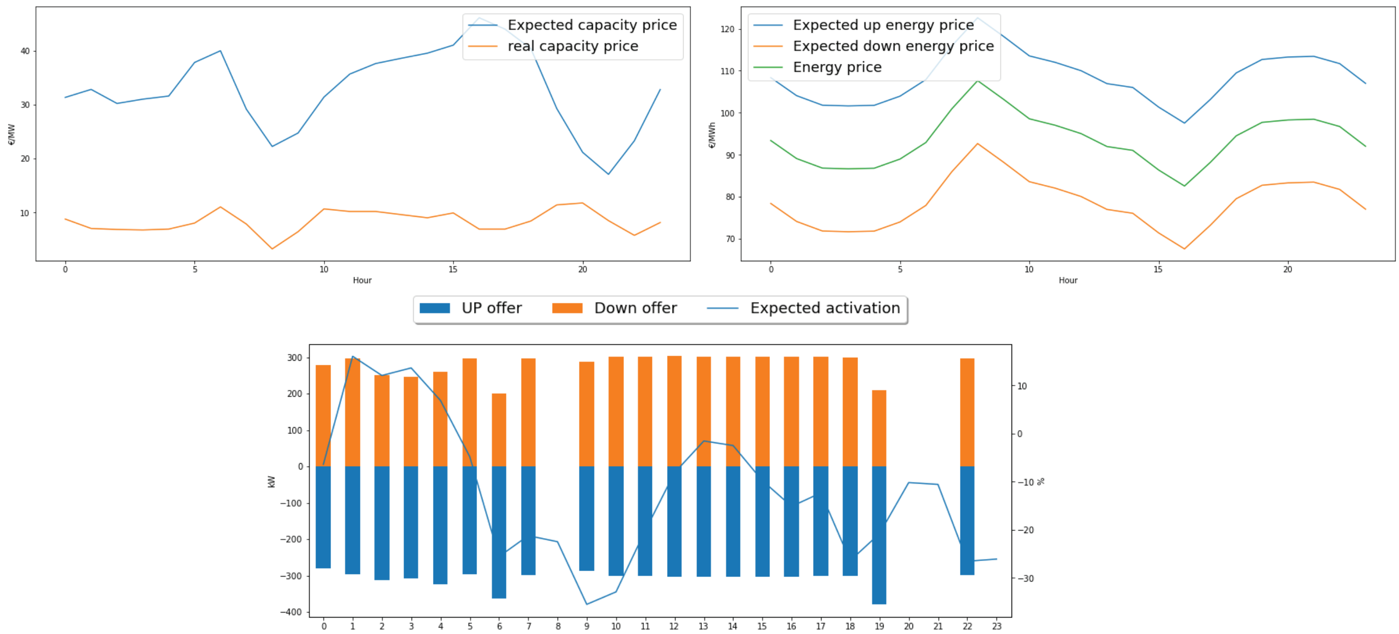

Fig. 6-3 Day ahead electricity market information and bidding strategy for the day 2021 - 07 – 09

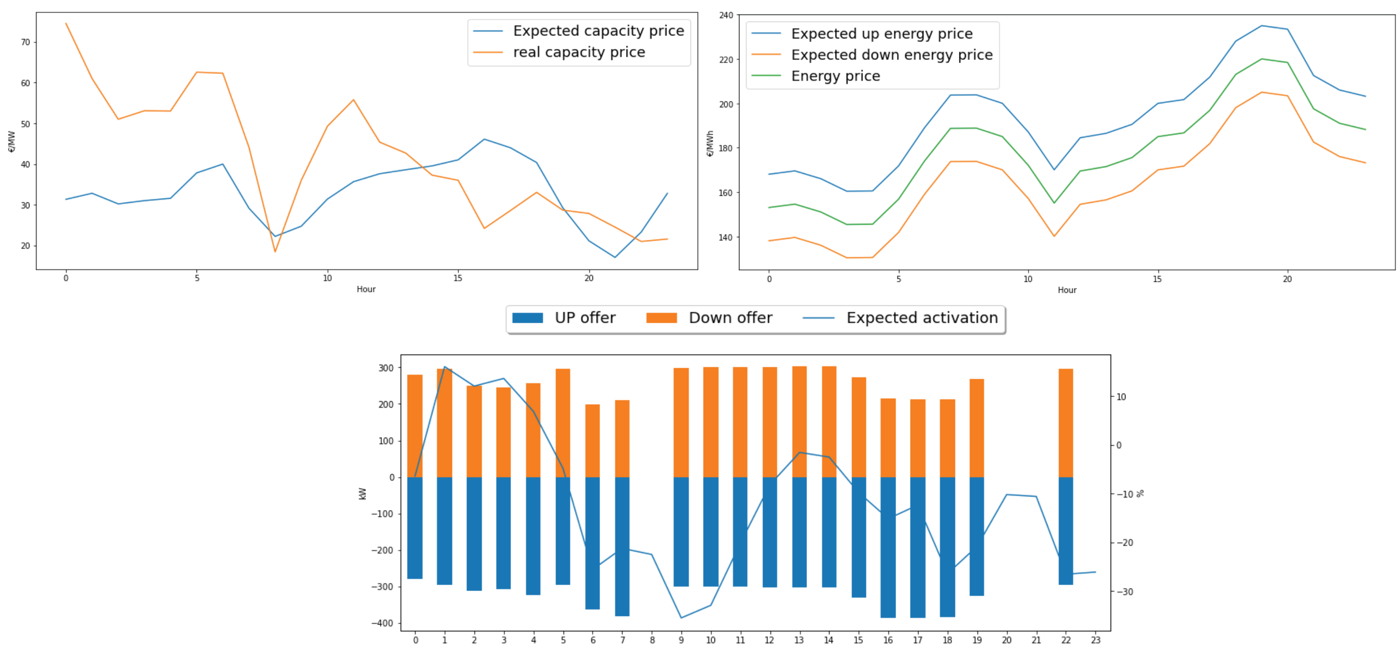

Fig. 6-4 Day ahead electricity market information and bidding strategy for the 2021 - 11 – 09

Fig. 6-5 Compares the day ahead bidding strategy in the two days analyzed using the expected and the real capacity band prices. In both cases, the aggregator does not bid at hour 8 and at hour 23 such as in the scenario where the aggregator uses the forecasted capacity price, being 8 the hour with the lowest capacity price in both days. On 9th July, due to low capacity prices, the aggregator would have decided to not place any offer at hour 9 and 22 being the hours with lowest capacity prices. During this day, the real band benefits would have been just 3 % higher than the case with expected capacity band price. On the contrary, on 9th November, day with higher capacity prices, the aggregator would have placed an offer for 21 hours instead of 20 hours of the case with expected capacity band price, deciding to not place any offer at 19:00. During this day, benefits from capacity band would have been just 1 % more than the band benefits reached in the case with expected capacity band price (with 1 hour less of secondary market participation). The sum of the expected energy benefits and activation benefits are the same as in the scenario using expected band price.

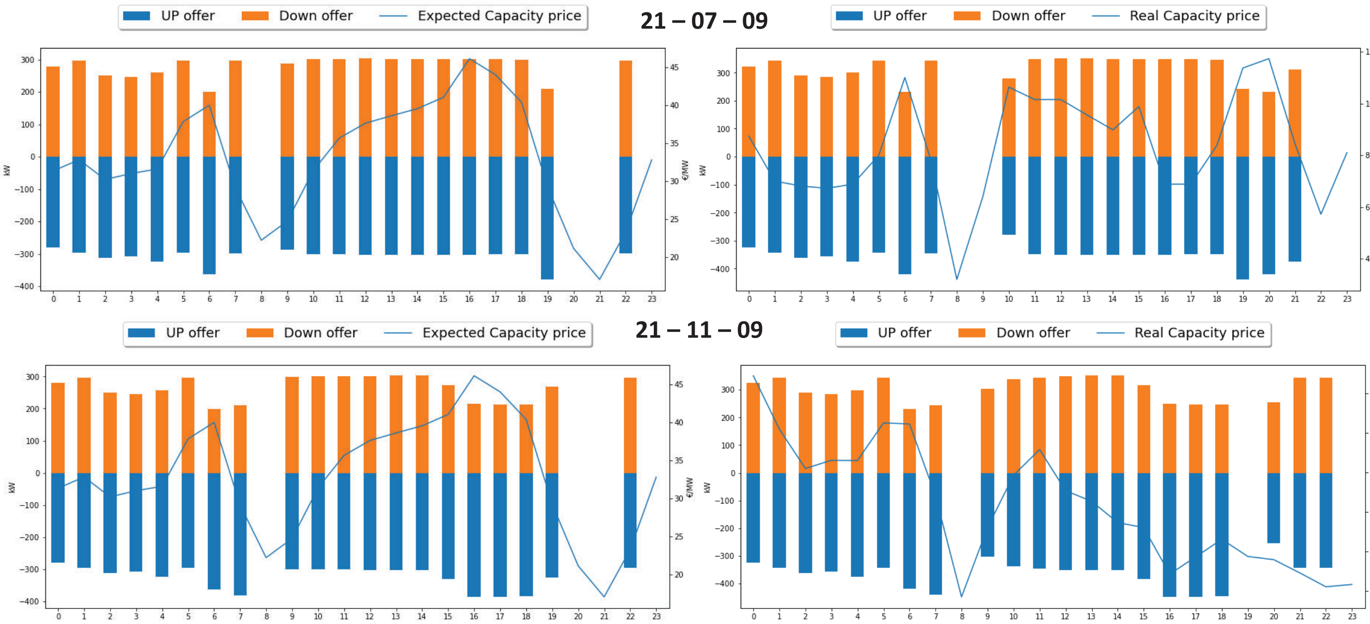

Fig. 6-5 Comparison of the bidding strategy using expected and real capacity price

With this first analysis, it is possible to conclude that the aggregator bidding strategy results is not strongly conditioned from the hourly capacity price. However, expected, and real band benefits can be very different due to the daily capacity price volatility.

Disaggregation of the Cumulative Bidding Results per resource type

Table 6-4 presents the disaggregation of the cumulative bidding results per resource type in the two days analyzed. In both days, thermal loads are the assets that provide most of the expected upward and downward band activated. Due to the forecasted activation ratio, the expected downward band activated is between 2.5 and 3.5 times higher than the upward flexibility activated. It is worth notice that PVs assets are not expected to provide any flexibility, since downward activations are charged to the aggregator, and the curtailed generation cannot be recovered in next hours. This means that downward activations from PV assets represent a cost for the aggregator. However, they are an important resource in the bid construction to reach the ratio between the offered up and down flexibility and as a back-up resource to avoid penalizations during operations.

Table 6-4 Disaggregation of the cumulative bidding results per resource type

	Expected upward band activated [kW]	Expected downward band activated [kW]	Maximum upward band potentially activated [kW]	Maximum downward band potentially activated [kW]
		2021-07-09		
Thermal loads	245	539	5801	5143
Batteries	121	416	2400	1914
PVs	0	0	0	870
		2021-11-09		
Thermal loads	213	506	5686	5247
Batteries	49	307	2794	1642
PVs	0	0	0	870

Execution time

The average execution time and sizes of the bidding optimization model in the case study analyzed and in the case of solving the same optimization with 100 flexible assets (34 batteries, 33 thermal loads and 33 PV) are described in Table 6-5. The execution times are suitable for the market timeline.

Table 6-5 Sizes and average execution times of the bidding optimization model

	Average case study	Average with 100 assets
Continuous Variables	1273	8081
Binary Variables	312	1704
Constraints	1546	8788
Execution times [s]	59	429

6.2.4.2 Real-time Control Results

Cumulative secondary reserve provided

Table 6-6 resumes the results of the aggregator's operations in the secondary reserve market in the 12 days analyzed.

In all the days analyzed the expected total band activated is much lower than the real total band activated (sum between upward and downward band activated). However, as expected by the aggregator, during most of the days the total downward band activated is higher than the total upward band activated. This is well reflected in the benefits coming from the activation of the secondary reserve. This represents a benefit (positive value) just in the days where the total upward band activation is higher or closed to the downward band activation.

The activation benefits vary consistently among days. For example, during 2021-06-09, where the downward activated band is more than six times higher than the upward band activated, the aggregator would have paid 127 € for the activated energy. On the contrary, during 2022-01-09, where the upward activation rate is slightly higher than the downward activation rate, the aggregator would have received 276 € for the energy activated in the secondary reserve. Activation costs and benefits depend on the upward and downward activation prices, which are not published before operation.

The table shows the percentage of hours where the reserve is not delivered. This value varies between the 40 % of 2022-02-09 to the 85 % in 2021-07-09, with an average of 68.5 %. The percentage of hours in which the band is not correctly delivered directly affects the penalizations, which are 1.5 times the band benefits of the hours in which the reserve is not provided correctly. It is important to highlight that the days with higher monetary penalizations does not correspond to the days with the lowest ratio of corrected delivered band. In fact, during 2022-01-09, the aggregator pays 347 € of penalization, which are the highest monetary penalizations among the days analyzed, although this is one of the days with highest percentage of correct delivery of the reserve. On the contrary, during 2021-02-09, which is the day with lowest ratio of band correctly provided (40 %) the total penalizations have been 98 €. This means that highest capacity band prices, that bring to potentially higher penalizations in case of not delivery, incentives the aggregator to correctly supply the band when an economic optimization is performed. Finally, the table shows the benefits coming from the unbalances in its portfolio. Although this is counterintuitive, the aggregator take advantage from the current Spanish regulation that pays (or charge) market participants for its unbalances at the unbalance market price when it is generating more (or less) or consuming less (or more) than the expected by the SO. This voice, in most of the days, compensates activation costs and penalizations. Basically, since the aggregator activates mostly downward reserve it is free to consume less than the baselines during the hours in which it is not participating in the secondary reserve and other times the aggregator prefers to pay a penalization (especially when the band price is low) and charge for the upward expected energy unbalance. However, the final unbalance price is known by the aggregator during the settlement period (see Table 6-2).

Table 6-6 Resume of the secondary reserve operation results in the 12 days analyzed. Negative values are costs and positive values are revenues

Day	Expected total band activated [kWh]	Total Downward band activated [kWh]	Total Upward band activated [kWh]	Activation benefits and costs [€]	% Hours band correctly provided	Penalizations [€]	Unbalance benefits and costs [€]
2021-06-09	872	3171	500	-127	81	-44	196
2021-07-09	904	1890	856	-45	85	-21	134
2021-08-09	885	1605	1514	8	65	-128	83
2021-09-09	880	1619	604	-50	85	-51	187
2021-10-09	851	447	1112	47	62	-209	152
2021-11-09	852	2100	575	-13	80	-117	214
2021-12-09	839	2145	609	0	58	-153	194
2022-01-09	780	1173	1181	276	75	-347	79
2022-02-09	833	1225	1261	105	40	-98	128
2022-03-09	693	1398	607	-28	56	-330	602
2022-04-09	860	2835	98	-69	65	-319	302
2022-05-09	828	1945	700	-5	70	-75	220

Real time operations

Fig. 6-6 shows the aggregator portfolio position compared with the secondary reserve activations and the expected and real energy prices during the two days previously analyzed 2021-07-09 and 2021-11-09. Notice that when the reserve activation is equal to zero, it means that during that hour the aggregator did not place any secondary reserve bid, therefore there is no penalization on the band offer. During both days, in the hours without secondary reserve participation, the aggregator decides to consume less than the baseline to charge from the SO the unbalance price. Also, in all the hours in which the activation is not respected, apart from the second hour of 2021-07-09, the activation was downward, and the aggregator decides to create an upward unbalance because the expected unbalance price was high enough to justify the band penalization. For example, at 14:00 of 21-07-09, the SO demands 185 MWh of downward secondary reserve and the aggregator decides to create an upward unbalance of 378 MWh, preferring to pay a penalization for the band not delivered, that at that hour is quite low, being the band price at 5.43 €/MW and charging at the expected downward energy price (70 €/MWh) the unbalance instead of saving the band penalization and pay for the downward activation.

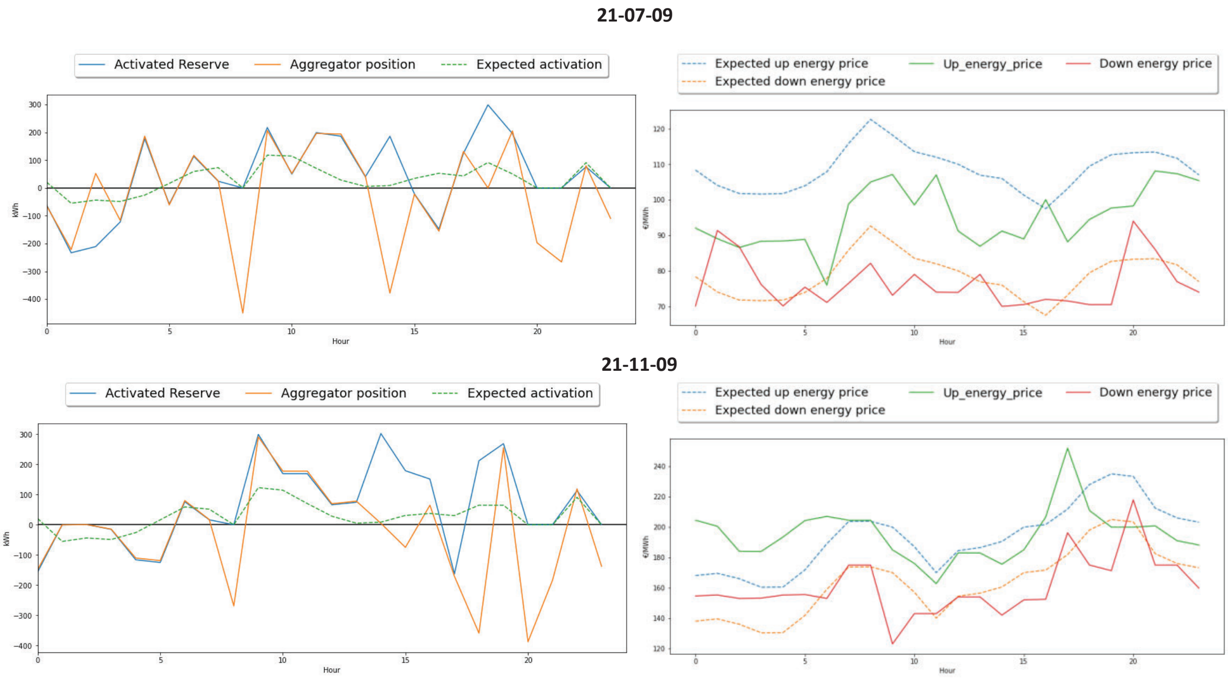

Fig. 6-6 Aggregator position and activated reserve (left) with expected and final energy prices (right) during 21-07-09 and 21-11-09

The right part of Fig. 6-6 shows the difference between the expected activation prices and the real ones. In both cases, there is an important difference among expected prices and the real ones, which impact on the aggregator decisions. To analyze the impact to have perfect activation and energy price forecasts in real time operations, Fig. 6-7 shows the aggregator decision on 21-07-09 and 21-11-09 in case of having perfect energy activation price forecasts and perfect information on the reserve volume activated during real time operations.

During the first day analyzed with perfect activation price information, the aggregator does not respect the SO activations one hour more than in the case that uses the expected activation price , receiving consequently 8 € (8 %) more of band penalizations. In addition, the sum of activation and unbalance benefits is also reduced by 15 € (17 %). In this case, having perfect energy price information without perfect volume activation information does not improve the aggregator's results. To have perfect information on the volume activated does not improve the percentage of hours with correctly delivered reserve, and the hours in which the reserve is not correctly delivered are the same as in the scenario without perfect activation price formation. However, aggregation benefits for activation and unbalances improve by 13 € (15 %).

During 21-11-09, if the aggregator would have had perfect energy price information, it would have delivered correctly the secondary reserve activated for one hour more than in the case without perfect activation price formation, having 28 € (31 %) less of penalization. However, also in this case, to have perfect energy price information without perfect information on the volume activated, does not improve activation and unbalance benefits, which are 34 € (17 %) less than the case with perfect activation price formation. To have perfect information on the volume activated in this case improves the percentage of hours with correctly delivered reserve, reaching the 90 % of accuracy and reducing penalizations by 52 € (44 %). However, aggregator's benefits for activation and unbalances remain the same (+1 €).

Fig. 6-7 Aggregator decision comparison with perfect price information and perfect activation information

Disaggregation of the secondary reserve delivered

Table 6-7 presents the disaggregation of the cumulative upward and downward flexibility activated, and the flexibility activated to provide secondary reserve by resource type. In both days, thermal loads are the assets that provide most of the upward and downward band activated. PV assets does not provide any flexibility, as expected from the bidding algorithm (Table 6-4). It is worth notice that most of the downward flexibility activated by the aggregator is activated to provide secondary reserve. On the contrary, most of the upward flexibility activated is not used to provide secondary reserve. Cumulatively, the aggregator activates more upward than downward reserve, meaning that the portfolio consumed less energy than in the case without any aggregator, while respecting the conditions defined by the asset owners. In comparison to the expected activated energy in the secondary reserve of Table 6-4, the real delivered upward and downward flexibility is higher.

Table 6-7 Disaggregation of the cumulative upward and downward flexibility activated

	Upward flexibility activated [*kW*]	Downward flexibility activated [*kW*]	Upward flexibility delivered secondary reserve [*kW*]	Downward flexibility delivered secondary reserve [*kW*]
		2021-07-09		
Thermal loads	1676	1109	702	1107
Batteries	475	487	48	437
PVs	0	0	0	0

2021-11-09				
Thermal loads	1640	1073	477	1003
Batteries	448	378	29	378
PVs	0	0	0	0

Execution times

The average execution time and sizes of the real time optimization model in the case study analyzed and in the case of solving the same optimization with 100 flexible assets (34 batteries, 33 thermal loads and 33 PV) are described in Table 6-8. The execution times are suitable for the market timeline.

Table 6-8 Sizes and average execution times of the real time optimization model

	Average case study	Average with 100 assets
Continuous Variables	314	7780
Binary Variables	81	1656
Constraints	364	8487
Execution times [s]	0.25	1.22

6.2.4.3 Settlement Results

Table 6-9 resumes the settlement results of the 12 days analyzed. Thanks to the secondary reserve participation, the aggregator gains on average 427 €/day, corresponding to 155 k€/year. 47 % of the total gains come from the capacity payment of the band, considering the penalizations form the band not correctly delivered. The rest of the benefits come from activation and portfolio's unbalances, although secondary reserve activations represent a cost for the aggregator most of the time with the current Spanish regulation. The expected benefits during the bidding construction are quite close on average to the real benefits, being the real ones just 15 % lower than the expected.

The last column of

Table 6-9 shows the total benefits that the aggregator would have had with perfect information, meaning that the aggregator knows in advance, before the bidding process, the upward and downward flexibility activation prices λ_t^{eU} and λ_t^{eD}, the band capacity price λ_t^{B} and the ratio of the activated upward and downward band ρ_t^{+} and ρ_t^{-}. In the case study analyzed, although the aggregator knows the activation ratio in advance, the risk aversion constraints (Eq. 6-8) and (Eq. 6-9) have been maintained to compare the solution. However, perfect forecasts will never be possible due to the uncertain nature of the market input information. Therefore, this result should be interpreted, as the maximum theoretical benefits that the aggregator could obtain with the portfolio analyzed. The difference in the total benefits in the two cases varies from just 13 € in 2021–07-09 to 360 € in 2022-01-09. The percentage difference between the case with perfect market information and the case with estimated market information is the range of 7 – 37 % during the days analyzed. It is worth noticing that the days where the percentage difference is higher than 30 %, which is during 2021-08-09, 2021-10-09, 2022-01-09 and 2022-04-09 correspond with the days with highest penalizations for the aggregator. The results obtained shows that there is room for improvements in the aggregator's performance with better market forecast, but at the same time, these results highlight the robustness of the method proposed.

Table 6-9 Settlement of the day-ahead and real-time transitions for the twelve days analyzed

Day	Band benefits [€]	Activation benefits and costs [€]	Unbalance benefits and costs [€]	Penalizations [€]	Total expected benefits [€]	Total benefits [€]	Total benefits with perfect information [€]
2021-06-09	167	-127	196	-44	469	192	218
2021-07-09	99	-45	134	-21	477	167	180
2021-08-09	278	8	83	-128	501	241	381
2021-09-09	171	-50	187	-51	507	257	310
2021-10-09	382	47	152	-209	563	372	536
2021-11-09	528	-13	214	-117	535	612	707
2021-12-09	367	0	194	-153	543	408	439
2022-01-09	855	276	79	-347	571	863	1223
2022-02-09	111	105	128	-98	568	246	324
2022-03-09	528	-28	602	-330	776	772	1005
2022-04-09	573	-69	302	-319	604	487	746
2022-05-09	255	-5	220	-75	560	395	492

6.2.5 Final Remarks and conclusions

This Chapter describes two novel optimization models to support the participation of an aggregator in the secondary reserve markets. The first methodology consists of a MILP model to define band bids for the day-ahead secondary reserve market. The second algorithm is a MPC to dispatch the operation of the flexible resources in real time.

The models proposed demonstrate that an aggregator of flexible consumers can participate in the secondary reserve market in a reliable way and with important economic benefits. In addition, for the first time up to the author knowledge, this Chapter presents a strategy for demand aggregator secondary reserve participation respecting all the market technical requirements, including execution times and available information at each step.

Due to the secondary reserve market characteristics, that require to place the bids during day ahead without the possibility to be modified, energy prices and activated volumes are variables that cannot be known with precision in the bidding construction, due to their high volatility and uncertainty. The model proposed proposes the risk factor parameter to keep into account uncertainties in the volume activated, reaching a reliability in the delivery of about the 70 % on the band offered. However, the band not delivered is due mainly to economic reasons and not for a lack of the reserve available. To optimize its offer the aggregator decides to offer in hours with highest expected capacity prices and with lower energy prices.

During real time operations, the aggregator follows the SO providing mostly downward reserve, and recovers the flexibility used activating upward reserve when no bid is placed to charge that energy at the unbalance price. From the analysis performed, it looks like knowing the real energy price in advance without knowing the activation rate would not benefit the aggregator, while knowing in advance the activation rate would increase the aggregator benefits. This Chapter also analyzes the aggregator's performance improvements considering perfect market information from the bidding process, concluding that a theoretical economic improvement between 7 and 37 % would be possible. However, these results highlight the robustness of the method proposed.

This Chapter also concludes that PV panels are not a good candidate to deliver secondary reserve in an economic way. To curtail PV production is not beneficial for the aggregator neither in the bidding process, neither in real time operations. This can be interesting for regulators, since in a 100 % renewable energy system the only candidates to provide regulation services are renewable generators and demand side resources. To incentivize renewable generators to participate in these services, payments should be higher. Also, it has been found that the days with low band price in comparison to the energy prices, are the days in which the aggregator performed worst in terms of reliability, since it is not incentivized to avoid penalizations.

Execution time are well suited for market participations with a portfolio of up to 100 assets. However, execution times increase with the number of assets and future research could focus on reduce the execution time of the problem with a portfolio of thousands of assets, for example using clusterization or by optimizing the configuration of the solver and the model's constraint declaration. Future research can extend the proposed bidding optimization models and real-time management algorithms to enable the participation of the aggregator in secondary and energy reserve market. This would allow the aggregator to participate in an energy market to buy and sell energy instead of paying or charge its unbalances, increasing benefits. Also, it would be interesting to compare the methodology proposed with a stochastic optimization approach by finding what are the stochastic variables that most affect the aggregator strategy. In addition, a sensitivity analysis on the risk factor parameter should be performed to find the right tradeoff between the risk aversion strategy and the economic optimization.

Moreover, algorithms used to predict capacity and energy prices and activated volume could be improved and check their impact on the aggregator business model, although the activated volume forecast looks like the most difficult to predict and at the same time the variable with the biggest impact in the aggregator's decision. An initial work to predict flexibility activation prices can be found in Annex B, based on the work performed during the internship in the framework of this thesis. Furthermore, the model could be extended to include new types of assets such as electric vehicles, which promise to have a great flexibility potential, as introduced by the author of this thesis in Annex C. Finally, include degradation costs for battery usage in energy and flexibility markets could help increase the battery lifespan and its economic reliability, as demonstrated by the author of the thesis in the article of Annex D.

6.3 Real time participation in energy and flexibility markets

6.3.1 Market description

6.3.1.1 Spanish energy market

In Spain there are 31 energy markets managed by OMIE. There is one day-ahead market, six national intraday markets and 24 continuous European energy markets, which technical characteristics are explained in Sections 3.1.1 and 3.1.2. The energy markets of OMIE are a double-sided auction, where market agents submit energy hourly bids for the remaining hours of the next day. The bid prices can go from -500 €/MWh up to 3000 €/MWh, and the bid quantities offered must be greater than 0.1 MWh. The energy bids of MIBEL and other markets are collected and submitted to the EUPHEMIA platform (European market solver [168]). The EUPHEMIA clears the offers (MWh) and prices (€/MWh) such that the social welfare is maximal and the power flows between the European bidding areas are not exceeded.

Days after the delivery, the OMIE and the REE settle the energy transitions and eventual unbalances. The aggregator pays the energy bought and charges the energy sold in the energy markets to OMIE. The real-time energy deviations are settled at imbalance prices by the SO. Spain uses the two-price system to value load and generation energy imbalances, as described in [163]. In this framework, the aggregator assumes the role of Balance Responsibility Party (BRP), participating both in intraday energy markets and tertiary reserve market. Its participation in the day ahead spot market is not considered, as it is the baseline to evaluate the value of flexibility.

Fig. 6-8 describes the timeline of the energy markets.

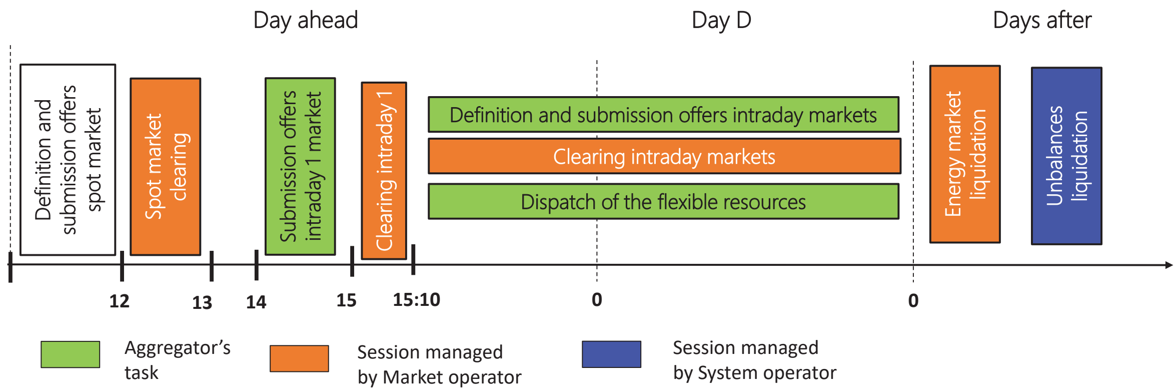

Fig. 6-8 Aggregator's tasks and market sessions based on the timeline of the Spanish energy market.

6.3.1.2 Spanish tertiary market

Tertiary reserve is a service manually activated by the TSO to handle forecasts' errors and/or to replace the secondary reserve. In Spain, the market is managed by REE, and its main characteristics are explained in Section 3.3.5.The notification time is 15 minutes, and the maximum duration could be up to 1 hour. Downward and upward tertiary reserve bids are presented to the TSO until 25 minutes before the operating hour (e.g until 14:35 for the reserve between 15:00 and 16:00). The reserve bids comprise a volume (MW) and an hourly price (€/MWh). During the operating day, the TSO dispatches the tertiary reserve bids by economic merit order, selecting most cheaper upward offers and most expensive downward offers to reach the reserve needed to assure the stability of the grid.
Selling downward reserve is equivalent to buy energy, while selling upward reserve is equivalent to sell energy. The downward and upward reserves are charged and remunerated at downward and upward marginal prices respectively.

Days after the delivery of the reserve services, the TSO pays the reserve bought and charges reserve not supplied. Fig. 6-9 shows the timeline of the tertiary reserve market.

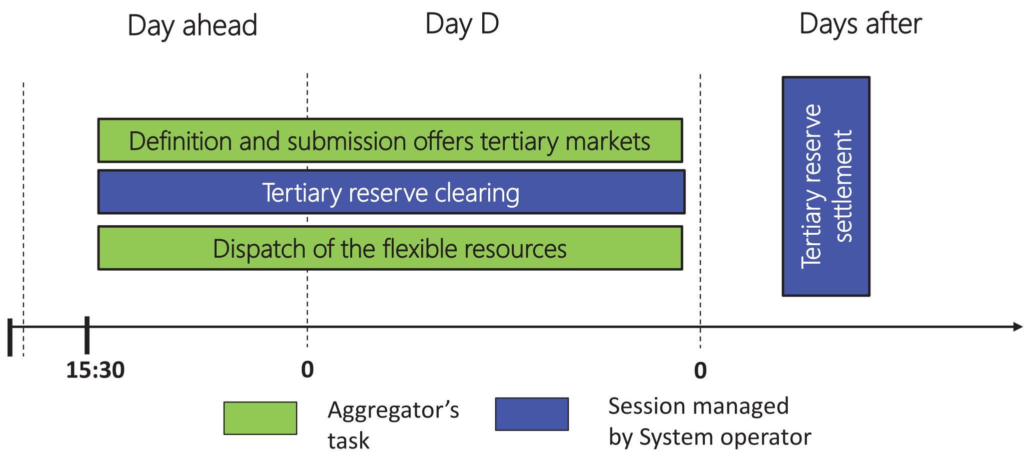

Fig. 6-9 Aggregator's tasks and market sessions timeline of the tertiary reserve market

6.3.1.3 Aggregator's timeline in the energy and tertiary markets

The joint participation of the aggregator in the energy and tertiary market requires the submission of energy bids during a day ahead market sessions (intraday 1 market) that sets the energy program of its portfolio for the next day. The aggregator bids to maximize economic profits assuring to not affect the thermal comfort or industrial processes of its clients. During the operating day, the aggregator continuously offers in the downward and upward tertiary reserve for the next hour (without knowing if that reserve will be activated or not), and in parallel the aggregator bids in the continuous intraday markets for the next two market sessions modifying its original portfolio's energy program. In the meanwhile, in real time, the aggregator sets the operation of the flexible resources considering the set-points communicated by REE and the scheduled program. The optimization algorithms to define bids and control the operation of the flexible resources are described later.

The day ahead aggregator' tasks are the following, represented in Fig. 6-10:

1. The aggregator receives energy market price information from OMIE.
2. The aggregator receives eventual unavailabilities and preferences from its clients.
3. The aggregator submits the intraday 1 bids (MWh and €/MWh).
4. OMIE communicates to the aggregator the accepted bids and the marginal price.
5. The aggregator program the new schedule for its portfolio and communicate it to the consumers.

The real-time tasks are repeated 24 times a day, here explained for hour H:

6. Continuous exchange of data between the aggregator and the consumers. The data includes state of operation of the appliances, availability, consumption, etc…
7. Continuous communication with REE for the eventual activation of the downward or upward band.
8. If the TSO activates downward or upward reserve, communication of the aggregator of the control set-point to the consumers.
9. At H:30, the aggregator sends energy bids to OMIE for the continuous intraday market for the hours H+2 and H+3.
10. At H:35, the aggregator sends downward and upward reserve bid to REE for the next hour H+1.

Days after the delivery of the energy and reserve services, REE and OMIE settle the following market transactions:

11. Energy transitions and imbalances (€).
12. Mobilized tertiary reserve and reserve not supplied (€).

Participating in multiple markets at the same time allow to increase the benefits from the flexibility traded. However, it is necessary to limit the bidding and real time optimization model using some frozen periods to avoid infeasibilities over the day. So, the horizon used in the continuous intraday market, tertiary reserve market and real time scheduler is limited. This is because when flexibility offers are sent, it is not possible to know if that flexibility will be activated or not. Fig. 6-11 shows an example for the specific hour 13:00. Notice that the "out of scope" time step means that due to regulation it is not possible to change the global portfolio position during that time step during that market session; the "decision time" step is the time step in which the output of the model modifies the portfolio position by offering in the related market or by providing the activated flexibility in the case of the real time module; the "frozen time step" is the time in which although it could be possible to modify the global aggregator position, due to internal restrictions to avoid infeasibilities, the model is forced to maintain the portfolio position (but it is still possible to modify a consumer’s scheduling that must be balanced by changes from other consumer); the “planning time step” is the time step where it could be possible to change the portfolio position in the market, the model considers this possibility, but the aggregator will not send an offer for that time step in the market. This is part of the strategy selected by the aggregator with the objective to maximize benefits by participating mostly in flexibility markets instead of energy markets. With the current Spanish market characteristics and timelines, the decision, planned and frozen periods of the model are the following.

a) In the continuous intraday session at hour 13:30 due to the regulation, it is possible to trade in the horizon from 15:00 until the end of the day. In the model presented in this Chapter, the decision hours are the first two hours the aggregator can trade energy (15:00 h and 16:00h). For the next hours of the day, the model considers that the aggregator can trade energy, but the offer is not sent to OMIE.
b) In the downward and upward tertiary market at hour 13:35, it is possible to trade the available flexibility in the horizon from 14:00 h until the end of the day. However, the aggregator does not know if that flexibility will be dispatched by REE or not. In this case the decision hour is the first hour the aggregator can trade flexibility (14:00 h). However, there are two frozen periods in which the model cannot assume to change the position of the aggregator in the market (15:00 and 16:00 h) because the only gate available to change the position of the aggregator are the next intraday markets. The next intraday market available will be at hour 14:30; in that moment it is possible to bid for the hour 16:00. However, the last activation from REE could happen until 14:45, after the next intraday session, that could create a possible unfeasibility if energy would be traded without considering the last activation.
c) The real time model does not imply any market operation. It reschedules the flexible resources in case REE redispatches in real time. In this model, the decision time step is during the hour of the activation to provide the flexibility activated. The next two hours are used as frozen time step, meaning that the global aggregator position cannot change but it is possible to schedule a flexibility activation at the site level.

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The follov ing secſions are encrxpſed for confidenſial reasonsi

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6.3.3.1 Optimization algorithm horizon

In the day D-1, the aggregator uses the bidding optimization model to define the energy bids for the day-ahead intraday 1 market using forecasted energy prices. In real time, the aggregator simultaneously bid upward and downward tertiary reserve, buy and sell energy in the continuous intraday market and manage real time activations from the tertiary reserve using an MPC to set the operation of the flexible resources considering forecasted activation and energy prices and real time state of the flexible assets.

6.3.3.2 Data

The case study data includes information of the consumers and the electricity market. The consumer's information comprises battery's parameters, thermal load's parameters, and shiftable load parameters. The electricity market information includes flexibility activation prices, energy prices, gathered from the ESIOS web page [165]. The flexumers data and electricity market information are described in Annex E.

6.3.3.3 Implementation

The optimization algorithms were implemented in Python using the Pyomo library [166] and solved by the SCIP solver [167] on a server machine with 7.41 GB usable RAM and an Intel Core i5-1135G7 clocked at 2.40GHz.

6.3.4 Results

The results are divided into three main sections. Section 6.3.4.1 describes the day-ahead bidding results in the intraday 1 market. Section 6.3.4.2 discusses results of the real time participation in the energy and flexibility market. Finally, Section 6.3.5 resumes the financial benefits of the aggregator participating in the energy and tertiary reserve market.

6.3.4.1 Day-ahead Bidding Results

Day ahead Cumulative Bidding Intraday 1 Results

Table 6-11 shows the bidding results in the 12 days analyzed. During the day ahead, the aggregator forecasts the hourly electricity price curve, using the method explained in Annex E. In the first columns, the table presents the daily mean spot price and the daily electricity price volatility, which are two most important factors for the demand aggregator day ahead strategy. The daily volatility is calculated as the standard deviation of the logarithmic ratio between consecutive hours (Eq. 6-80).

$$volatility_d = \text{stdev}\left(\ln(\lambda_{t+1}^{sp}/\lambda_t^{sp})\right) \qquad \textbf{(Eq. 6-80)}$$

It is worth notice how the average spot price increased during the year, and the big difference among days. In the 12 days analyzed, the average spot price ranged from a maximum of 473 €/MWh during 9th March 2022 to 81 €/MWh during 9th June 2021. Regarding the hourly volatility, without considering 9th January 2022 that had an exceptional volatility of 55 %, the hourly volatility ranged from 2.8 % to 9.4 %.

The table compares total energy traded in the market session, which is quite constant during all the days analyzed. This behavior is the expected one, because the aggregator maximizes the revenues using as much flexibility as possible. However, there is a huge difference in the total benefits produced, that range from 109 € during 9th June 2021 up to 1768 € during March 2022. The total benefits are strongly influenced by the daily average price, which is correlated to the average costs/revenues generated in each market transition. On the other side, the hourly volatility gives an idea on the market opportunities coming from selling energy during expensive hours and buying the same energy during cheaper hours. For this reason, the three days with lowest benefits, which are 9th June 2021, 9th July 2021, and 9th August 2021, are the three days with lowest average spot price and lowest volatility. On the contrary, the two days with the highest total benefits are 9th January 2022, which is the day with the highest daily volatility, and 9th March 2022, which is the day with highest average spot price. On average, during the days analyzed, the average daily benefits to participate in the intraday 1 market have been 599 €, equal to 219 k€/year managing the 15 flexible assets described in Annex E.

Finally, Table 6-11 presents the percentage savings for the aggregator participating in the intraday 1 market in comparison to a business-as-usual retailer strategy where the energy is bought during the day ahead at spot market price and without the possibility to manage the flexibility of its clients. The hourly daily volatility looks to be the most important factor to determine the % savings in the intraday 1 market. The two days with highest volatility (9th March 2022 and 9th January 2022), are the two days with highest percentage savings. On average, the percentage of savings over the total costs is 7.8 %, that would be a very interesting saving on the annual electricity bill for the consumer.

Table 6-11 Cumulative day ahead intraday 1 bidding results in the 12 days tested

Day	Average spot price [€/MWh]	Hourly daily volatility [%]	Total Energy traded [MWh]	Total revenues generated [€]	Total costs generated [€]	Total benefits [€]	Savings [%]
2021-06-09	81	4.2	20.5	909	800	109	3.7
2021-07-09	93	4.3	19.3	1005	846	159	4.4
2021-08-09	106	2.8	19.7	1139	1004	153	3.4
2021-09-09	141	4.1	20.5	1601	1379	222	4.0
2021-10-09	226	7.2	20.9	2683	2150	533	6.1
2021-11-09	178	5.8	18	1927	1439	488	6.6
2021-12-09	216	7.8	17.9	2290	1795	495	6.0
2022-01-09	119	55	19.4	2143	746	1397	29.5
2022-02-09	210	7.2	20.5	2587	1991	596	7.5
2022-03-09	473	9.4	19.1	5583	3785	1768	9.4
2022-04-09	241	7.0	21.4	3079	2324	766	7.8
2022-05-09	208	5.2	19.8	2377	1886	511	5.7

Placement of the Intraday 1 Bids

Fig. 6-12 and Fig. 6-13 illustrate the intraday 1 energy price (blue line), the forecasted intraday 1 energy price (orange line), and the energy bids of the aggregator during 2022-01-09 and 2022-02-09, respectively. Positive values are demand bids (increase consumption), while negative values represent supply bids (reduce consumption). First, it is worth notice in both days, the slightly difference between the forecasted energy price (using the method described in Annex E), and the real energy price. For this reason, the benefits generated with perfect market information are the same than using forecasted prices in both days analyzed. This highlights the residual importance for a demand aggregator to implement complex energy price forecasting algorithms for the intraday 1 market participation. In both days analyzed, the aggregator reduces the consumption during high price periods, while increase the consumption of the flexible assets during low price periods.

During 2022-01-09, as shown in Fig. 6-12, the electricity price curve has a morning peak, which is much lower than the evening peak. Electricity prices range from a maximum of 236 €/MWh at 19:00 to a minimum of 19 €/MWh at 15:00 h. High prices are mostly concentrated during last hours of the night, where the aggregator reduces the flexible asset consumption. Periods with higher energy traded does not coincide with times with higher or lower prices for two reasons. From one hand, because available flexibility depends on flexible asset constraint, and possibly, hours with highest flexibility available does not coincide with the hours with highest price. On the other hand, because due to the rebound effect of flexible assets, it is most important to consider the price difference between the hours the consumption will be shifted than the profits or costs generated with a single operation.

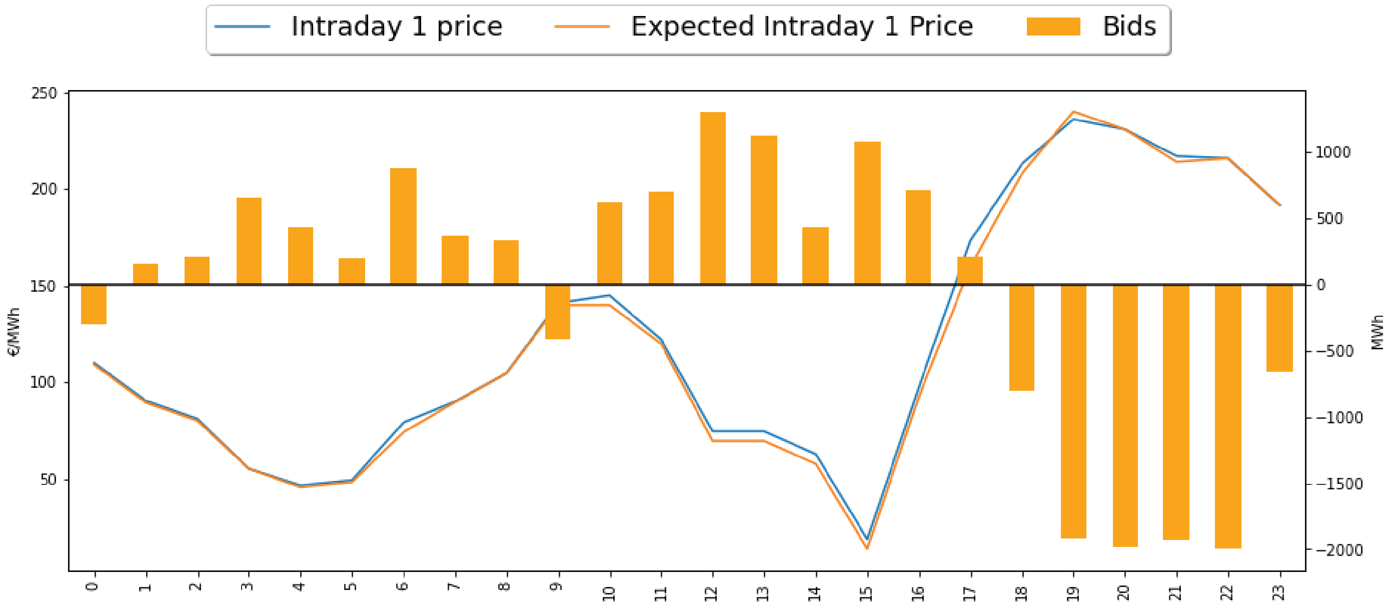

Fig. 6-12 Intraday 1 bidding results in 2022-01-09

During 2022-02-09, the electricity price curve has two peaks with similar prices: during the morning peak, at 8:00 the price reach 244 €/MWh, while during the evening peak, at 19:00, the price reached 254 €/MWh. In this case the range of price is smaller than in 2022-01-09, as the minimum price is registered at 4:00, being 181 €/MWh. In this case, the aggregator reduces the consumption both during morning and evening peak.

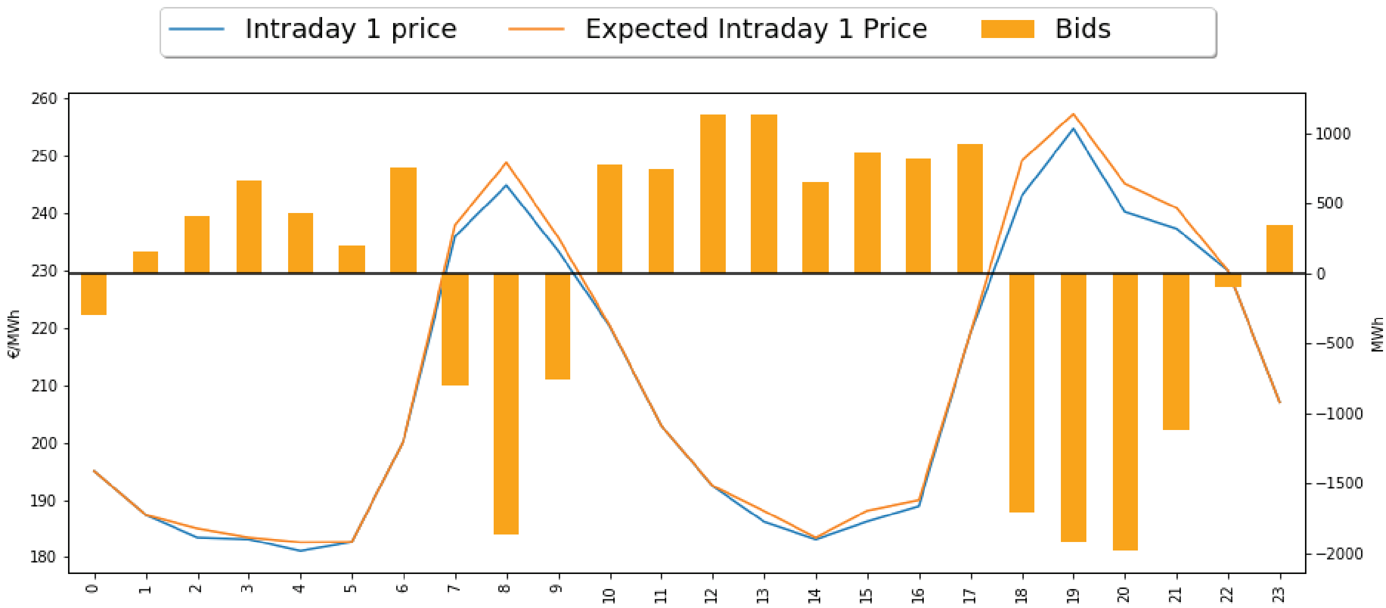

Fig. 6-13 Intraday bidding results in 2022-02-09

Disaggregation of the Cumulative Bidding Results per resource type

Fig. 6-14 and Fig. 6-15 show the original baseline (blue dashed line) and the optimal flexibility asset schedule after the intraday 1 market optimization for Shiftable loads, batteries and thermal zones in the 2 days analyzed.

During 2022-01-09, the shiftable loads gather all the consumption during the first hours of the day, avoiding consuming during the most expensive hours, which are at the end of the day. The maximum power consumed by the shiftable loads is the same as the baseline consumption. The battery behavior is quite different, because their optimal schedule has four peaks during the day, where they charge, or discharge at maximum power, being the peak power produced much higher than the baseline. In this case, the charging peaks coincide with the cheapest morning and evening hours (15:00, 4:00). While the discharging period coincide with the morning and evening hours with highest spot price (9:00 and 19:00). Regarding thermal loads, the consumption is concentrated in low price hours.

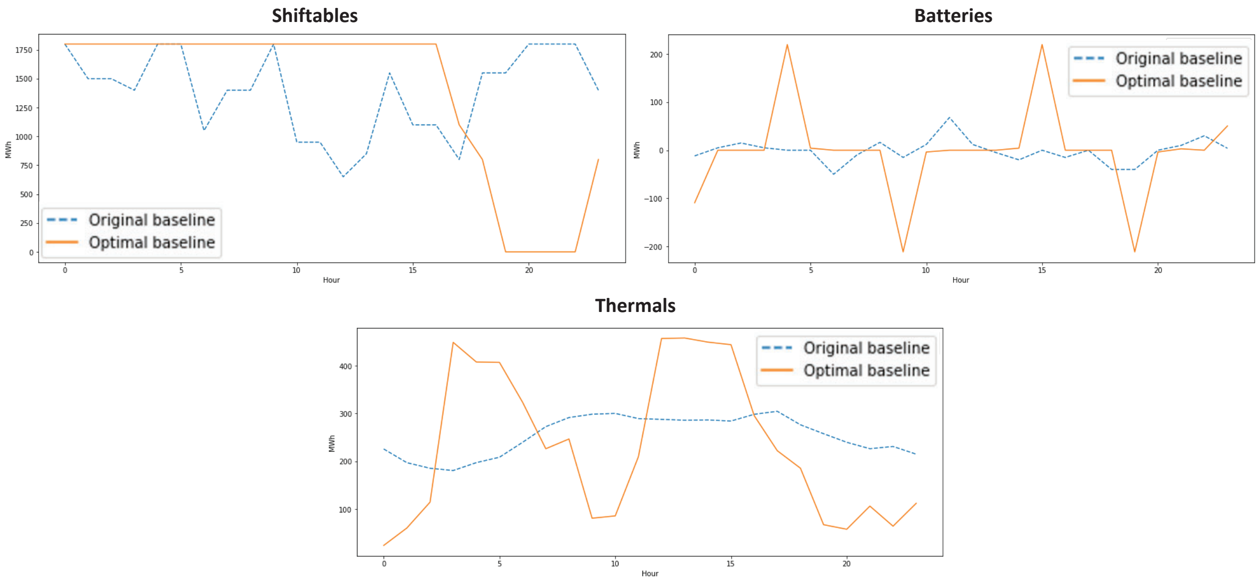

Fig. 6-14 Original and optimal baseline after intraday 1 market optimization during 2022-01-09

During 2022-02-09, differently from the previous day analyzed, the shiftable loads reduce its consumption during morning and evening high price periods, being the morning and evening price peak quite similar. The batteries have a similar behavior to the previous day. Also in this case, the battery makes four power peaks during the day, where they charge, or discharge at maximum power. These peaks coincide with the morning and evening peaks of the spot market prices. Finally, the shape of the thermal load curve is quite similar to the previous day analyzed and the consumption is concentrated during low-price hours.

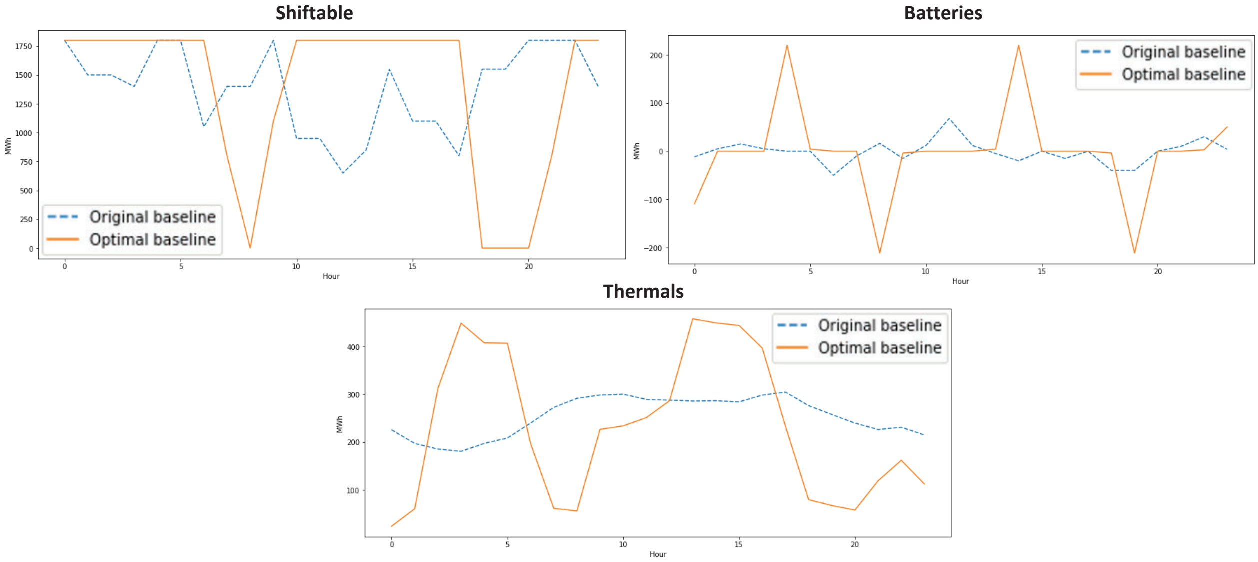

Fig. 6-15 Original and optimal baseline after intraday 1 market optimization during 2022-02-09

Table 6-12 shows the total energy shifted in the two days analyzed by type of asset. In both days, shiftable loads are the loads that shift most of the energy traded in the intraday 1 market, followed by thermal loads and batteries. The shiftable loads recover all the upward flexibility activated by the end of the day. In the case of batteries, the amount of energy moved in the two directions is almost the same, the small difference is due to charging and discharging efficiency. Depending on the baseline and on the activation a bit more or a bit less energy need to be sold in comparison to the energy bought. Finally, thermal loads, can reduce their total consumption. This is due to two reasons: from one side, when the internal temperature of the zone is lower (higher) and the thermal load is heating (cooling), thermal loses are lower. This means that reducing the consumption in a zone indirectly bring an energy saving. From the other side, the model assures the internal temperature of the thermal zone to stay between the minimum and maximum during all the time, meaning that by the end of the day the temperature will be close to the minimum or maximum temperature limit, bringing a reduction in the total consumption.

Table 6-12 Disaggregation of the cumulative bidding results

	Total Upward activated [kWh]	Total Downward activated [kWh]
	2022-01-09	
Shiftable loads	8300	8300
Batteries	634	643
Thermal loads	1750	1425
	2022-02-09	
Shiftable loads	8600	8600
Batteries	650	641
Thermal loads	1627	1397

Execution time

The average execution time and sizes of the bidding optimization model in the case study analyzed and in the case of solving the same optimization with 100 flexible assets (34 batteries, 33 thermal loads and 33 thermal loads) are described in Table 6-13. The model is scalable for an aggregator to fit the market's timeline.

Table 6-13 Sizes and average execution times of the intraday 1 bidding optimization model

	Average case study	Average with 100 assets
Continuous Variables	1373	8793
Binary Variables	888	5592
Constraints	2770	16842
Execution times [s]	0.36	6.64

6.3.4.2 Real time trading and asset management results

Cumulative offers provided and accepted

Table 6-14 shows the results of the intraday real time operations during the 12 days analyzed, using the price forecast methodology described in Annex E and the market parameter w of the continuous intraday market problem described in Section 6.3.2.3.1.1. With these conditions, it is possible to notice that the total offered tertiary reserve Up and Down during a day is inversely proportional to the average of the daily spot market price, showed in Table 6-11. This is because the expected activation price during the tertiary bidding process is always equal to the spot price $\lambda_t^{eU}, \lambda_t^{eD} = \lambda_t^{sp} \pm 16$. When the spot price is lower and there is less volatility among hours, this price incentive is higher in comparison to the same expected price difference in a day with highest prices. For this reason, the days with highest up and down flexibility offered are 2021-06-09, 2021-07-09 and 2021-08-09, with more than 30 MW offered in the market during the day.

However, the flexibility activated is not proportional to the flexibility offered. Specifically, the three days with highest flexibility offered and 2022-03-09 are the days with lower flexibility activated. This is because for a flexibility activation to happen, three conditions are necessary: to have a flexibility offer send, the SO has a flexibility need in the direction of the flexibility offered, and the price offered is higher (lower) than the marginal price of that hour in case of downward (upward) tertiary reserve. During these days, because of the low spot price, the offer sent by the aggregator was not competitive in comparison to other market participants and for this reason the aggregator was not activated. Same happened during 2022-03-09 where, although spot market prices were high, activation prices were not attractive for the aggregator. On the contrary, the days with highest volumes of flexibility activated, which are 2021-09-09, 2021-10-09 and 2022-04-09, are the days with highest average energy prices, need of flexibility from the TSO, and higher activation prices.

The continuous intraday is used to compensate the energy activated in the tertiary reserve. For this reason, since in most of the days analyzed there have been more upward activations than downward, the continuous intraday is usually used to buy energy. However, during 2022-02-09 and 2022-05-09, where most of the activation were downward, the continuous intraday is a source of benefits because the aggregator uses this market to sell electricity previously bought.

Total benefits from real time operations vary a lot among the analyzed days, ranging from 0 € during 2021-08-09 to 258 € during 2021-10-09, with an average of 92 €/day, equivalent 34 k€/year. Days with lowest benefits are, in general, days where no or very low flexibility has been provided in the tertiary reserve. However, in the case of 2021-07-09 or 2022-05-09, the low profits are also due to a too high penalization in the model for buying in the continuous intraday market that prevented the aggregator buying energy in the continuous intraday market during cheaper hours. On average, the benefits per MWh activated up or down in the tertiary reserve market is 40 €/MWh.

Table 6-14 Cumulative results in real time energy and flexibility markets*

Day	Total tertiary reserve up offered [MW]	Total tertiary reserve down offered [MW]	Total tertiary reserve up activated [MWh]	Total tertiary reserve down activated [MWh]	Total energy bought/sold continuous intraday [MWh]	Total Benefits tertiary reserve activations [€]	Total Benefits continuous intraday [€]	Total Benefits [€]
2021-06-09	17.2	14.1	0.4	0.0	-0.4	41	-34	7
2021-07-09	18.0	13.2	1.5	0.0	- 1.5	145	-132	13
2021-08-09	21.0	10.6	0.0	0.0	0.0	0	0	0
2021-09-09	17.5	6.8	8.3	0.5	-7.8	1291	-1210	90
2021-10-09	10.5	7.6	4.3	3.1	-1.3	563	- 305	258
2021-11-09	7.1	3.3	3.3	1	-2.3	506	-420	86
2021-12-09	6.0	6.5	3.0	0.5	-2.3	642	-546	96
2022-01-09	2.1	1.4	2.0	0.0	- 2.0	498	-354	144
2022-02-09	4.4	6.3	0.9	4.4	3.5	-651	795	144
2022-03-09	4.0	4.4	0.4	0.1	-0.3	163	-65	98
2022-04-09	7.2	6.1	4.5	2.5	-2	655	-489	165
2022-05-09	7.3	4.8	0.3	1.4	1.1	-166	176	10

***Negative values represent energy bought and positive values represent energy sold**
***Negative values represent costs and positive values represent benefits**

Placement of the Bids and intraday operations

Fig. 6-16 and Fig. 6-17 show the tertiary market operations. The bars represent the tertiary up (blue bar) and down (orange bar) made by the aggregator during the previous hour. The continue lines represent the hourly activation price of the tertiary up (blue continue line) and down (orange continue line) reserve of the day. Finally, the dashed lines represent the price offered by the aggregator for the tertiary up reserve (blue dashed line) and the tertiary down reserve (orange dashed line). Notice that the offered price is 0 when no offer was sent to the SO, while the activation price is 0 if there was no activation during that hour. It is worth remembering that a tertiary up offer is activated just if the SO has a flexibility need in that direction and the activation price is higher than the offered, while a tertiary down offer is activated just if the SO has a flexibility need in that direction and the activation price is lower than the price offered.

During 2022-01-09, the aggregator sent a flexibility offer during half of the hours, being activated upward for 6 hours. As shown in Fig. 6-16, during this day, up activation prices were higher than the expected by the aggregator, and for this reason all the offers sent when the SO has need of flexibility have been finally activated. During the last part of the day, despite of high up activation prices, there has not been any activation because no offer was sent. No downward activation happened because downward offers were sent when there was no need of flexibility from the SO.

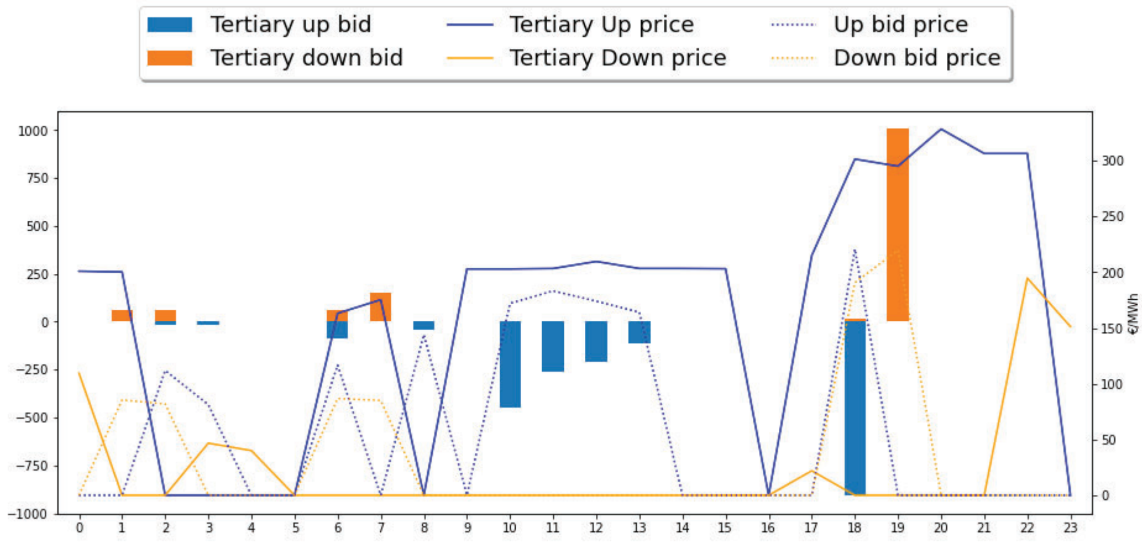

Fig. 6-16 Tertiary reserve bid and prices 2022-01-09

During 2022-02-09, the aggregator's operations are quite different from the previous day analyzed. The aggregator sent a flexibility offer for 17 hours, being activated also in this case for 6 hours. However, in this case, 5 of the 6 activations are downward. As shown in Fig. 6-17, during this day, up activation prices were a bit lower than the expected by the aggregator, and for this reason just one tertiary upward offer was finally activated. It is worth noticing as the difference between the price offered by the aggregator and the activation price was less than 5 €/MWh at hour 10 and 17. This indicates how the pricing strategy adopted by the aggregator can strongly influence the number of activations during the day. A more aggressive strategy, with lower bidding prices would imply more activations and accepting lower prices, while a more conservative strategy would bring to less activations but assure higher activation prices. Also in this case, during the last part of the day, despite of high up activation prices, there has not been any activation because no offer was sent. Regarding downward activations, offers from 7:00 to 10:00 have been activated since the offered price was higher than the activated one. Same happened at 18, where the activation price was much lower than the offered. During this operation day, it is possible to appreciate how the aggregator can provide both upward and downward flexibility to the SO during the same hour, being an important flexibility resource for the whole system.

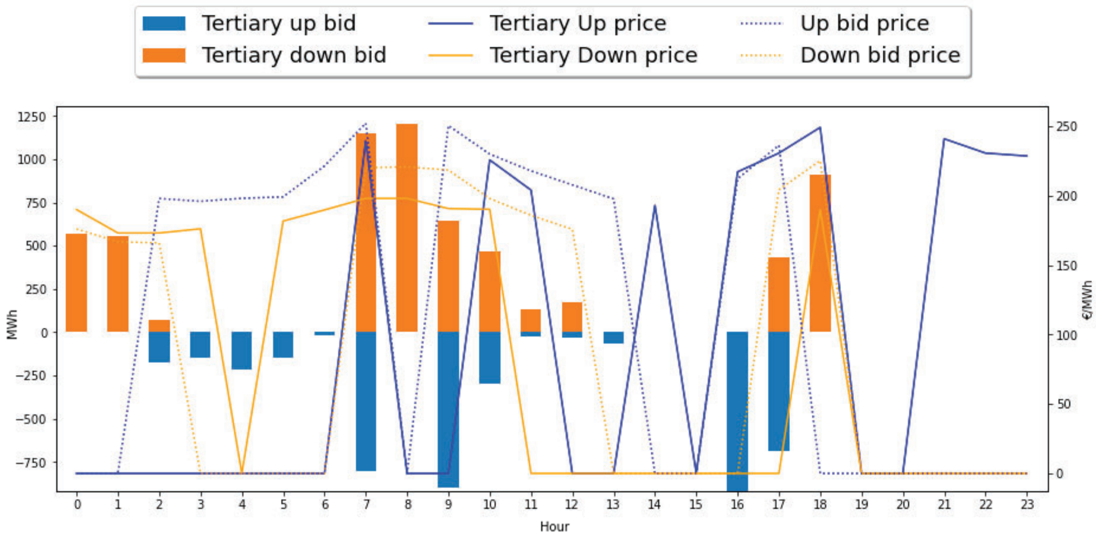

Fig. 6-17 Tertiary reserve bid and prices 2022-02-09

Fig. 6-18 and Fig. 6-19 show the real time operations on flexible assets and prices for activations in the tertiary reserve market and for buying or selling energy in the continuous intraday market. The bars show the activated flexibility from the tertiary reserve market (blue bar) and the electricity bought or sold in the continuous intraday market (orange bars). The blue line represents the upward and downward activation price of the hours where the offer of the tertiary reserve market was activated, while the orange line represents the hourly price of the continuous intraday market along the day, at the last gate closure. Negative values represent upward activations (reduce consumption), while positive values represent downward activations (increase consumption). The best strategy for the aggregator is to be able to sell upward flexibility at high prices, and recover that energy used or providing downward flexibility at a cheaper price or by buying energy at a cheaper price in the continuous intraday market.

Fig. 6-18 shows the tertiary reserve and continuous intraday market operations and prices during 2022-01-09. During this day, all flexibility activations from the tertiary market are upward activations. During the intraday market session of 14:00, the aggregator buys energy to recover the flexibility activation of hour 6:00 and part of the flexibility activation of hour 10, at a price a bit lower than the activation price of hour 10:00. The remaining part of the upwards activations happened between 10:00 and 14:00 is recovered at 17:00 hour at the price of 163 €/MWh, quite lower than the average price of the four consecutive activations, that was 204 €/MWh. In fact, at that hour the aggregator buys more energy than the energy previously activated, with the perspective to resell that energy in future intraday sessions (at 20:00, when the price was higher). This because over the different continuous intraday market sessions, prices change and a new opportunity for the aggregator appeared that was not present with the first optimization performed for the intraday 1 market. However, a new upward flexibility activation was performed at 18:00, paid at 301 €/MWh and recovered at hour 22, at a price of 219 €/MWh. Thanks to these operations, and without violate any restrictions from the flexumers, the aggregator generated 144 €.

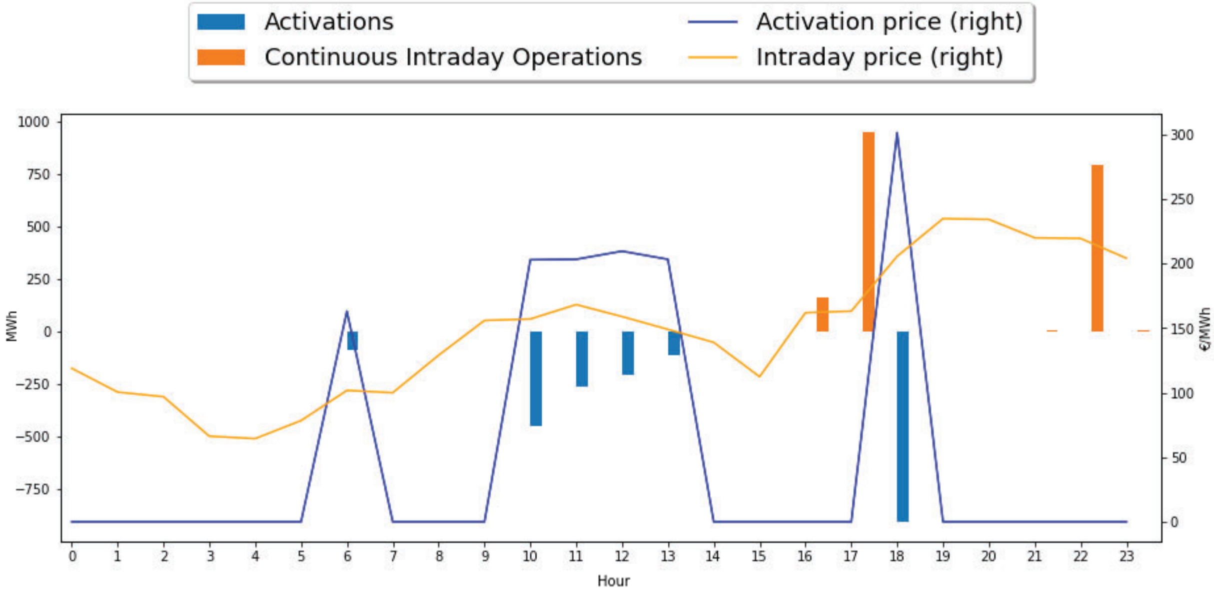

Fig. 6-18 Tertiary reserve and continuous intraday market operations and prices 2022-01-09

Fig. 6-19 shows the tertiary reserve and continuous intraday market operations and prices during 2022-02-09. The firsts daily downward activations happened between 7:00 and 10:00 hours of the morning, at an activation price between 190 and 198 €/MWh. Hour 9:00 is a perfect example of how the demand aggregator can benefit from real time operations. To compensate part of the flexibility activation at hour 7:00, at 7:30, the aggregator sells about 500 kWh at hour 9:00, at a price of about 234 €/MWh. However, at 9:00, the SO needs to increase the consumption or reduce the generation and activates downward tertiary reserve. The aggregator, that previously offered downward flexibility in the tertiary market was activated, consuming additional 600 kWh, charged at an activation price of 190 €/MWh, 44 €/MWh cheaper than the energy previously sold for the same hour.

Similarly, tertiary reserve activations in opposite directions, are a good example of how the aggregator takes advantage of the activation prices to make benefits while helping the system stability. At hour 16:00, the SO needs an increase in the generation or a decrease in the consumption. The aggregator provides almost 1 MWh of flexibility by reducing the consumption of its clients, and this service is paid at 217 €/MWh. Almost the same flexibility, but in an opposite direction was activated at hour 19:00, charged at 190 €/MWh. By the end of the day, the aggregator sold all the additional energy consumed due to the downward tertiary market activations in the continuous intraday market, at a price between 230 and 240 €/MWh, much higher than the downward activation prices.

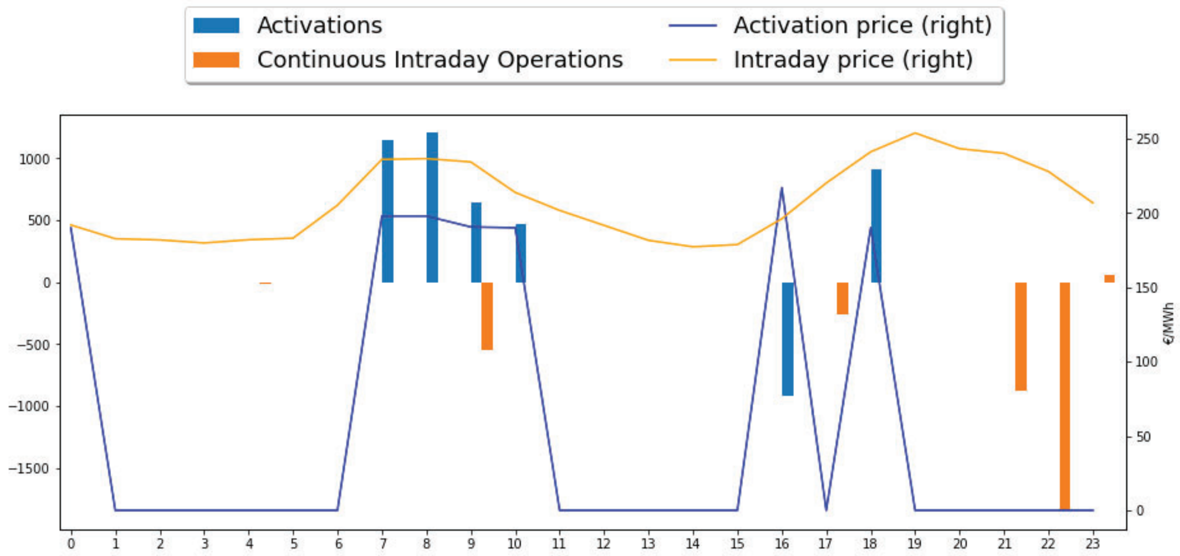

Fig. 6-19 Tertiary reserve and continuous intraday market operations and prices 2022-02-09

Real time operations on flexible assets

Fig. 6-20 and Fig. 6-21 show the optimal flexibility asset's schedule after the intraday 1 market optimization (blue dashed line) and the final consumption after real time operations in the tertiary and continuous intraday market for shiftable loads, batteries and thermal zones in the 2 days analyzed.

During 2022-01-09 real time operations, as represented in Fig. 6-20, shiftable loads contribute to the upward tertiary reserve provided at hour 10 and 11, reducing its scheduled consumption, in combination with the thermal load's consumption reduction. Thermal loads are also able to provide upward tertiary reserve at hour 12:00 and 13:00. At 17:00, the additional energy bought in the continuous intraday market by the aggregator is consumed by shiftable loads and thermals. The upward tertiary reserve at hour 18:00 was provided by thermal loads and shiftable. Finally, the energy bought by the aggregator at hour 22:00 was consumed mostly by shiftable loads to recover the upward flexibility provided to the system operator. During this day, batteries does not modify their consumption.

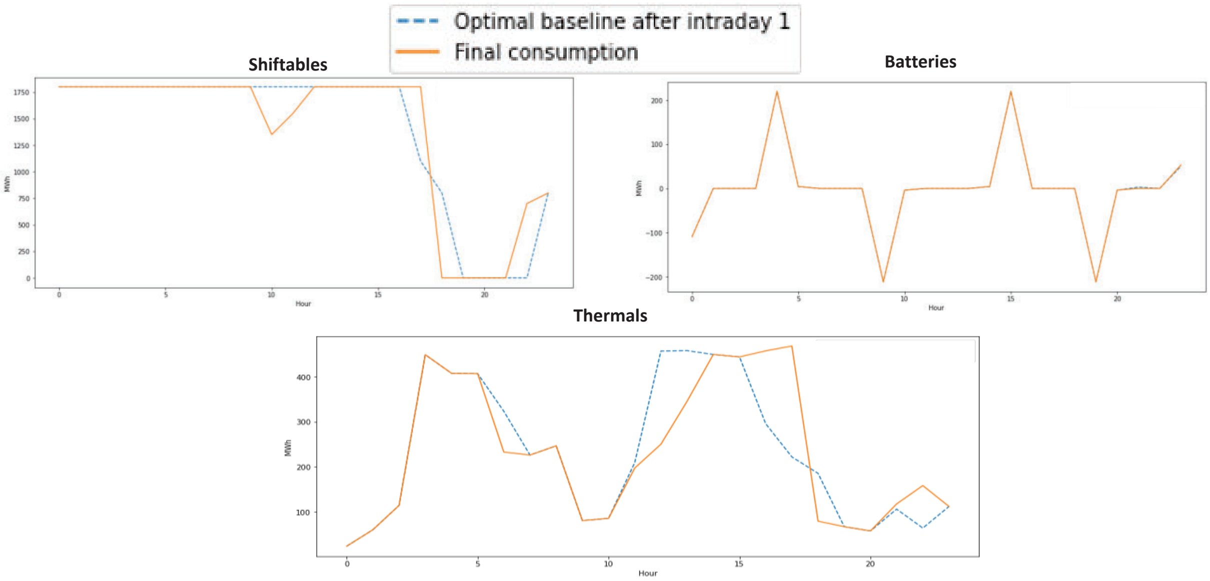

Fig. 6-20 Comparison between expected consumption after intraday 1 market optimization and final consumption during 2022-01-09

During 2022-02-09 real time operations, shiftable loads provide most of the downward tertiary reserve activated between 7:00 and 10:00, while thermal loads contribute at the activation of hour 7:00. During the downward flexibility activation of hour 9:00 and 10:00, thermal loads consume a bit less than the original schedule, although the tertiary activation was in the opposite direction. This decrease is compensated by the shiftable loads, that activate more downward flexibility to reach the desired consumption at the aggregator portfolio level. The upward flexibility provided at hour 16:00 comes mostly from shiftable loads, while a smaller part is provided by thermal loads. The energy bought at hour 17:00 by the aggregator in the continuous intraday market is consumed by the shiftable loads, that consume more energy than the schedule. However, the energy bought by the aggregator is lower than the increase in the consumption of the shiftable loads. The remaining part is compensated by the thermal load's consumption reduction. This is another example of how to aggregate different type of loads allow to self-balance the aggregator's portfolio, maximizing its benefits. The downward tertiary reserve provided at hour 18:00 was mainly provided by shiftable loads, although thermal loads contribute to the service provision too. Daily downward flexibility activations are compensated by the end of the day, at hour 21:00 and 22:00, when the aggregator sells energy in the continuous intraday market. Neither in this day batteries contribute to real time operations, although this is not the case in other days analyzed.

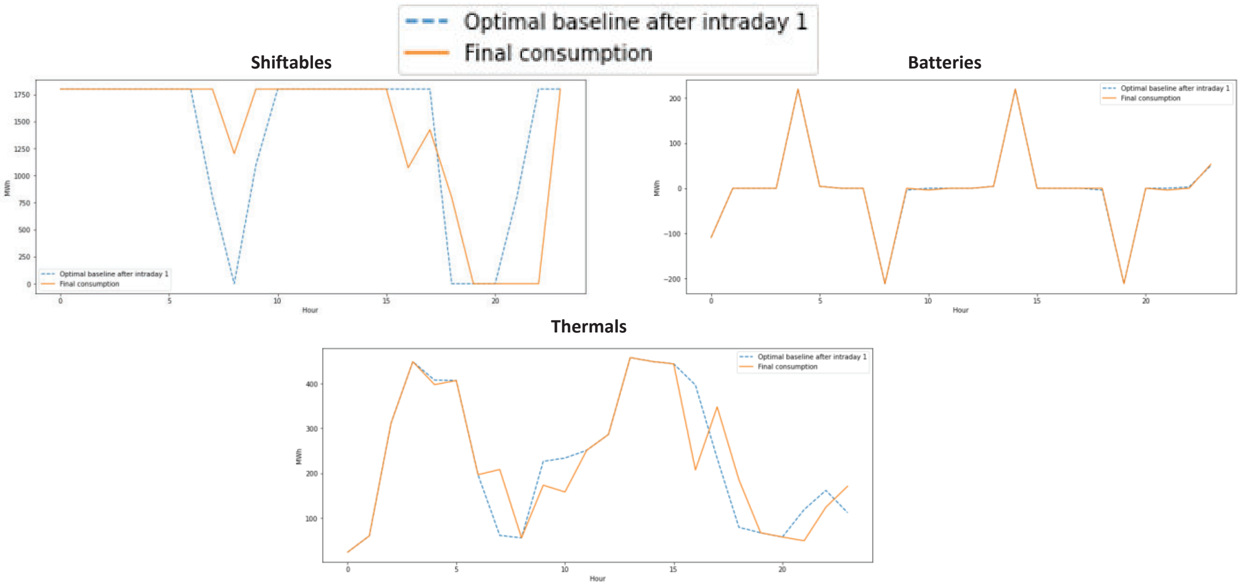

Fig. 6-21 Comparison between expected consumption after intraday 1 market optimization and final consumption during 2022-02-09

Table 6-15shows the total energy shifted in the two days analyzed by type of asset during real time operations. In both days, shiftable loads are the type of loads that activate more upward and downward flexibility, followed by thermal loads and batteries. Notice that this does not mean that shiftable loads are more flexible, since it strongly depends on the asset's characteristics, resumed in Annex E. The shiftable loads recover all the upward flexibility activated by the end of the day during 2022-02-09, while during 2022-01-09, shiftable loads consume 100 kWh less energy than the scheduled by the intraday 1 market. This because the shiftable load number 3 accepts a maximum energetic debt of 200 kWh. Also, during 2022-02-09 the energy shifted by thermal loads is more than the double than 2021-01-09. Regarding batteries, the amount of energy moved in the two directions is almost zero in the two days analyzed. Finally, thermal loads, move about 500 kWh upward and downward during the two days analyzed. Comparing these results with Table 6-12 is possible to conclude that with these market conditions, the energy shifted due to the intraday 1 market optimization is higher than the energy shifted for real time operations. This is because the flexibility asset schedule was already optimized.

Table 6-15 Disaggregation of the cumulative real time operation results

	Total Upward activated [kWh]	Total Downward activated [kWh]
	2022-01-09	
Shiftable loads	1500	1400
Batteries	3	3
Thermal loads	528	513
	2022-02-09	
Shiftable loads	3700	3700
Batteries	10	10
Thermal loads	435	427

Execution times

The average execution time and sizes of the tertiary up and down bidding optimization model, of the continuous intraday bidding optimization model and the real time optimization model in the case study analyzed and in the case of solving the same optimizations with 100 flexible assets (34 batteries, 33 thermal loads and 33 shiftable loads) are described in Table 6-16. The execution times are suitable for the market timeline. The fastest algorithm is the real time algorithm, while the slowest one is the continuous intraday bidding optimization model.

Table 6-16 Sizes and average execution times of the tertiary up and down bidding optimization model

Tertiary up and down bidding optimization model		
	Average case study	**Average with 100 assets**
Continuous Variables	629	4809
Binary Variables	324	2400
Constraints	1366	9270
Execution times [s]	1.53	36.22
Continuous intraday bidding optimization model		
	Average case study	**Average with 100 assets**
Continuous Variables	762	4822
Binary Variables	384	2432
Constraints	1475	9259
Execution times [s]	3.2	44.5
Real time optimization model		
	Average case study	**Average with 100 assets**
Continuous Variables	632	4413
Binary Variables	326	2789
Constraints	1431	8454
Execution times [s]	0.42	3.89

6.3.4.3 Settlement Results

The left part of Table 6-17 shows the settlement results of the aggregator's real time market operations in the twelve days analyzed. The right part of the table shows the settlement results of the aggregator with perfect market information, meaning that the aggregator knows in advance the continuous market price of the last market session and the activation prices of the tertiary reserve. This is not realistic, since it would not be possible to know with 100 % precision the activation prices and direction of the tertiary reserve, neither of the continuous market price. However, this gives an idea about the maximum possible benefits for the aggregator with the given market conditions. In addition, since the aggregator knows in advance continuous market prices, the penalization on the trading in the continuous intraday market w is set to 0 €/MWh.

Without perfect market information, total benefits from the intraday 1 market operations represent almost the 85 % of the total benefits, ranging from a minimum of 67 % in 2021-10-09 to a maximum of 100 % in 2021-08-09. The remaining part of benefits comes from real time market operations in energy and flexibility markets. The uncertainty on activation and continuous intraday prices reduces the benefits for the aggregator in real time operations.

The average daily total benefits in the case without perfect market information are 692 €, equal to 252 k€ with the 15 flexible assets considered. There is a wide range of benefits depending on the market and system conditions, with a maximum of 1866 € during 2022-03-09 and a minimum of 116 € during 2021-06-09. This represents an average saving in comparison to a scenario without any flexibility activation of 9 % on the aggregator's energy costs.

With perfect market information, intraday 1 market results are almost the same as in the scenario with market price's forecasts. The increase in benefits in the intraday 1 market is just 0.34 % having perfect market information, or 25 € considering the 12 days analyzed. However, in real time operations, results with perfect market information outperform the results using expected market conditions, being the total benefits from tertiary reserve and continuous market participation 3.5 times higher. Looking at total benefits, when the aggregator has perfect market information generated on average 48 % more benefits than in the case of using forecasted market data. The benefits generated represent, on average, more than 13 % of the baseline costs without flexibility activations.

Notice that penalizations are not included in the settlement results because the aggregator is able to always provide the offered tertiary reserve and respect its market position, demonstrating to be a reliable flexibility provider for the SO.

Table 6-17 Cumulative financial results for the 12 days analyzed comparing the case without perfect market information with the case with perfect market information

	Settlement results				**Settlement results with perfect information on the current intraday market session and tertiary market**			
Day	Intraday 1 benefit [€]	Tertiary Reserve benefits and costs [€]	Continuous intraday benefit and costs [€]	Total benefit [€]	Intraday 1 benefit [€]	Tertiary Reserve benefits and costs [€]	Continuous intraday benefit and costs [€]	Total benefits with perfect information [€]
2021-06-09	109	41	-34	116	111	212	-174	149
2021-07-09	159	145	-132	172	159	300	-231	228
2021-08-09	153	0	0	153	153	0	88	241
2021-09-09	222	1291	-1201	312	222	1683	-1026	879
2021-10-09	533	563	- 305	791	549	-174	1123	1498
2021-11-09	488	506	-420	574	488	217	34	740
2021-12-09	495	642	-546	591	497	1135	-786	846
2022-01-09	1397	498	-354	1541	1398	892	-473	1817
2022-02-09	596	-651	795	740	596	-298	803	1101
2022-03-09	1768	163	-65	1866	1768	-311	794	2251
2022-04-09	766	655	-489	932	769	1499	-668	1600
2022-05-09	511	-166	176	521	512	-402	855	965

***Negative values represent costs and positive values represent**

6.3.5 Final remark and conclusions

This Chapter describes five novel optimization models to support the jointly participation of an aggregator in the energy intraday and the Spanish tertiary reserve markets. First, the aggregator bids during the day ahead session in the Iberian intraday 1 market, taking advantage of the flexibility of its clients using a MILP algorithm; then, during the same day, at each hour, the aggregator decides to offer flexibility in the Spanish upward and downward tertiary reserve and in the European continuous intraday market using an MPC algorithm. Finally, when the flexibility offered in the tertiary reserve market is activated by the SO, the aggregator decides how to manage the flexible assets to deliver the desired flexibility, through an MPC. The joint market participation in a national (tertiary reserve), regional (intraday 1) and European (continuous intraday) market highlights the opportunity raising from the integrated European market, described in Section 3.1.4, and is an absolute novelty in literature up to the author knowledge.

The models proposed demonstrate that an aggregator of flexible consumers can trade in real time in multiple energy and flexibility markets, providing tertiary reserve to the grid with 100 % reliability and with important economic benefits. In addition, for the first time up to the author knowledge, this Chapter presents a strategy for a demand aggregator participating in intraday energy market and tertiary reserve participation reproducing all the market technical requirements, including gate closure times, available information at each step and real market price and activations. By doing so, the concept of “frozen”, “planning” and “decision” time step in the models is introduced to respect the different gate closures and horizons of the markets where the aggregator is participating.

Another novelty of this work is to propose a methodology to include the participation of shiftable loads, batteries, and thermal loads in the same portfolio, being able to respect all the conditions imposed by the asset owners. In addition, a new methodology is proposed for the participation of thermal loads, whom only possible control is an on/off signal to distinguish this type of loads to modulable thermal loads. However, include this type of loads with the current methodology makes the model non-linear.

From the settlement results of the 12 days analyzed, on average, the participation in the intraday 1 market represents almost the 85 % of the total aggregator's benefits. This means that using flexibility to minimize costs participating in the intraday 1 market (implicit demand response) untaps most of the economic potential of flexibility, with the current Spanish market conditions. The remaining part of benefits is related to the participation in the tertiary up and down reserve and the continuous intraday market (explicit demand response). This result is interesting if related to the possible aggregator's business models presented in Section 2.3.3, since only an aggregator-retailer could actively participate in the intraday 1 market. However, in the case all the flexibility available would have been traded in the tertiary reserve market without previously optimize the consumption's schedule depending on energy prices, benefits from tertiary market reserve would be higher than the case presented. This scenario could be analyzed in the future.

From the results, it is highlighted that intraday 1 market benefits mostly depend on two factors: average daily energy prices and volatility. Average daily energy prices mainly affect the absolute savings reached by the aggregator, while the daily market volatility directly affects the percentual savings reached. This fact reinforces the importance for consumers to be able to adapt their consumption in energy crisis times and in contexts with high renewable penetrations, such as the current time. This because during energy crisis times, the energy prices are higher than usual, while with high renewable penetrations, prices are more volatiles, due to the volatility of renewables [169]. In addition, the difference between having perfect market information and using the simplest forecasting algorithm described in Annex E is just 0.34 %, meaning that an aggregator should not focus in improving the price forecasting algorithm of the intraday 1 market to boost its benefits from the market.

The aggregator does not receive any penalization from the system operator in the 12 days analyzed, since it is able to always respect the flexibility activations from tertiary reserve and its position in the energy markets. This is possible thanks to the jointly participation in energy and flexibility markets in real time, that allow to always adjust the aggregator position. This, respecting all the different real markets' characteristics, times, and prices. This is a great improvement from the Iria work, which was the reference in the field, that reached a reliability of 63 % in the delivery of the tertiary reserve, due to the fact that in the work proposed by Iria the aggregator offered just once during the day ahead in the energy and tertiary reserve market [170].

Compared with the scenario where the aggregator has absolute perfect market information, on average, total gains are 48 % higher than in the scenario without perfect market information. When looking just on real time operations (tertiary + continuous intraday), gains are 3.5 times higher than in the scenario proposed. This means that there is room for improvement for the aggregator real time strategy. From one side, in the future, a sensitivity analysis on the parameter introduced in the model to penalize the bought or sell of energy in the continuous intraday market w, should be performed to find the best trade-off. Then, the activation price forecasting algorithm (described in Annex E), out of the scope of this thesis, should be improved to keep into account the hourly market conditions instead of assuming a flat price difference in comparison to the spot market price, disregarding any external factor. In this way, the aggregator would be able to adapt its offers to the daily conditions.

Furthermore, the model could be extended to include new types of assets such as electric vehicles and include additional random events, such as that a flexible asset suddenly does not behave as expected, to analyze the effect of not expected events on the technical reliability of the aggregator and analyze how this would affect economically the business model of the aggregator. Further research could include stochasticity on the activation price to analyze the economical improvements to include it and the costs in terms of execution times.

Finally, execution times of the models analyzed demonstrate the scalability of the model, and the possibility for the aggregator to allow the simultaneous participation of hundreds of assets, by respecting the market timelines and asset's restrictions.

Chapter 7 - Conclusions and Future Research

This Chapter summarizes the main contributions of this thesis and identifies possible research paths for future work.

7.1 Main contributions

The objective of the thesis consisted in facilitating the integration of flexible demand-side resources in the energy system throughout a new market actor: the Demand Aggregator. The DA will become an important figure that will empower consumers, giving them the possibility to participate in electricity markets, saving money and helping the transition toward a 100 % renewable energy system. Since DA are new actors in the European electricity market, the research contributions presented next are an important step towards making demand aggregation a reality in Europe. Hereafter the summary of the main contributions of the thesis are presented, following the objectives proposed in Section 1.

1) ***To analyze critically the European electricity markets' regulation scheme to find main enablers to reinforce and barriers to remove to unlock the full demand-side flexibility potential in Europe.***

The first contribution, in Section 2 is conceptual and consists in presenting different possible business models for demand aggregation, with its dependencies and implications on the specific country electricity market regulation, the grade of automation of the solution developed and the cost and revenue structure of the aggregator. The two main categories of business models individuated and presented are the independent aggregator and the aggregator as energy retailer.

After that, in Section 3, an analysis on the current electricity market design in Europe is performed, comparing four countries: UK, Finland, France and Spain. The analysis was necessary to deeply understand the market mechanisms that directly affect the aggregator's participation in energy and flexibility markets, described in Chapter 6, and resulted directly in three practical contributions:

- Barriers and enablers were classified in three groups: regulatory, technical, and economical and the link among them was analyzed. The main regulatory barrier consists in the not recognition of the figure of the independent aggregator and the unclear relationship with other market participants, especially with the consumer's retailer. The main technical barriers in the markets analyzed consist in a too high minimum bid size to allow participation of distributed flexibility resources and the prequalification process done at the asset level. Main economic barriers consist in a too high upfront cost for the hardware needed to participate in balancing markets for distributed demand-side resources.
- The analysis of the four balancing markets, highlights the need to harmonize rules to reach a common European electricity market. At the same time, it highlights that even the most mature markets in Europe in terms of demand response still present important barriers for consumer's participation.

2) ***To propose and analyze new statistical techniques that well adapt to forecast electricity consumption.***

Although literature is plenty of papers analyzing the performance of different machine learning algorithms on different type of datasets, performing meta-analysis on these studies is challenging as they adopted different granularity on the response, as well as different number of available variables and error metrics. For these reasons, Section 4 proposes a new methodology to compare the performance of three different algorithms (Time Series Factor Analysis, Kernel Regression and k-Nearest Neighbors) not only based on accuracy measures, but also keeping into account the computational time, the number of variables needed and the impact of the data set size. The main contributions are:

- The methodology proposed allows to determine the best model for each consumption type and user's objective.
- For the first time, Time Series Factor Analysis is proposed for energy consumption's prediction of buildings.
- Kernel Regression has shown to be the most robust method in terms of accuracy among all the presented.
- k-Nearest Neighbors and Time Series Factor Analysis have fast computational time, while Kernel Regression can be up to 2000 times slower. This can strongly influence the decision of the aggregator to opt for a k-Nearest Neighbors algorithm, that performs close to the Kernel Regression in terms of accuracy.
- Kernel Regression significantly improve the prediction accuracy when more variables are available, while k-Nearest Neighbors improves moderately.
- Kernel Regression is the one the best fits on smaller data sets while k-Nearest Neighbors and Time Series Factor Analysis clearly reduce their performances when less data is available.

3) To develop a new modeling for different type of flexibility assets able to keep into account their rebound effect.

Section 5 presents how to identify flexibility assets within a consumption site, how to quantify the flexibility available during the day ahead and how to model flexible assets to allow their participation in energy and balancing markets, keeping into account their rebound effect. The modeling of flexible assets proposed in this Chapter is the one used in Section 6 and allow the aggregator to optimize the flexibility offer of different type of assets in multiple flexibility markets. The main contributions of the Chapter are:

- New concepts are introduced for the modelling of thermal loads (T^{flex}), batteries (D_t^{aux} and U_t^{aux}) and shiftable load (E^s) to keep into account the rebound effect of the flexible assets, essential for their correct market participation.
- For the first time, different flexible assets are compared depending on their characteristics to evaluate their fit in balancing markets. The comparison shows that none of the asset is ideal and each of them presents some barrier and best fit in a specific type of market.

4) To propose an optimization model for the DA bidding strategy in the Spanish secondary electricity market including demand side resources and develop the model to manage their participation in the market during real time operations.

The literature review performed in Section 6 shows that while several approaches have been proposed for the usage of different demand-side resources for selected market-based services, there is still a need for the consideration of heterogeneous resource groups for cascaded services. This Chapter describes two novel optimization models to support the participation of an aggregator in the secondary reserve markets. The first methodology, presented in Section 6.2 consists of a MILP model to define band bids for the day-ahead secondary reserve market. The second algorithm is a MPC to dispatch the operation of the flexible resources in real time. The main contributions of the Chapter are:

- For the first time up to the author knowledge, this Chapter presents a strategy for demand aggregator's secondary reserve participation respecting all the market technical requirements, including execution times and available information at each step for the Iberian Market.
- To maximize its benefits, the aggregator offers secondary reserve in hours with highest expected capacity prices and with lower energy prices.
- The model developed reaches a reliability in the secondary reserve delivered is about 70 %. However, the band not correctly delivered is due to economic reasons and not for a lack of the reserve available.
- From the analysis performed, knowing the real secondary activation price in advance without knowing the activation rate would not benefit the aggregator, while knowing in advance the activation rate would increase the aggregator benefits.
- The aggregator's economic performance improvements considering perfect is between 7 and 37 % in the days analyzed. These results highlight the robustness of the method proposed.
- PV panels are not a good candidate to deliver secondary reserve in an economic way. To curtail PV production is not beneficial for the aggregator neither in the bidding process, neither in real time operations.
- In the days with low band price, the aggregator performed worst in terms of reliability, since it is not incentivized to avoid penalizations.

5) To propose an optimization model for the DA bidding strategy in short – term electricity markets and develop the model to manage demand side flexibility resources in real time.

Section 6.3 describes the modelling of a cascade MPC for participation in continuous energy and tertiary reserve markets considering real time control to allow the participation shiftable and thermal loads, and stationary batteries in those markets. The main contributions are:

- For the first time, the Chapter describes five novel optimization models to support the jointly participation of a demand aggregator in the energy intraday and the Spanish tertiary reserve markets. First, the aggregator bids during the day ahead session in the Iberian intraday 1 market, using a MILP algorithm; then, at each hour, the aggregator decides to offer flexibility in the Spanish upward and downward tertiary reserve and in the European continuous intraday market using an MPC algorithm. Finally, when the flexibility offered in the tertiary reserve market is activated by the SO, the aggregator decides how to manage the flexible assets to deliver the desired flexibility, through an MPC.
- The models proposed demonstrate that an aggregator of flexible consumers can trade in real time in multiple energy and flexibility markets, providing tertiary reserve to the grid with 100 % reliability and with important economic benefits.
- The concept of "frozen", "planning" and "decision" time step in the models is introduced to respect all the market technical requirements and information available at each time step, including the market's gate closure periods and allowed bidding periods of the markets where the aggregator is participating.
- Another novelty of this work is to propose a methodology to include the participation of shiftable loads, batteries, and thermal loads in the same portfolio, being able to respect all the conditions imposed by the asset owners.

- Intraday 1 market benefits mostly depend on two factors: average daily energy prices and volatility. Average daily energy prices mainly affect the absolute savings reached by the aggregator, while the daily market volatility mainly influences the percentage savings. In addition, the economical difference between having perfect market information and using a simple forecasting algorithm is just 0.34 % in this market.
- With perfect market information, on average, total gains are 48 % higher than in the scenario without perfect market information, due to higher benefits in the tertiary and continuous intraday market.

6) ***To develop a DA execution tool able to combine all the functionalities developed in a unique platform.***

Probably, the main contribution of this thesis is to have developed the knowledge and the algorithms to make demand aggregation a reality. The author of this thesis, with its thesis director, funded in 2020 Bamboo Energy, a spin-off of the Catalan Energy Research Institute (IREC) created precisely to enable the provision of flexibility from the demand. The company offers a scalable and versatile platform for independent aggregators and retailers to efficiently manage distributed energy resources. The platform is based on a combination of cutting-edge technologies and uses Machine Learning for predicting the flexibility of the client portfolio and market conditions, robust mathematical modeling, and combinatorial optimization algorithms for the optimal management of electricity demand.

Now, the company counts on 15 employees and manages more than 10 MW of demand side flexibility in a full automatized way, being the first company in Spain to effectively operate demand side flexibility.

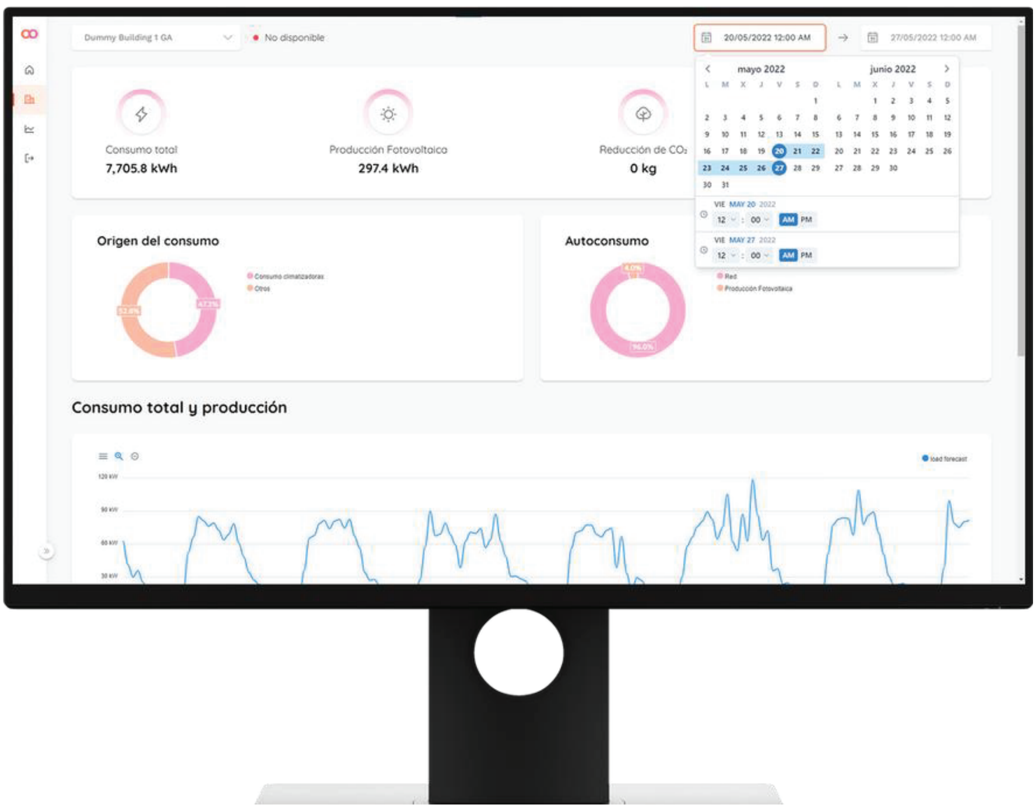

Fig. 7-1 Snapshot of the Bamboo Energy platform

7.2 Further research

Optimal DA's strategy is a relatively new field, which means there is still much further research to perform to cover all the aspects related to it. Following the objectives stated in Chapter 1, the main research topics to work on are:

1) ***To analyze critically the European electricity markets' regulation scheme to find main enablers to reinforce and barriers to remove to unlock the full demand-side flexibility potential in Europe.***
- Section 3 analyzes and compare 4 European balancing markets. This analysis can be extended to other European and non-European countries to enlarge the scope of the analysis.
- The analysis of the balancing market design itself is far from completed, considering its complexity, the effect of other design variables, such as unbalance price formation, connectivity and hardware requirements, and aspects related to the market operation should be further analyzed to understand the reliability for a demand aggregator to participate in these markets.
- Demand aggregators can potentially participate in a multitude of different markets, besides energy and balancing markets. The analysis per country could be extended to include non-balancing markets such as voltage control markets, local markets, energy markets, capacity mechanisms, network tariffs and direct incentives for demand response.

2) ***To propose and analyze new statistical techniques that well adapt to forecast electricity consumption.***
- Section 4 compares the performance of three statistical methods on four different types of consumption. The comparison should be extended, including more data sets in the comparison.
- Similarly, the analysis should be extended to other algorithms, such as NN, Support Vector machine, deep learning algorithms or grey-box models.
- Further research can focus in improving the Time Series Factor Analysis algorithm. To use a non-parametric model, e.g., NN, for the factor's prediction could help to include more weather variables in the model and finally improve the model's accuracy.
- Study how to reduce the computational time of the kernel regression. With the objective of working on the scalability of the algorithm, the author suggests analyzing the possibility to cluster similar consumption types and use the trained algorithm to predict consumptions with a similar behavior.
- Improve the accuracy of the k-Nearest Neighborhoods by assigning a specific weight to each variable. The weight should be optimized during the training within the other parameters.
- Include new external variables and analyze its impacts on the algorithm's performances.

3) ***To develop a new modeling for different type of flexibility assets able to keep into account their rebound effect.***
- Section 5 presents the modeling for shiftable loads, batteries, thermal loads, and curtailable loads. New types of flexible assets can be modeled, such as electric vehicles or water treatment plants.
- Analyze and validate with experimental data on field the rebound effect and the efficiency of a demand response activation on the different assets.
- When enough data are available, explore new ways for forecasting flexibility using black box models.
- Keep into account degradation costs due to flexibility activation in the asset modeling.
- Linearize of on/off thermal loads model.

4) ***To propose an optimization model for the DA bidding strategy in the Spanish secondary electricity market including demand side resources and develop the model to manage their participation in the market during real time operations***

- To implement a stochastic model that keeps into account the stochasticity of the flexibility's activation direction. This new implementation could be compared with the one proposed in this thesis considering economic benefits and computational costs.
- Future research can focus in analyze the performance of the algorithm with millions of assets managed. Increasing the portfolio's size to millions of assets may increase the execution times making them unsuitable for the market timeline. Further research can focus in developing approaches to reduce the size of the optimization problems.
- Include new assets such as electric vehicles in the model.
- In this thesis energy market sessions are excluded from the scope of the model. The day ahead market session is assumed to fix the baseline for the aggregator. The scope of the model can be extended to enable the participation of the aggregator in day ahead market first, considering its impact on the next secondary reserve market session. In addition, if the models would also consider the aggregator's participation in the continuous intraday market, it would allow the aggregator to buy and sell energy in real time instead of paying or charge its unbalances, increasing benefits
- Further research could focus in improving the algorithms used to predict capacity and energy prices and activated volume and analyze their impact on the aggregator's profits. Although the activated volume forecast looks like the most difficult to predict and at the same time the variable with the biggest impact in the aggregator's decision. An initial work to predict flexibility activation prices can be found in Annex B, based on the work performed during the internship in the framework of this thesis.
- A sensitivity analysis on the risk factor parameter should be performed to find the right tradeoff between the risk aversion strategy and the economic optimization.

5) ***To propose an optimization model for the DA bidding strategy in short – term electricity markets and develop the model to manage demand side flexibility resources in real time.***

Recommendations for the previous objective regarding extending the model to new flexible assets, implement a stochastic model to analyze the performance's improvements, improve the scalability of the model and consider the joint participation in energy markets and secondary and tertiary reserve are valid also for this objective. The specific recommendations for short – term electricity markets are:

- Make a sensitivity analysis to find the best strategy to fix the parameter introduced in the model to penalize the bought or sell of energy in the continuous intraday market.
- The activation price forecasting algorithm should be improved to keep into account the hourly market conditions instead of assuming a flat price difference in comparison to the spot market price.
- To include non-controllable loads in the aggregator's portfolio considering consumption's forecast errors on this loads and include additional random events, such as that a flexible asset suddenly does not behave as expected, with the objective to analyze the effect of not expected events on the technical reliability of the aggregator and analyze how this would affect economically the business model of the aggregator.

Annexes

8.1 Annex A: Case Study Data secondary reserve

This appendix Section presents the case study data used to test the optimization algorithms described in Section 6.2. Two different sets of data are described:
A-1 – flexumer's information;
A-2 – electricity market information.

A-1 – Flexumers Information

Three types of flexumers information are considered: thermal load parameters; battery parameters and and photovoltaic generation.

A-1.1 – Thermal load Parameters

The thermal load parameters represent the physical and operational characteristics of the thermal zones, as described in Section 5.3.1
Table 8-1 shows the thermal zone parameters calculated by the training model described in Section 5.3.1.2 from 5 different data set.

Table 8-1 Thermal zones' estimated parameters participating in the secondary reserve market

	Thermal Resistance $\left[\circ\frac{C}{kW}\right]$	Capacitance $[kWh/°C]$
Zone 1	3	70
Zone 2	5	280
Zone 3	1.9	35
Zone 4	5	200
Zone 5	2	35

Table 8-2 shows the fixed or configured parameters of the five thermal loads analyzed. are:

Table 8-2 Fixed or configured parameters of the five thermal loads analyzed

	$T^{min}$and T^{Max} $[°C]$	P^{max} $[kW]$	$Mode$	*COP*
Zone 1	[-3; 3]	40	Heating	3.5
Zone 2	[-2;2]	200	Cooling	3.5
Zone 3	[-4;4]	32	Cooling	3.5
Zone 4	[-5;5]	150	Heating	3.5
Zone 5	[-2;2]	60	Heating	3.5

Regarding the $type$ of the thermal load, just direct power controllable thermal loads can participate in the secondary reserve market.

Fig. 8-1 shows the forecasted power consumption of the thermal loads ϕ_h using the methods described in Section 4.

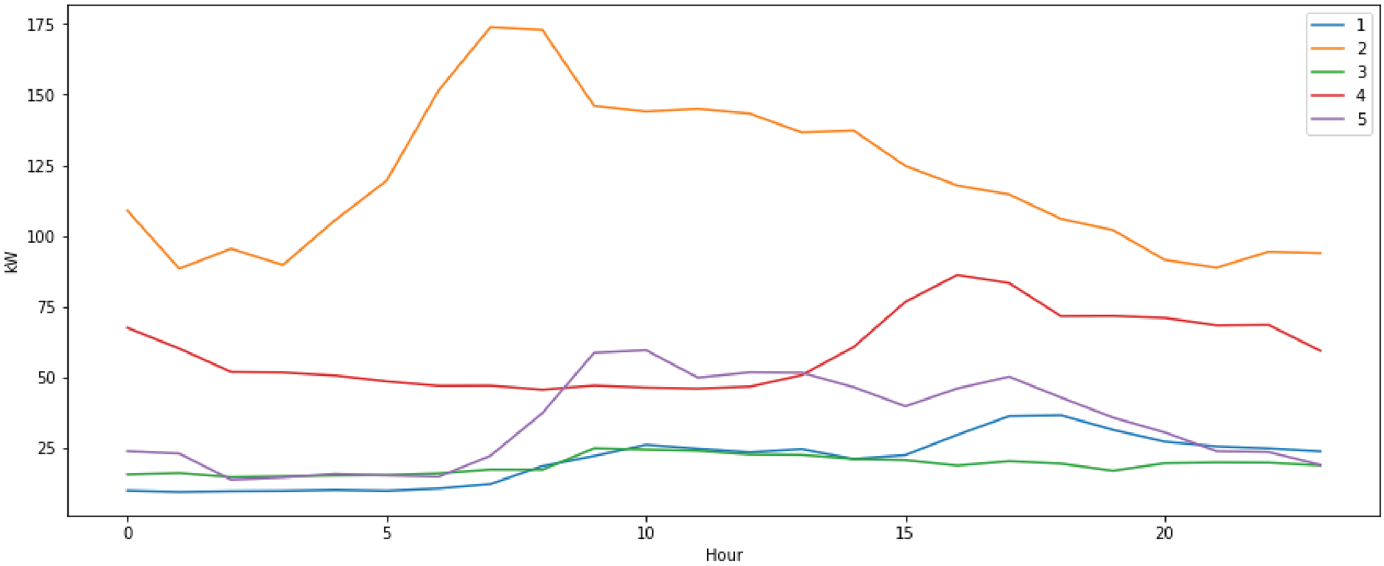

Fig. 8-1 Heating or cooling electric power provided by the five thermal loads participating in the secondary reserve market

A-1.2 – Battery Parameters

The battery parameters represent the physical and operational characteristics of the batteries, as described in Section 5.3.2.

Table 8-3 shows the fixed or configured parameters of the five batteries participating in the secondary reserve market.

Table 8-3 Fixed or configured parameters of the five batteries participating in the secondary reserve market

	E^b [kWh]	$SOC^m, SOC0$ and SOC^M [%]	P^{Mc} and P^{Md} [kW]	η^c and η^d [%]
Battery 1	50	[0.2, 0.5, 0.8]	50	0.98
Battery 2	70	[0.2, 0.5, 0.85]	70	0.98
Battery 3	40	[0.2, 0.5, 0.9]	39	0.98
Battery 4	100	[0.2, 0.5, 0.9]	40	0.98
Battery 5	30	[0.2, 0.5, 0.8]	90	0.98

In the case analyzed, the batteries are reserved for secondary market participation, indeed its baseline is equal to 0 during all hours.

A-1.3 – PV Parameters

Fig. 8-2 shows the forecasted power generation of the PV power plant pv participating in the secondary reserve market.

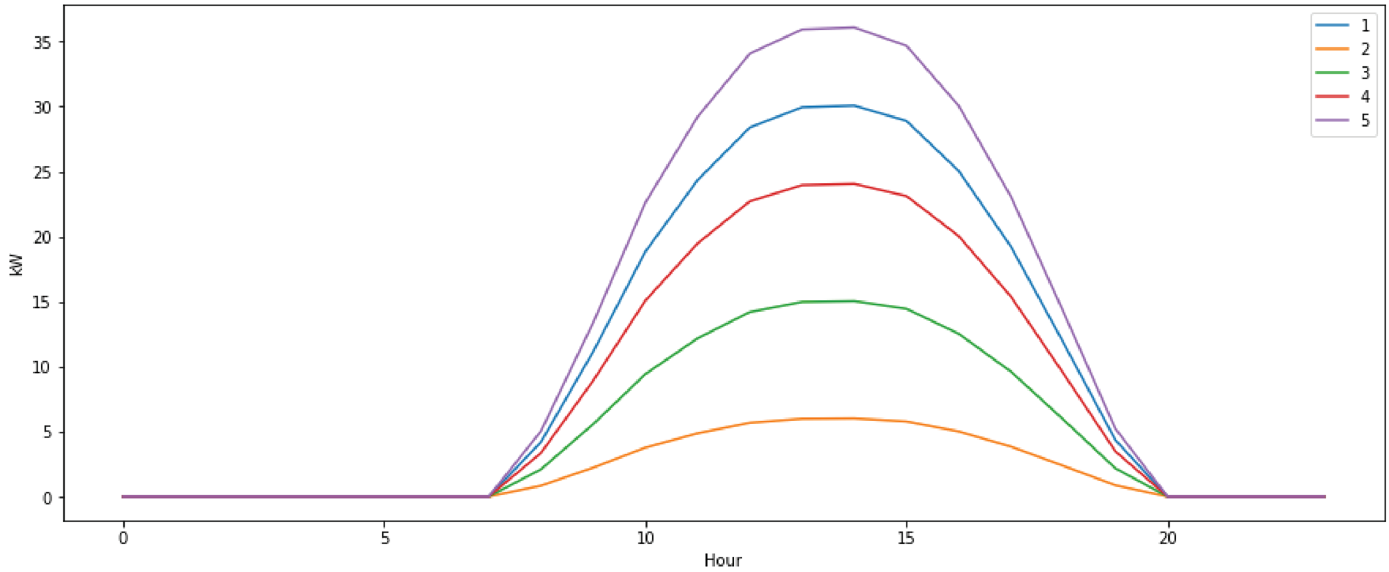

Fig. 8-2 Forecasted power generation of the PV power plants participating in the secondary reserve market

A-2 – Electricity market Information

The market information used by the aggregator is available at the ESIOS web page [165], which collects information from the Spanish's energy market operator OMIE and the Spanish TSO's REE.

A-2.1 Activation prices

The participation of the aggregator in the energy and flexibility markets requires the forecasting of the unbalance and flexibility activation prices, which are directly correlated, as showed in Table 6-2.

In the day ahead stage, the aggregator forecasts the upward and downward activation prices. The algorithm to forecast flexibility activation prices is out of the scope of this thesis. To demonstrate the reliability of the methods proposed the aggregator of the case study analyzed uses the average difference between the activation prices λ_t^{eU}, λ_t^{eD} and the spot market price λ_t^{sp} to forecast the activation price. Typically, $\lambda_t^{eU} \geq \lambda_t^{sp} \geq \lambda_t^{eD}$. During 2021, the average price difference between activation and spot prices was 16 €/MWh. Table 8-4 shows the average error during the days analyzed. There is margin of improvements in the day ahead activation price forecast.

Table 8-4 Performance metrics of imbalance prices from May '21 to May '22

	MAPE [%]	CV(RMSE) [%]
Upward activation price λ_t^{eU}	26	21
Downward activation price λ_t^{eD}	23	19

A-2.2 – Secondary activation ratio and band prices

The participation of the aggregator in the secondary reserve markets requires the day ahead forecast of the upward and downward flexibility activated and band price

The algorithm to forecast flexibility activation ratio ($\rho_t = \rho_t^{+} - \rho_t^{-}$) and the band price λ_t^{b} is out of the scope of this thesis. To demonstrate the reliability of the method proposed, the aggregator of the case study analyzed uses the hourly average activation band ratio and band price from the last year, showed in Table 8-5.

Table 8-5 Average activation up and down percentage and band price per hour

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
ρ_t [%]	-6	16	12	14	7	-5	-26	-21	-22	-36	-33	-20	-8	-2	-3	-9	-15	-12	-26	-20	-10	-10	-27	-26
λ_t^b [€/MW]	31	32	30	31	32	38	40	29	22	25	31	36	38	39	39	41	46	44	40	29	21	17	23	33

Table 8-6 shows the average error during the days analyzed. The performance on the band price is acceptable, while there is margin for improvements in the activation ratio forecast.

Table 8-6 Performance metrics of activation ratio and band prices in the day analyzed

	MAPE [%]	CV(RMSE) [%]
Activation ratio ρ_t [%]	60	60
Band price λ_t^b [€/MW]	14	18

8.2 Annex B: Detection of spike imbalance prices in the French electricity market using machine learning methods

Introduction

Electricity price is a key factor in determining short-term operating schedules and bidding strategies in competitive electricity markets for retailers, Balance Responsible Parties and Aggregators [171]. Existing literature mostly focuses on day ahead electricity prices' forecast for the spot market, but traditional price forecasting techniques show poor performance in handling price spikes [172]. On the other hand, imbalance markets have not yet been deeply explored, although, due to the entrance of even more renewable plants in the electricity system, they are expected to take more importance in the next future.

In the French Balancing Market (BM), FSPs are paid as bid, which means that the price at which they offer their flexibility is the same at which they are paid in case of activation, worth nothing the marginal price reached. For this reason, if FSPs can accurately forecast spike prices, they could boost their benefits in this markets and better schedule their bids in different electricity markets.

In [173] Cartea et al. proposed an interesting method that include seasonality and capacity constrains to identify the weeks of the year when price spikes are more likely to occur in the UK spot market. It was found that the relation between the national demand forecast, and the forecasted generation capacity is the variable that best explains spike prices. In [174] Christensen et al. used an Autoregressive Conditional Hazard (ACH) to forecast the one-step-ahead probability of a price spike in the Australian Spot market. Abnormal loads were found to have a significant impact on the probability of a price spike and on the severity of the spike.

The approach to forecasting spot and BM prices is necessarily different. While spot prices are fixed on a day ahead basis, BM prices are fixed closer to real time, and they strongly depend on fortuitous events. For example, an accidental downtime of a generation plant or a sudden reduction in the production from wind power plants could cause a spike in BM prices. In addition, few actors participate in these markets, their strategy therefore having a strong influence on the final price. For all these reasons, forecasting high prices in BM may prove particularly challenging.

In [175] Shao et al. proposed a Support Vector Machine with Recursive Feature Elimination (SVM-RFE) to classify energy prices in the Ontario real-time joint energy and reserve electricity market during the day ahead in low, medium and high prices. In [176] Klæboe et al. compared time series models to predict BM prices in Norway. They concluded that it is not possible to predict the BM price appropriately during the day-ahead, as it is designed to handle unforeseen events and fluctuations. Also Dimoulkas et al. in [177] tried to forecast Nordic day-ahead BM prices using Hidden Markov Models (HMM), failing to give good results.

This study proposes a new day-ahead classification method to detect winter spike prices occurrences in the French BM using an ensemble of Support Vector Machine (SVM), Random Forest (RF) and Extreme Gradient Boosting (XgBoost).

Following Sections are organized as follows: Section II describes the study case and the forecasting methods used in the study, Section III presents the results achieved. Conclusions and final remarks are presented in the last Section.

Methodology

This Section presents the case study and the models used. All the model were developed using the CARET package from the R software environment [178].

Case Study

The objective of the study is to predict if during day *D* there will be a spike price in the French BM using the information published by RTE [179], the French Transportation System Operator (TSO), until 18:00 h of *D-1*. Data from January 2017 to December 2018 are used to train the models, which are tested over 2019. In this study only winter months are considered, e.g. from October to March, as this is the period where most of spike prices occur.

The threshold to determine if a price is considered a spike or not is 150 €/MWh, which represents quartile 95 of the half-hour prices. The role of BM in France are: to reestablish the equilibrium between demand and production in the national grid, to solve local congestions, to reconstitute the system ancillary reserves and to reconstitute the margins when the demand is too high in respect to the production capacity installed.

All data for hour *t* and day *D* are gathered from the RTE web page and they are all public. In the study we use the spot price *SP(t)*, the forecast of the load *L(t)* and of the renewable production *RP(t)*, the total import capacity *IC(t)* and the total commercial exchange *CE(t)*, the weekly available hydraulic stock *HS*, the unavailability *UN(t)* communicated by the power plants to RTE for the next day and the total available production of the French electricity system *TAP(t)*.

Apart from this direct information, the models use other calculated variables. The Reserve Margin (RM) is calculated as:

$$RM(t) = TAP(t) + RP(t) + IC(t) - L(t) - CE(t) \quad (1)$$

The models also use the percentage RM, calculates as

$$RM_{per}(t) = \frac{RM(t)}{L(t)} \quad (2)$$

And the Delta, which represents the difference of the RM between two consecutive days.

$$Delta(t) = RM(t,D) - RM(t,D-1) \quad (3)$$

Input variables for the daily classification are the daily maximum *SP*, *L*, *RP* and *Delta,* the daily minimum *RM* and *RM_per,* the *HS,* the month and the type of day considered.

Support Vector Machines with Radial Basis Function Kernel

Support Vector Machine (SVM) was firstly introduced in [180]. It can be applied to a variety of areas, including classification and regression. The idea is to map the input vectors into some high dimensional feature space *Z* through some non-linear mapping chosen a priori. Support vector learning consists in finding a hyperplane that separates positive from negative classes in a high-dimensional space with the largest margin. The margin of a hyperplane is defined as the shortest distance between the positive and negative instances that are closest to the hyperplane. If the data cannot be clearly separated by a hyperplane, it is possible to introduce a slack variables ξ_i that relaxes the assumption of linear separability. Equation (4) describes the problem in case of nonlinear separable classes.

$$\begin{cases} w * x_i + b \geq 1 - \xi_i & y_i = 1 \\ w * x_i + b \leq -1 - \xi_i & y_i = -1 \\ \xi_i \geq 0 & \end{cases} \qquad (4)$$

Where *w* is the normal to the hyperplane, *b/||w||* is the perpendicular distance from the hyperplane to the origin and *||w||* is the Euclidean norm of *w*.

The objective function to minimize is represented in (5), subject to constrains in (4).

$$\text{Min} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{m} \xi_i \qquad (5)$$

The cost coefficient *C>0* gives the weight to the misclassification penalty. It is based on the structural risk optimization, so the objective is to minimize an upper bound of the generalization error consisting of the sum of the training error and a confidence level. For this reason, SVM is considered more generalized than other machine learning algorithms that keep into account just the training error [181].

The SVM presented by Vapnik in 1998 [182] consists of two principal components: the kernel and the optimization algorithm. The kernel is used to reduce the dimension of the problem, passing from high dimensional data to one-dimension data linearly separable. In general the Radial Basis Function (RBF) kernel is a reasonable first choice [183]. The RBF on two input vectors x_1 and x_2 has the form of (6):

$$\mathrm{K}(x1, x2) = e^{-\Upsilon\|x1 - x2\|^2} \qquad (6)$$

The goal is to optimize the two parameters *C* and *ϒ* so that the classifier can accurately predict unknown data. In order to handle the unbalance among the two classes of the classification problem, the SMOTE algorithm [184] was used. The general idea of the method is to artificially generate new examples of the minority class using the nearest neighbors of these cases.

Random Forest

Decision trees have been largely used in the past. The recent revival is due to the discovery that the ensemble of slightly different trees tends to increase generalization and provide better results on unseen data. The concept of random forest was introduced in [185] and is a combination of randomized decision trees predictors.

A decision tree is a hierarchical structure of connected nodes. During testing, a split node applies a test to the input data and sends it to the appropriate child. The process is repeated until a leaf, or terminal node, is reached. Training a decision tree means sending all the training data *v* into the tree and optimize the parameters of the split nodes to minimize a certain cost function.

At each node it is necessary to decide on what variable to split. First, it is necessary to choose the best split for a given variable. For node *τ*, *p(k| τ)* is the probability that an observation *x* is in class *k* given that it falls in node *τ*. Equation (7) is defined as the information function for node τ, that is the entropy function.

$$i(\tau) = -\sum_{i=1}^{k} p(k|\tau) \log \mathrm{p}(\mathrm{k}|\tau) \qquad (7)$$

Now suppose that at node *τ* we apply a split *s* that sends a proportion p_L of the observations to the left child-node τ_L and the proportion p_R of the observations to the right child-node τ_R, *I(s,τ)* indicates the “goodness of split” or, equivalently, the reduction of impurity gained in the split (8).

$$I(s, \tau) = i(\tau) - p_L\, i(\tau_L) - p_R\, i(\tau_R) \qquad (8)$$

The best possible split is the one with the largest value of *I(s,τ)*.

In order to grow a tree, the "goodness of split" rule is applied to the root node for each variable and the best split *s* is the one with the largest value. We repeat the same with the right and left child node, considering just the observations that fall into each node until arrive at the last partitioning. The most typical stopping rule is to declare a node to be terminal if it fails to be larger than a critical size n_{min}.

Single trees can easily be over fitted over the training set. The great advantage of RF is to grow randomly different trees, which allows to increase the accuracy and the robustness. Randomness is injected into the trees during the training phase. There are two principal methods used to create randomness, that can be used at the same time. The first one consists in train each tree with randomly different observations from the training set, the other one is to use different variables to train the trees.

The output of the random forest $\hat{y}_{rf}$ composed of B trees is given by (9), where $\hat{y}_b$ is the output of a single tree.

$$\hat{y}_{rf}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{y}_b(x) \qquad (9)$$

The parameters that the algorithm optimizes though a grid search are the number of variables taken into account in each tree and the minimum size of the node n_{min}. In order to handle the unbalance among the two classes of the classification problem, a weight inversely proportional to the number of examples belonging to that class is assigned to each class.

XgBoost

In 2016, it was presented a new gradient boosting machine algorithm, called XgBoost in [186]. The method was proved to have performances that outreached conventional algorithms, being the winning algorithm of most machine learning competitions [187]. XgBoost is a new classification tree-boosting method. Predictions are made from weak classifiers that constantly improve over the previous classification problem. Incorrectly classified samples receive higher weights at the next step, forcing the classifier to focus on their performance in the following iterations.

In general, a tree ensemble model uses *K* addictive functions *f(x)* to predict the output, as represented in (10).

$$\hat{y}_i(x) = \sum_{k=1}^{k} f_k(x) \qquad (10)$$

Each f_k corresponds to an independent tree structure *q* and leaf weights *w*. To build the *k* functions *f* used in the model, the algorithm minimizes the regularized objective $\mathcal{L}(\Phi)$, represented in (11).

$$\mathcal{L}(\Phi) = \sum_i \mathfrak{l}(\hat{y}_i, y_i) + \sum_k \Omega\ (f_k) \qquad (11)$$

Where

$$\Omega(f_k) = \Upsilon T + \frac{1}{2}\lambda \|w\|^2. \qquad (12)$$

Here l is a differentiable convex loss function that measures the difference between the prediction $\hat{y}_i$ and the target y_i. The second term Ω penalizes the complexity of the model and avoids overfitting. T represents the number of leaves in the tree and w is the leaf weight. Υ and λ are arbitrary cost parameters.

Equation (8) includes functions as parameters that cannot be optimized using traditional optimization methods in Euclidean space. Instead, the Gradient tree boosting is trained in an additive manner. Let $\hat{y}_i^{(t)}$ be the prediction of the *i-th* instance at the *t-th* iteration and we add f_t to minimize (13).

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} \text{l}\left(y_i, \widehat{y_i^{(t-1)}} + f_t(x_i)\right) + \Omega(f_t) \qquad (13)$$

f_t is the function that most improve the model according to (11). In [186] an interested reader can find further details on the method used.

Here the parameters optimize through a grid search are the learning rate, the minimum loss reduction required to make a further partition on a leaf node, the maximum depth of a tree, the minimum number of instances in a leaf and the ratio of training data used to train one tree. As in the case of RF, to handle the unbalance among the two classes of the classification problem, a weight inversely proportional to the number of examples belonging to that class is assigned to each class.

Proposed ensemble method

In order to improve the robustness of the forecasts and to reduce false positives, this study proposes an ensemble of the different methods. This means that we train the three methods already presented, we make three different forecasts and we put them together. Only in the case in which the three methods forecasted a spike price, the algorithm predicts a spike price for the next day.

Evaluation measures

After testing the statistical methods proposed, it is necessary to evaluate the results in order to compare the different methods. The Mean Percentage Classification Error (*MPCE*) is one of the most used metrics in classification problems. $MPCE(\%) = 100*(N_{mc}/N_{tot})$, where N_{mc} is the number of misclassifications and N_{tot} is the total number of classification instances. The true positive rate (*TPR*), which is represented as TPR (%) = 100*(TP/ N_{sp}), where TP represents the number of spikes correctly classified and N_{sp} represents the total number of spikes, is used to evaluate ability of the model to detect spike prices. The precision (*P*), calculated as $P\ (\%) = 100\ *(TP/PS)$, where *PS* represent the number of predicted spikes, gives an indication about the reliability of the model.

Finally, in order to better represent the objective of the forecast, which is to capture the days with the highest economic value in the BM, an economic indicator is introduced. The Economic Value Captured (EVC_x) is calculated by summing the price of all the half hours with a price over the *x* threshold in the days in which the algorithm predicted a spike. For example, the EVC_{150} would be calculated as:

$$EVC_{150}(\%) = 100 * \sum_{D=1}^{D} \sum_{t=1}^{48} \frac{\widehat{y_D} * y_{D,t,150} * P_{D,t}}{y_{D,t,150} * P_{D,t}}$$

Where D is the number of days considered in the testing set, t = {1,..48} represents the daily half hours, $\hat{y}_D$ takes value 1 if the model predicts a spike and 0 if not, $y_{D,t,150}$ takes value equal to 1 if the price is higher than 150 €/MWh at time *t* and day *D* and 0 if not and $P_{D,t}$ is the actual value of the BM price at time *t* and day *D*. In the study the EVC_{150} and EVC_{300} are considered.

Results and discussion

Fig. 8-3 shows the confusion matrix of the four methods proposed over the 2019 data set. The numbers over the principal diagonal represent the well predicted observations; on the top left there are the well predicted spikes (true positives) while on the bottom right of the matrix there are that days in which the model predicted that no spike would occur and no spike occurred (true negative). The wrong predictions are represented in the secondary diagonal; on the top right there that days in which the model predicted a spike but no spike occurred (false positive) while on the bottom left of the diagonal there are the days in which a spike occurred but the model did not predict a spike (false negative).

SVM

37	**37**
21	**74**

RF

28	**23**
30	**88**

Xgboost

31	**22**
27	**89**

Ensemble

27	**10**
31	**101**

Fig. 8-3 Confusion matrix of the methods proposed

Note that the objective of the study is to propose a reliable method to detect winter spike prices in the French BM over the next day, for this reason different evaluation metrics are proposed. For reliable method the authors understand that false positives need to be minimized, still capturing the maximum economic value and true positives. Table 8-7 shows the results over the 2019 data set.

Table 8-7 Errors per method proposed

	SVM	RF	XgBoost	Ensemble
MPCE (%)	66	89	71	**76**
TPR (%)	**64**	48	53	47
P (%)	50	55	58	**73**
EVC_{150}(%)	**89**	85	86	85
EVC_{300}(%)	**99**	98	98	98

Regarding MPCE (%), the model that best performs is the Ensemble model. This is due to the fact that it is more conservative than other models (as it predicts a spike just if all the other methods predict a spike). The SVM is the one that worst performs in this metric, because it predicts a lot of false positives, i.e. spike predictions which reveled to not be a spike. However, this metric alone cannot give a realistic evaluation of the model, as also a model that predict all no-spike days would reach an MPCE (%) of 76, as during the 76 % of 2019 winter days no spike prices in the BM occured.

Regarding the TPR (%), which represents the ratio between the corrected predicted spikes over the total, the model that best performs is the SVM. This is due to the fact that SVM is the method that predict most spikes, giving also a lot of false positives. The method that correctly predicts less spikes is the ensemble model, closed to XgBoost and RF. This is because the ensemble will predict spike price just in the case in which the three methods predict a spike.

However, when looking at the P (%), it is yet the ensemble method the one who performs better, and with difference. The value of 73 means that almost three over four spike predictions reveled to be effectively a spike, which is a good result in terms of reliability of the method. The other methods have a P (%) value which ranges between 50 and 58, which means that just a half of the predicted spikes reveled effectively to be a spike.

In addition, when looking deeper in the results, all the false positives given by the ensemble method are days which are right before or right after a spike day. This means that probably there were all the market conditions to have a spike price, but real time events did not bring to a BM spike price.

Looking at the economic results, the tree methods perform similar. Regarding the EV_{150} (%), the SVM is able to capture the 89 % of the economic value considering prices over 150 €/MWh, followed by the XgBoost, which captures the 86 % of the total value and the RF which captures the 85 % of the value, as well the Ensemble method. Note that although the SVM correctly predicted the 64 % of spikes against the 47 % of the Ensemble method, there is an economic difference of just 4 %. This means that all the spike days correctly predicted by the SVM and not correctly predicted by the Ensemble method are days with a low total number of hours with a price over 150 €/MWh.

The conclusions are yet more evident looking at the EV_{300}. Looking at this parameter, all the models perform almost the same, with the SVM that is able to capture 1 % more of value in respect to the other methods proposed when considering prices over the threshold of 300 €/MWh. In this case, all the models are able to capture the great majority of the economic value, which means that prices squeeze when there is a stressed situation in the electric system that can be already predicted during the day ahead.

Conclusions and further research

Electricity price spike forecast in balancing markets is of vital importance for electricity market participants in a competitive environment. This study proposes a Support Vector Machine, a Random Forest, an Extreme Gradient Boosting and an Ensemble of the three to predict if during the next day a spike price will occur in the French Balancing market. Although the difficulties to predict during the day ahead balancing market prices due to the market nature, which strongly depends on real-time events, the methods proposed show good results. Including external variables as the Reserve Margin, the forecasted load and the Spot price proved to substantially increase the prediction compared to the other few studies focused on predicting balancing market prices such as [176] and [177], which adopted a time series approach.

The ensemble method proposed is the most reliable among the methods proposed, as three out of four spike predictions are correct and it is able to capture more than the 85 % of the economic value among 2019, using data from 2017 and 2018 as training data set.

Further research will focus in forecasting spike prices during the morning and the evening peak, instead of a daily forecast, to improve the precision of the method. Further research could also focus in predicting the maximum price for the next day instead of classifying the price depending on a threshold. Finally, these predictions could be incorporated in a decision-making tool for market arbitration used by market participants to optimize their bids in different electricity markets.

8.3 Annex C: Battery Electric Buses Participation in Electricity Markets and Power Systems

Introduction

The electrification of the transport sector is a central EU strategy to address climate change and tackle air pollution in cites [188]. However, this transition brings significant challenges for the power system, such as growth in peak system load, system imbalances, local network congestions and voltage deviations [189]. To address such challenges, different strategies have been proposed to optimize EV charging schedules to achieve peak shaving and load reprofiling [190,191]. EVs can also be considered as a crucial source of active flexibility to increase the share of renewables and to provide ancillary services to the grid. This opportunity requires a new market actor, called Demand Aggregator (DA), that can aggregate the demand of different consumers and sell their flexibility to Transportation (TSO) and Distribution System Operators (DSO) and Balancing Responsible Parties [192].

To date, research in this area has focused on electric cars, whilst limited attention have been paid to the electrification of public transport vehicles. Yet, city bus systems across Europe are undergoing a process of rapid electrification, with many major EU cities committed to only procure zero-emission buses from 2025 [193]. Whilst a number of studies have explored the technical, economic and operational implications of BEBs [194–196], the effects of charging BEBs on the power system, along with the opportunities to optimize charging schedules and extract flexibility, are not well understood.

Due to the specific characteristics of city bus systems – such as high daily mileages, deterministic behavior and centralized overnight parking – BEBs are likely to have distinct implications for the power system compared to electric cars. Another key consideration is the choice in design of the BEB charging system, of which two main approaches exist [197]:

- Overnight charging: based on BEBs with large onboard battery capable of supporting all day operation, so that bus charging only happens overnight at the depot.
- Opportunity charging: consists of BEBs with a smaller onboard battery, which receive regular charges whilst in operation, utilizing high power chargers installed at bus stops and line terminals. In addition, BEBs receive a small overnight charge at the depot.

In [198], the authors simulate load profiles from overnight bus charging at eight depots in Hamburg. The study indicated potential need for a high voltage connection to meet peak charging load at one depot. In another study [199], researchers use a Monte Carlo simulation to predict the load profiles at an opportunity charging stations on a major bus line in Bogota. During rush-hour it was found that a typical stop had a load factors of 0.27 and would require a 300 kW transformer. However, these studies did not investigate the economic implications of different bus charging approaches nor flexibility potential.

The objective of the study is to explore opportunities for BEB fleets to implement charging strategies in order to reduce peak load at the bus depot, reduce electricity purchase costs and generate income by providing Demand Response (DR) services via a DA. Both overnight and opportunity charging systems are considered in order to compare the two approaches. Whilst the study is motivated by BEB deployment plans in Barcelona, the outcomes from this work are mostly generalized and relevant to any BEB system planner.

Methodology

Economic Analysis

In this study, the DA is the figure in charge of optimizing the consumption of its portfolio, taking advantage of the load's flexibility. Consumers can offer two types of Demand Side Flexibility (DSF) [24]: Implicit or Explicit.

Implicit or "price-based" DSF: Energy prices depend on the hour in which the energy is consumed. The tariff considered has separate charges for energy consumption and the peak power supplied during each period, as represented in Table 8-8. Benefits can be reached by shifting consumption from high to low price periods or by reducing the power peak.

Table 8-8 Summer tariff rates for Spain

	Hour	Power Charge [€/kW/day]	Energy Charge [€/kWh]
Period 1	11-15 h	0.140	0.122
Period 2	8-11 h + 15-24 h	0.084	0.105
Period 3	0-8 h	0.056	0.070

Explicit or "incentive driven" DSF: Usually this flexibility is traded and managed in different energy markets by a DA. In this study, the French TSO balancing mechanism called "Complementary reserve" is taken as reference [200], since DA cannot participate in balancing markets in Spain. However, Europe is currently harmonizing balancing markets, so the model presented is easily adaptable to other European markets. The main technical requirements to participate in the balancing service and typical payments in the market considered are presented in Table 8-9.

Table 8-9 Specification of Complementary Reserve Market

Max. number activations	Duration of delivery	Availability Payment [€/MW/h]	Utilization Payment [€/MWh]
2/day	1.5 h	2.2	50

The DA gains income in this market through availability and utilization payments. Availability payments are paid for make flexibility available to the TSO, whilst utilization payments are paid only when upward or downward flexibility is activated [29].

Electric buses would be well suited to provide this service, as they are able to provide flexibility for at least 1.5 hours with a notification time of 30 minutes. Regarding the maximum number of activations, it is important to remember that the bus fleet is integrated in a larger DA portfolio that is able to respect all technical requirements thanks to other flexibility sources.

In this study, we assume that all flexibility from bus charging is made available to the market to maximize availability payment income, whilst activation of this flexibility occurs randomly once a day for a one-hour duration.

BEB Operation and Charging Profiles

The model consists of a fleet of 100 BEBs, has a resolution of one hour and runs for a period of one day. Daily bus schedule is based on all-day operation, with buses leaving the depot in the morning and returning in the evening. The bus schedule was created following a Gaussian distribution to generate diversity, with each bus leaving the depot at a start time with mean 06:00h and standard deviation of 1 hour. The duration of operation for each bus is generated in the same way, with mean of 16 h and standard deviation 1 hour. Times are rounded to the nearest hour to reflect the resolution of the model. Fig. 8-4 shows the fleet operation profile generated.

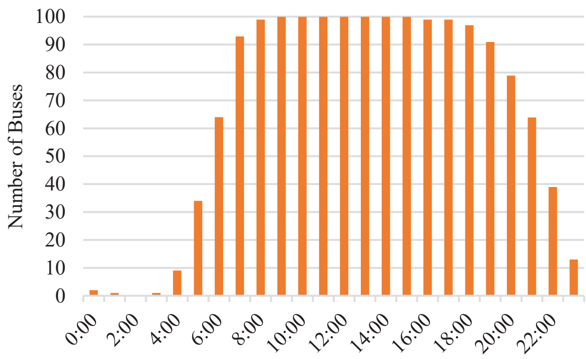

Fig. 8-4 Operational profile of BEB fleet

Energy consumption from bus driving is assumed to be 20 kWh for every hour of operation. This is equivalent to a bus driving at an average speed of 10km/h and consuming 2 kWh per kilometer [7]. The longest duration of operation for a bus in the fleet is 19 hours, which corresponds to a daily energy consumption of 380 kWh. This figure is consistent with current battery capacity and weight limits for BEBs. When each BEBs returns to the depot in the evening it is fully charged before it is scheduled to leave the next day.

Three overnight charging scenarios are tested based on different charging algorithms:

- Immediate charge (IC): supplies each connected bus at maximum power (75 kW) from the moment they arrive at the depot until fully charged.
- Continuous charge (CC): supplies power at a continuous rate from the moment a bus returns to the depot until it is next used.
- Off-peak charge (OC): supplies buses at maximum power from the beginning of the off-peak period (Period 3). If insufficient energy can be supplied during the off-peak period, then charge is also supplied at a continuous rate during other periods.

In addition to overnight charging, an opportunity charging (OPP) scenario is also proposed. In this scenario, each bus receives 15 kWh charge for every hour it is in operation. This is equivalent to 3 minutes' charge per hour using a 300 kW fast charger. Buses also continue to receive a small overnight charge at the depot (based on the IC charging algorithm) in order to balance their daily energy consumption. These characteristics reflects the real-life operating requirements of opportunity charging systems, which utilize slow depot charging to improve the health and longevity of the battery.

Peak power consumption at the depot and for opportunity chargers is evaluated to assess the potential impact for the distribution grid and calculate tariff charges for power capacity. For depot charging, power is supplied at constant rate for each hour so peak power during each tariff period is captured within the resolution of the model.

However, to reflect the peak power of fast opportunity chargers, a different approach is required. To do this an assumption is made that a single 300 kW fast charger is able to support the operation of 5 BEBs, so 20 fast chargers are required to support the operation of the entire fleet during peak hours. This figure is in line with the load factor of opportunity charging infrastructure simulated in Bogota in [199]. We assume that total power capacity for all opportunity chargers (6 MW) must be contracted over all tariff periods to reliably meet the operational requirements of the fleet.

BEB Flexibility

Opportunity charging is generally not considered as a source of flexibility due to the operational constraints associated with fast charging on bus lines. In contrast, overnight depot charging profiles may deliberately deviate from the baseline load profile in order to provide DR services through a DA.

Upward flexibility is provided by reducing power consumption below the baseline load profile, whilst downward flexibility is provided by increasing power consumption. The flexibility offers that can be made in the market are limited by the following three constraints, which capture the key technical and operational requirements of the BEB system:

- Charge power must be between 0 and 75 kW.
- Battery SOC cannot exceed 100%.
- Buses must be able to fully-recover the energy deficit caused by a single one-hour duration flexibility activation before it next leaves the depot. In other words, it must be possible to achieve a fully charged battery during the same night.

Results and discussion

Overnight Charging

Fig. 8-5, Fig. 8-6 and Fig. 8-7 show the baseline depot charging load profiles and upwards and downward flexibility offers of the fleet under the three different overnight charging scenarios. It can be seen that the IC load profile has a peak of 5.8 MW and charge is supplied mostly during late evening and first few hours of the morning. In contrast, the CC load profiles is smoother with peak power of 4.0 MW and a greater proportion of charging occurs during off-peak hours in the early hours of the morning. On the other hand, the OC scenario has the greatest peak of 7.5 MW, which is equivalent to all 100 of the 75 kW chargers supplying their rated power simultaneously. Although the OC algorithm requires the greatest power connections at the depot, since this consumption only occurs during the off-peak period the impact on the distribution network could be less significant than the IC case.

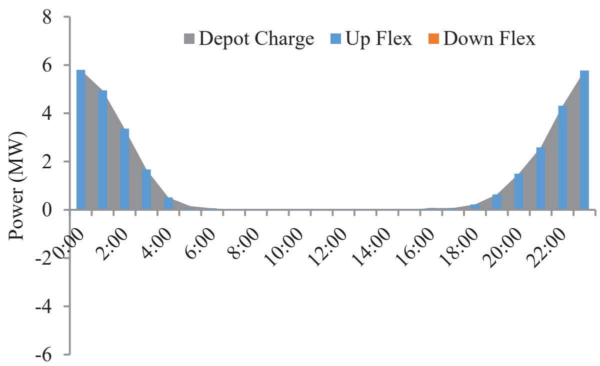

Fig. 8-5 Immediate charge (IC) depot load profile and flexibility offers

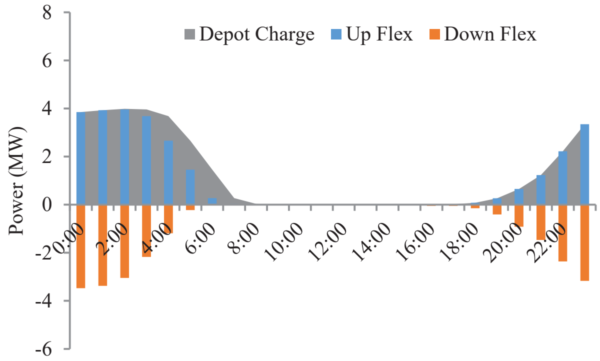

Fig. 8-6 Continuous charge (CC) depot load profile and flexibility offers

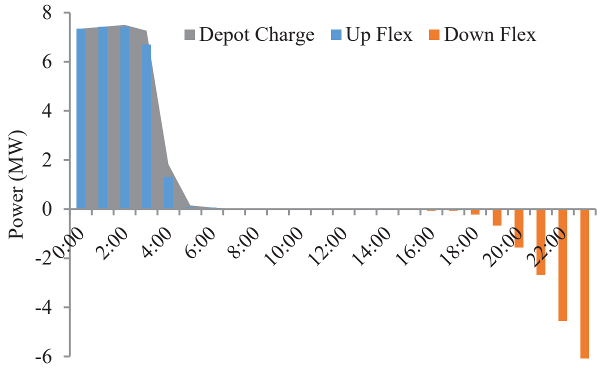

Fig. 8-7 Off-peak charge (OC) depot load profile and flexibility offers

There is also significant contrast between the flexibility offers of each charging algorithm. IC can only offer upward flexibility since buses are either charging at maximum power or battery SOC has already reached 100%. In contrast, CC can provide upward and downward flexibility simultaneously throughout the period when buses are charging. This is because charging typically occurs at a medium power so there is always the possibility for both upwards and downward modulation. OC can also offer both upward and downward flexibility but cannot be offered simultaneously. This is because before the off-peak period begins the chargers can be switch on early and during the off-peak period chargers can only turned down.

Opportunity Charging

Fig. 8-8 shows the depot load profile and flexibility for the OPP scenario. Peak load at the depot is significantly reduced to 2.0 MW. This is caused by diversity in bus arrival times combined with reduced charging period: all buses take a maximum of 2 hours to reach full charge and therefore there is less coincidence in charging schedules.

Regarding flexibility offers in an OPP scenario, there is a reduction in upward flexibility of 75% compared with the IC scenario, caused by a decrease in the charging load, which diminishes the potential for curtailing load to offer upward flexibility. Downward flexibility remains at zero, which is explained by the same phenomenon as the IC scenario.

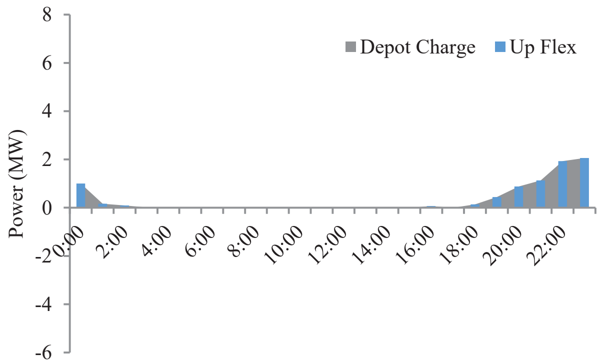

Fig. 8-8 Opportunity charge (OPP) depot load profile and flexibility offers

The peak power at depot and opportunity chargers, along with flexibility offers for all four scenarios are summarized in Table 8-10.

Table 8-10 Comparison between overnight and opportunity charging

	IC	CC	OC	OPP
Depot Charge Peak (MW)	5.8	4.0	7.5	2.0

Opportunity Charge Peak (MW)	0	0	0	6.0
Upward Flexibility (MWh)	32	27	30	8
Downward Flexibility (MWh)	0	22	16	0

Although opportunity charging reduces capacity requirements at the depot, fast charging on the lines requires a significant additional capacity, equivalent to 6.0 MW. Since opportunity charging is more likely to take place closer to urban centers, accessing grid capacity for this charging infrastructure will likely pose a greater challenge to most cities compared with depot charging, which tend to be situated in more industrial outskirts.

8.3.1.1 Economic Analysis – Electricity Purchase

The average cost of electricity purchasing for all four scenarios is shown in Fig. 8-9, which take into account both energy and power charges from the tariff in Table 8-7.

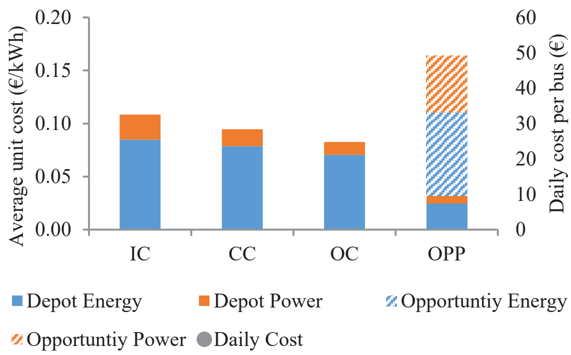

Fig. 8-9 Average unit costs (bars) and daily costs per bus (points)

For the overnight charge scenarios, the IC algorithm has the highest cost (0.108 €/kWh, or 34 €/day). This is due to a significant proportion of charging taking place in the late evening before the off-peak price period begins, along with high power charges due to a relatively high peak. The CC scenario achieves a reduced costs (0.095 €/kWh, or 30 €/day) equivalent to a saving of 13%, due to a smoother load curve and more off-peak charging. The OC scenario performs best, with an average electricity purchase cost of 0.083 €/kWh, or 26 €/day, a 24% saving on the IC case. This is despite having the highest peak, since capacity charges are lower during off-peak hours.

Opportunity charging stands out as being significantly more expensive (0.164 €/kWh, or 52 €/day) compared to all overnight charging scenarios, equivalent to double the OC scenario. The major contributing factor to this is power charges associated with opportunity charging, which represent over a third of electricity purchase costs.

The cost of electricity under the OPP scenario is highly sensitive to the number of buses that can share a single opportunity charger, assumed to be 5 above. To represent this sensitivity, Fig. 8-10 shows how the cost of electricity increases steeply when a single opportunity charger, whist only small benefits are gained above 5 BEBs per charger, serves only one or two BEBs.

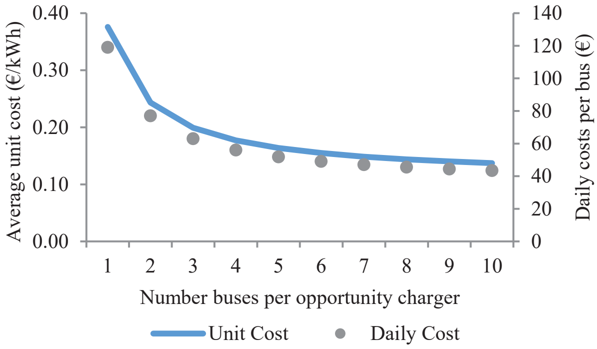

Fig. 8-10 Sensitivity of electricity cost with number of opportunity chargers

8.3.1.2 Economic Analysis – Flexibility Services

The bus fleet can also generate revenue by providing flexibility services. Fig. 8-11 shows the daily income potentials per bus from receiving availability and utilization payments. As mentioned, it is assumed that flexibility is activated randomly once a day for a one hour period.

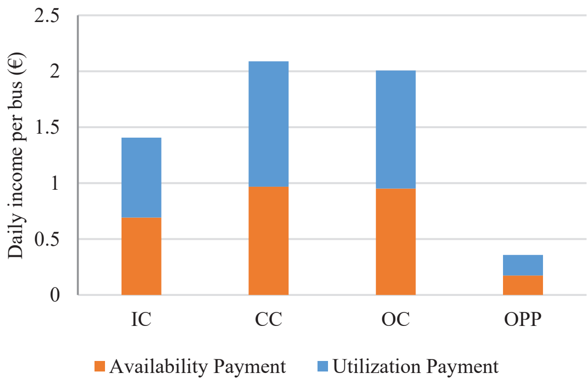

Fig. 8-11 Average daily income per bus from provision of flexibility

It can be seen that the split between income from availability and utilization payments for each scenarios is about equal for all cases. The CC and OC scenarios produce greatest income of about 2 € per bus per day. The IC scenario produces slightly less income of around 1.5 € per day. The OPP case generates very limited income potential, since only 25% of charging takes place at the depot and flexibility cannot be provided by fast opportunity charging on the lines.

Table 8-11 shows the impact of providing flexibility services on the average cost of electricity. Flexibility has a small impact on average costs, causing benefits in the region of 1-7% cost saving. Compared with the differences in cost between charging algorithms, which have the potential to half electricity purchase costs, the impact of providing flexibility is quite small. However, since both approaches require similar hardware and software solutions, there may not be significant added cost to the DA of offering flexibility if smart charging equipment is already in place.

Table 8-11 Average electricity cost with and without flexibility

	IC	CC	OC	OPP
Energy (€/kWh)	0.079	0.085	0.071	0.103
Power (€/kWh)	0.016	0.024	0.012	0.078

Total without Flexibility (€/kWh)	0.095	0.108	0.083	0.181
Flexibility (€/kWh)	-0.004	-0.007	-0.006	-0.001
Total with Flexibility (€/kWh)	**0.090**	**0.102**	**0.076**	**0.180**

Conclusion

The electrical aspects of operating a fleet of BEBs has been explored for overnight and opportunity charging approach, considering peak loads, electricity purchase costs and the selling of DR services.

It was shown that peak load growth at depots is highly dependent on the choice of charging algorithm and may be reduced by implementing opportunity charging. Another outcome is that electricity purchase costs vary widely, between 0.083 €/kWh and 0.164 €/kWh, depending on the choice of charging algorithm and charge system design. Not surprisingly, overnight charging combined with off-peak scheduling was demonstrated to perform best in terms of electricity purchase costs. As for flexibility potential, it appears that there is limited opportunity for income generation based on current reserve markets, which achieve typically up to 2 € income per day for each bus.

This paper can be seen as a first step towards estimating some of the key electrical aspects of BEB fleets. Further work should focus on adding detail to this model in order to better reflect the real life operation of BEB systems, using real fleet operation data and depot information. Optimal scheduling of bus deployment and charging is another area for further investigation, along with modelling impacts of flexibility on battery aging and health. In addition, it would be interesting to understand the capital and maintenance costs of different strategy, since opportunity charging buses use smaller batteries but require more charging infrastructure. Finally, network level studies are also required to understand potential for voltage and thermal impacts on the distribution grid around bus deports and on lines fitted with opportunity chargers.

8.4 Annex D Reused second life batteries for demand aggregation services

Introduction

Electric Vehicles (EV) are slowly but steadily entering into the automotive market proclaiming a cleaner future in the transportation sector. Although EV production entails higher environmental impacts than the internal combustion engine vehicle's (ICEV) manufacture [201], EV do not have tailpipe emissions (Nordelöf, Messagie, Tillman, Ljunggren Söderman, & Van Mierlo, 2014). Moreover, as their environmental impact during the use phase strongly depend on the power source that produces the electricity to charge their batteries [203], the usage of renewable self-produced energy for charging de battery would reduce the overall environmental impact. In fact, it is during the use phase when the overall environmental impact of EV improves, although in countries with high penetration of pollutant technologies in the electricity mix EVs and ICEVs might end up having a similar global warming potential at the end of their life-cycle.

It occurs that the end-of-life (EoL) of EVs is not fixed by a failure but by car manufacturer's marketing decisions (Canals Casals, Amante García, & Cremades, 2017). EV batteries performance and capacity reduces with its use in a similar way to batteries in laptops or cellphones. However, battery lifetime in small devices plays a minor role in comparison to what it is expected for EVs [205]. While laptops and cellphones can be charged almost everywhere and even when they are in use, an EV needs to reach its destination in order to charge the battery again. As the EV range reduces accordingly to the battery capacity [206], it is widely accepted that EV batteries are not useful for traction purposes when they lose between 20% and 30% of its initial capacity [207], [208]. Moreover, the loss of performance is widely known to be related to the battery internal resistance increase, which has a direct effect on efficiency, heating and maximum power [209], [210]. In fact, the power loss might be specially critical at low SOC [211], when the voltage drop caused by the internal resistance might suddenly cross the lower voltage limit causing an unexpected stop. Nonetheless, the effects of the internal resistance increase at 80% of State-Of-health (SOH) are relatively low in comparison to capacity fade. In consequence, it is fair enough to assume that the EoL of EV batteries is defined not by user's needs but by the interest of car manufacturer in having a client that does not notice a shortening in the performance of his EV.

Knowing that the EoL is fixed for commercial reasons rather than by real constraints or impediments, researchers took two directions when considering what to do next: some focused their work in determining a more accurate SOH limit of the battery while others considered alternative battery uses after the EV is dismantled and prior to recycling, which is the research line considered for in this study.

Regarding the SOH limit, Jaguemont et al. state that temperature can be a serious problem for cold countries due to its effect on ageing and instant performance [212]. Moreover, some voices indicate that there is a relation between ambient temperature and the distance driven by EVs [213], mostly based on cabin temperature control, but also affected by the driving habits [214]. Additionally, an experimental study on EV efficiency confirmed these analysis claiming that there is an increase in the EV consumption due to cold temperatures that is dramatically aggravated when temperature cabin control is active, having around a 65% to 75% consumption increment depending on the driving cycle [215]. These temperature changes occur along all seasons of the year and even during the day in many places worldwide. In addition to temperature, auxiliary loads [216], driving behavior [217] and type (urban vs highway) trips [218], can also affect the EV energy consumption. Therefore, the possibility that the EV owners notice the battery degradation is definitively blurred by all the possible driving conditions and variations, thus, owners would hardly identify when the battery reached this 80% SOH. Finally, Saxena et al. indicate that many EV owners would continue using his EV well beyond the 80% SOH limit according to their usual trips, as most of them do not need the whole battery capacity to reach their destination and because some cars owners may not want to acquire a new battery so early [219].

In addition to all previous analysis of the determination of the EoL, there is the issue regarding the accuracy of the existing methods to monitor SOH. In fact, inaccurate SOH estimation methods may delay or accelerate the moment when batteries are retired. The more precise and reliable techniques to evaluate SOH are those that need to test the battery on their own, such as the electrochemical impedance spectroscopy, the pulse and the capacity tests. However, these tests are expensive and time consuming, forcing researchers to study on-board estimation techniques. Nowadays, methods such as internal resistance monitoring [220] are being questioned due to the difficulties to obtain precise measures. Thus, internal resistance estimation models using several methods such as extended Kalman filter or recursive least squares among others, although they need too much computational efforts [221]. Then, there are other on-board alternatives such as voltage recovery [222], or the incremental of capacity vs voltage curves [223] that may properly work. Finally, new EV models tend to have higher capacity (and longer range as a consequence), confirming that maybe this 80% SOH limit of the battery EoL should be adjusted.

The second research branch analyzes the possibility to reuse these EV batteries [224] assuming that EVs will be dismantled after they reach the 80-70% SOH threshold. This idea appears as a link between two sectors, the transportation sector that should face the management of EV batteries as a waste product knowing that their cost is almost half of the EV cost, and the electricity sector that is eager to use affordable energy storage systems (ESS) for different stationary applications. In fact, although the price of lithium-ion batteries, which are the ones preferred by EV manufacturers, is in continuous descent, they are still too expensive to be massively deployed in stationary applications [225]. Thus, second life EV batteries can cover this market niche and definitively launch ESS for electricity grid purposes thanks to their lower expected prices [226], [227].

Grid services can be divided in three categories: power quality, grid support and bulk power management services. ESS fit in one or another category depending on the power they should offer in a period of time. Except for bulk management services that are generally covered by pumped hydro and compressed air ESS, lithium ion batteries are suitable for almost all other stationary services [228], [229].

Many of the services included in power quality and grid support categories require high power and energy installations, going from 100 kW to an order of MW, as many of the demonstrators already installed show [230]. This represents a large amount of EV batteries in a single installation. As EV batteries are not designed for second life applications [231], there are several impediments that difficult their stacking for these type of applications. For one side, there is the need to modify messages from each battery in order to identify which one is sending them as they all send the same messages. Then, it is also necessary to solve the electric isolation architecture caused by vehicle legislations [232]. Moreover, EV batteries are best sized for residential and commercial use [233], [234]. Unfortunately, ESS for residential use does not seems the best market to start with from an economic perspective, being grid support services the ones showing higher revenues [235].

However, this latter fact is maybe no more an impediment for massive reused battery deployment as the figure of the aggregator using distributed energy resources (DER) for demand response (DR) expands. The aggregator is understood as a stakeholder that acts into the energy markets taking advantage of different flexibility sources. One of the business model analyzed for this new stakeholder takes advantage of the intelligence in smart buildings to modify the energy consumption of the building according to the electricity grid needs. Considering that the impact of one single building on the electricity grid is almost negligible, aggregators add the energy flexibility of many buildings to significantly correct deviations in the electricity grid [236], [237]. As development goes on and cities convert to smart cities, the number of buildings counting with DER and controllable loads increase. Most smart buildings are able to adapt the thermal energy demand [154] and to manage renewable power sources they might have [238]. However, batteries [145], EVs [239] and household intelligent devices such fridges or washing machines among others may also contribute to the calculation of flexibility [240], [241]. To activate this flexibility of buildings, the use of economic incentives is a common practice [242]. It is thanks to the economic incentives of these secondary electricity markets that batteries in buildings may substantially increase their revenue expectations.

Moreover, adding flexibility to the grid from the consumer's side will be fundamental in Europe to reach the objectives of emissions reduction and increase of renewable's share. DR has been identified as a key actor for reaching these objectives [243]. The aggregator will allow consumers to trade their flexibility saving money and helping the system stability. This same author also indicates that batteries are probably the most reliable flexibility source for demand side response, as it is relatively simple to know exactly the power and the energy available in each moment, in contrast with all the others DR sources that directly affect consumers, such as HVAC or water heating systems. Furthermore, using batteries for changing the consumption pattern does not affect the comfort of the client, as their usage will not have a direct impact on consumers. That can be a great advantage for batteries to enter in secondary markets, assuming a low marginal cost for aggregators. Two main pillars for aggregators' selection of activated flexibility will be a low comfort affectation of its clients and a great reliability of the source.

This study takes advantage of the information retrieved from a second life EV battery installed in a public library near Barcelona within the framework of the REFER project to estimate its lifetime enlargement thanks to this second life opportunity. A battery electric equivalent circuit model will be used to estimate the battery ageing according to its use in the library comparing three different working scenarios, which are: self-consumption, self-consumption and DR, self-consumption, and DR with frequency regulation. The scenarios are defined in the material and methods' Section.

As seen, even though research and technology is ready to adopt second life batteries and that car manufacturers have launched many demonstration projects in this direction, there is still not an EV model whose battery is designed using eco-design methodologies neither considering the circular economy opportunities that these batteries have in the electricity market.

Therefore, this study aims to highlight how the EV market, which is growing and has huge expectations, begins with a planned or premature obsolescence even knowing that there are many economic and environmental interesting alternatives. Moreover, this study analyzes how the EV battery lifespan is enlarged by reusing them on stationary applications in buildings providing DR services to stabilize the electricity grid. With this, this study analyzes the current status of DR markets in Europe and presents a business model that contributes to enlarge the product lifetime perspective via multiple product cycles.

Material and methods

Technical requirements for participating in balancing markets are very strict and depend on the type of secondary market in which aggregators aim to participate. This Section describes the different types of secondary markets present in Europe and their main characteristics.

Following ENTSOE's terminology, secondary markets can be divided in three groups, depending on the function and on technical requirements needed for entering in the market [57]: FCR, FRR and RR.

Batteries are considered ideal for FCR and FRR services as they have a fast response and good relation between power and capacity to work continuously for 15 minutes. In this way, they can participate in FCR services injecting energy to the grid when the frequency is lowing or charging whenever there is an increase in the frequency. Moreover, thinking in second life EV batteries, this type of service can be very suitable to enlarge their life, as they have a great instantaneously power that is not common in stationary installations and batteries do prefer variations in their working profile and low Depth-of-Discharge (DoD). Similarly, for FRR services, most of the power of the battery may be intended for grid balancing in secondary response. Combining both services can suppose additional incomes without affecting the normal battery's ageing or even improving it.

Despite European Directives incentives European Countries to open their markets to demand aggregator agents and DR [60], only few countries (shown in Fig. 8-12) have already opened the market to aggregators, having each one of them their specific technical requirements. Nonetheless, there are some common aspects, such as a minimum bid size, the notification time, the maximum number of activations, the product resolution, the symmetry of the offer and the duration of the activation, that are considered in all countries although having different limitations.

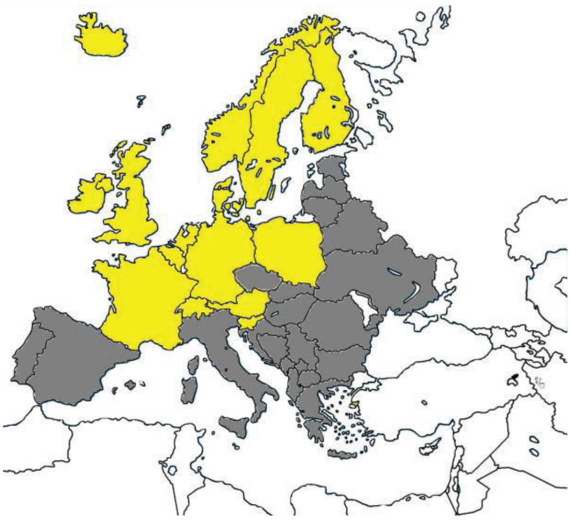

Fig. 8-12 European countries in which demand aggregator's market is opened (in yellow)

Table 8-12 shows the range of values for the technical requirement mentioned above for the principal European markets that allow the participation of an aggregator for DR (Nordic countries, UK, France, Germany, and Belgium). It can be appreciated that the minimum bid size is generally lower for FCR services than for other markets. Notice the particularities regarding the number of activations for each service as FCR are continuously activated, FRR are commonly activated several times a week (although it ranges from 2 times a year to unlimited calls depending on the country) and RR are activated more sporadically.

Table 8-12 Summary of technical requirements of major markets in Europe

Service	Minimum bid size [MW]	Notification time	Maximum activations	Product resolution	Symmetry	Duration
FCR	0,1-3	2 sec - 3 min	Continuously*	1 hour	NO-YES	Very fast
FRR	1-10	5 min -15 min	2 times/year – Unlimited	15 min 1 hour	NO	15 min 1 hour
RR	1-10	10 min - 4 h	< 10 h/year - Several calls/day	1 hour	NO	2 hours

** Except for Finland and Denmark that runs it only for several time per hour and the 0.1% of time respectively*

Apart from technical requirements, this study also takes into account the economic conditions for these services. These services have economic retributions regarding concepts such as availability and/or utilization. Payments for availability represent the incomes that the source receive just for being available in case of necessity from the TSO. Thus, these payments are in €/MW per h and usually correspond to the most important part of the gains for this type of services. The other part of revenues come from utilization, meaning the energy provided to the grid due to a change in the consumption/production pattern. Table 8-13 presents the ranges of these retributions in major European markets.

Table 8-13 Summary of availability and utilization payments in major secondary markets in Europe

Type of service	Availability payments [€/MW/h]	Utilization payments [€/MWh]
FCR	3,87 – 46	0-1,5
FRR	3,07 – 18,26	0 – regulating power price
RR	2,27 – 3,57	0 – 167,53

Economically speaking, penalizations might play an important role in the final accountability of these services, nonetheless, as the aggregator counts on different power sources, it is assumed that in the case of a failure in one of them, the aggregator will be able to switch rapidly to other sources to provide the desired response. Moreover, it is expected that the aggregator would always know the reality of each source, therefore, it would not ask for a service if, for instance, the building is not able to give it. For this reason, penalizations are not considered in this study.

8.4.1.1 Study Framework

This study is based in the installation of a 2nd life EV battery in a public library in Montgat, near Barcelona, within the framework of the REFER project. The original battery comes from a Renault Kangoo and had an initial capacity of 23 kWh. Due to its normal use in the EV, the actual capacity is around an 80 % of the original value, that is, 18,4 kWh. This battery is built in two series of 92 Nickel-Manganese-Cobalt (NMC) cells in parallel. Each cell has a capacity of 32,4 Ah. In its actual configuration in the library, the maximum power that the battery can provide is limited to 10 kW by the inverter or regulator. This regulator has been specially developed for this project by Cinergia.

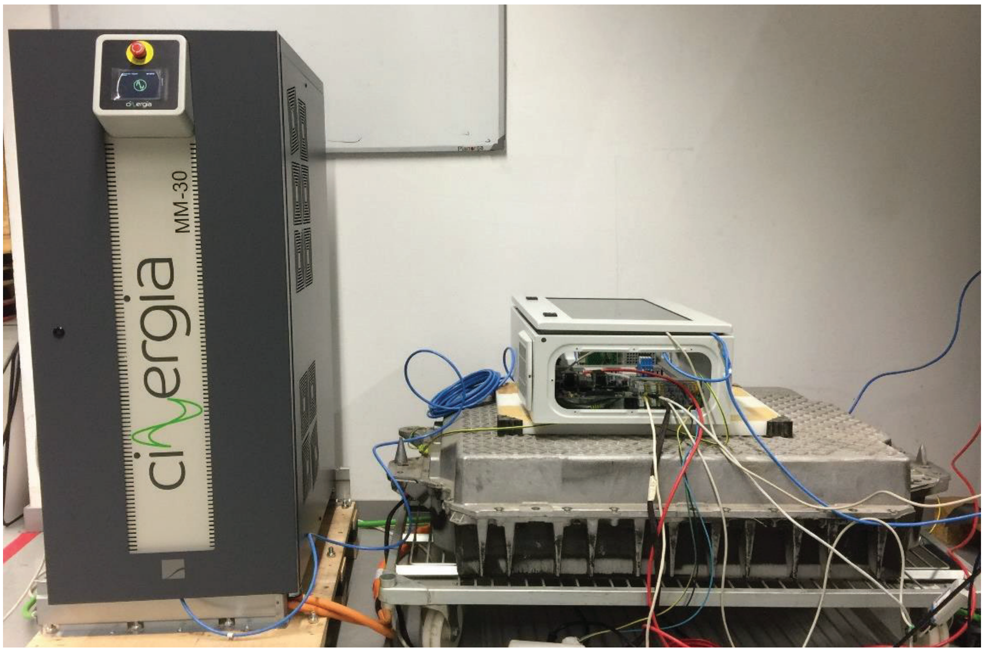

Fig. 8-13 Second life EV Battery (right) and regulator from Cinergia (left) in the testing facilities.

The battery is expected to initially work following two objectives: to store the excess of energy produced by the 96 PV panels on the rooftop of the library, which have a maximum generation power of 19,8 kWp, and to take advantage of the price differences in the electricity tariff, consuming energy at night, when fares are low, and delivering it whenever prices increase according to the hourly discrimination tariff contracted by the library (Table 8-14). Costs of energy and power are divided in three time periods. These tariffs do not include taxes. The power contracted by the library is 86,7 kW.

Table 8-14 Electricity hourly discriminated tariff of the library

	From 29/10 to 26/03	From 27/03 to 28/10	Term of power supply [€/kW per day]	Term of energy consumption [€/kWh]
Period 1	18-22 h	11-15 h	0,111185	0,097181
Period 2	8-18 + 22-24 h	8-11 +15-24 h	0,066952	0,083213
Period 3	0-8 h	0-8 h	0,044634	0,055568

The aim of this study is to evaluate the economic results regarding the electricity behavior of the building in different scenarios:

- Scenario 1, without battery: that is, the library as it was before the installation of the 2nd life battery. Notice that the energy excess from PV is delivered for free to the grid.
- Scenario 2, with battery: this is the initial configuration of the battery in the library. The energy absorbed and delivered from the battery is simulated based on the control program that manages the building's energy consumption. This EMS stores the energy whenever there is an excess from the solar panels and at midnight, when electricity prices are lower and the library energy consumption decreases. The energy stored during the night is then used during period 1 and 2, when electricity is more expensive.
- Scenario 3, battery with aggregated FRR services: this scenario incorporates the activity of an aggregator that will call the building to offer secondary frequency response sporadically. It considers the baseline consumption of the Scenario 2 adding the participation of the building in FRR markets

using the battery capacity and power (limited to 10 kW). The calls from the TSO are simulated using a summary of the various markets. The TSO does an average of 40 calls a month, resulting in 1,3 calls per day, with product resolution of 1 hour and a duration of delivery that can vary between 15 minutes and 1 hour. Each day, the number of activations comes from a normal distribution with an average of 1,3 calls per day and a standard deviation equal to 0,7. Similarly, the duration of the activation varies randomly between 15 minutes and 1 hour. Finally, the direction of the upward or downward regulation is also triggered randomly. Notice that if the battery is discharged before 8 h due to a TSO's call, it will be immediately recharged after the end of the service to take advantage from the cheapest energy price.

- Scenario 4, battery with aggregated FRR + FCR services: in this scenario, the building will participate in the primary frequency response markets in addition to the secondary frequency response markets from Scenario 3. The technical conditions of the FCR market are: continuous activations, symmetry of the offer and a product resolution of 1 hour. Nonetheless, as the available power of the battery is limited to 10 kW, the participation in both markets is split in two, reserving 8 kW for FRR (working in a similar way as in the third scenario) and 2 kW for FCR services.

Additionally, there are two more partial scenarios regarding the FRR+FCR aggregated services that will consider some restrictions to the sporadic frequency response market. In Scenario 4b the library will only participate in FRR services discharging the battery from 0 to 8h and in Scenario 4c it will not offer FRR services during peak hours when energy has a higher cost. These two scenarios are analyzed because the injection of energy to the grid is payed at lower price than the library energy tariff. Period 1 and period 2 in Table 8-14 are those in which the energy is clearly more expensive than the marginal price of energy in ancillary services; in consequence, it may occur that payments for delivering secondary market services would be not enough to compensate the faster ageing of the battery caused by the necessary additional energy exchanges.

Fig. 8-14 presents the available flexibility of the building in Scenarios 3, 4, 4b and 4c during the 24 hours of the day, showing the particularities of Scenarios 4b and 4c and the lower power availability for FRR services in Scenario 4 compared to Scenario 3. Flexibility should be understood as the power that the building provides for FRR services.

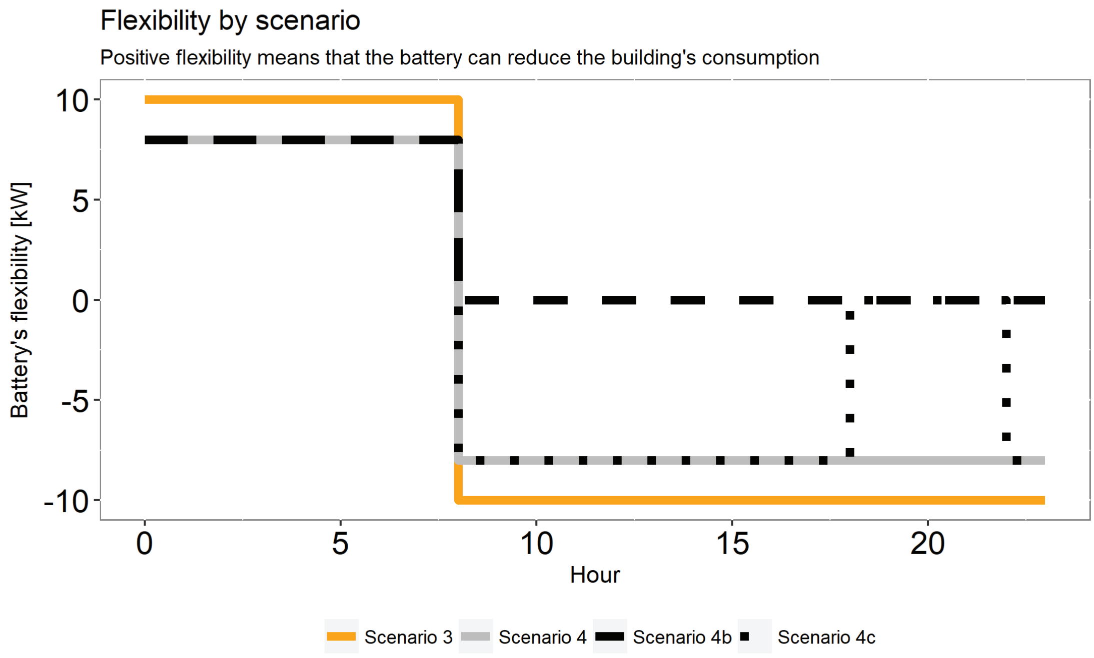

Fig. 8-14 Battery flexibility for each scenario per hour

Notice that in cases of coincidence of several factors such as hours of low consumption, high generation, and high SOC of the battery (that may occur in sometimes during weekends or holydays), the building will not participate in the FRR market, thus, it will not receive any income for availability from the aggregator.

8.4.1.2 Battery ageing

To correctly proceed with this economic evaluation, it is important to estimate the 2nd life battery cost and ageing in all scenarios, as the battery use normally accelerates ageing. Therefore, this study tries to determine if the higher energy demand of the battery caused by the participation in these secondary markets (and ageing consequently) worth its cost.

The ageing of the battery is estimated using a 2nd life battery electric-equivalent circuit model represented by a resistance and four resistance/capacitor pairs in series which runs on Matlab and Simulink. This model is described in full details in [244] and it has been used in similar second life applications by these same authors [245]. The particularity of this model is that it regards the ageing of the battery at cell level needing only the electricity current going through it and the working temperature, which are the main two factors affecting battery ageing [246]. Thus, the parameters of the cells where adapted to the ones from the battery of RENAULT, which have the same NMC technology, in order to obtain results that are more reliable. The model dynamically computes the Depth-Of-Discharge (DoD) and instant SOC, which are the other two relevant factors with direct impact on battery ageing [247]. Then, it evaluates the ageing occurred on each time-step of the simulation, obtaining the evolution of SOH along time and use. The specific configuration of this model considers both cycling ageing (due to the battery use) and calendar ageing (that occurs when stored or during stand-by periods).

The data acquisition of the current going through the battery was obtained after processing the data retrieved from the monitoring system that the library has installed. This system allowed us to retrieve the power generated by the solar panels, the energy consumed by the building, the amount of energy purchased from the electricity grid and the excess of solar energy injected to the grid whenever there was an overproduction every fifteen minutes. Fig. 8-15 shows the energy consumed by the building (orange) and how much of it came from the electricity grid (grey) for two weeks (30/10-12/11).

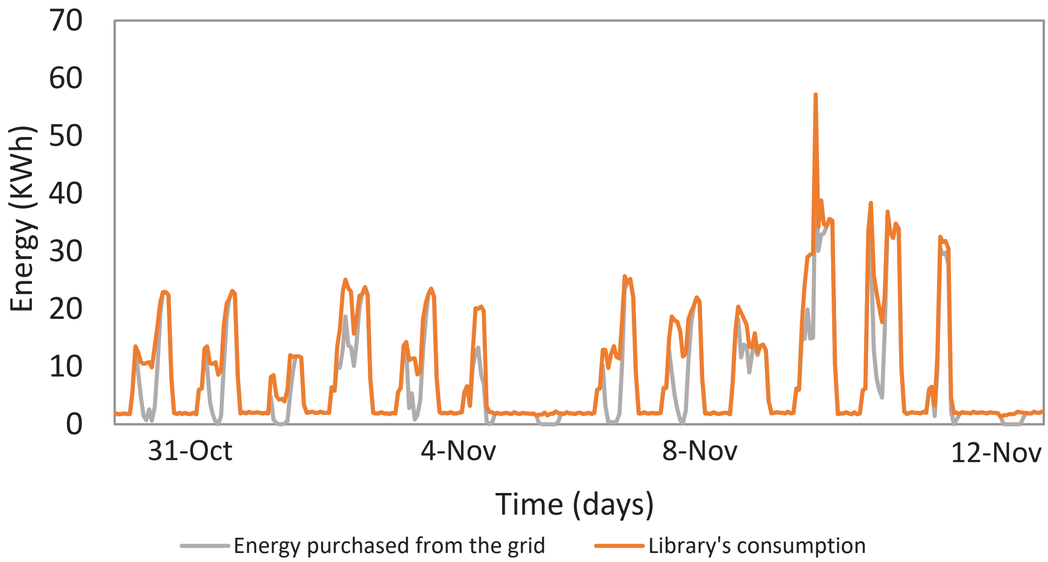

Fig. 8-15 Library's consumption and energy purchased from the grid during 2 weeks (30 October-12 November).

Notice that when the electricity grid curve is below the building's consumption curve, it means that the building consumes energy from the solar panels until it reaches the 0 value, when the library is fully powered by renewable energy power sources and there is an excess of power generation delivered to the grid.

The study counts on data stored during 352 days (from 1st October 2017 to 17th September 2018), since the monitoring equipment was installed. This information is enough for the economic calculation of the first scenario, as there is no battery in it. Knowing the open circuit voltage and SOC of the battery at all times, the current going through it is easily obtained by diving the power by the voltage of the battery according to the SOC.

The activity of the FCR service is taken from a signal that the Spanish TSO ,REE, sent during 31 hours to a company that participates in FRR + FCR markets. The FCR signal changes every 10 seconds and it fits to the maximum 2kW available in our case. This 31-hour period is repeated uninterruptedly for the whole duration of the simulation. Notice that, in Scenarios 4, 4b and 4c, although 2 kW of power are reserved for FCR services, the full battery capacity is available for the building and for FRR services.

Fig. 8-16 represents the current going through the battery that was used for the simulation of the battery ageing in these three scenarios for the hours 48 to 72 (third day of simulation) as an example. Notice that Scenarios 2 and 3 are almost similar except for a small deviation at hour 65 caused by the call of the TSO/DSO. Then, current from Scenario 4 is much more variable but peaks are of lower intensity.

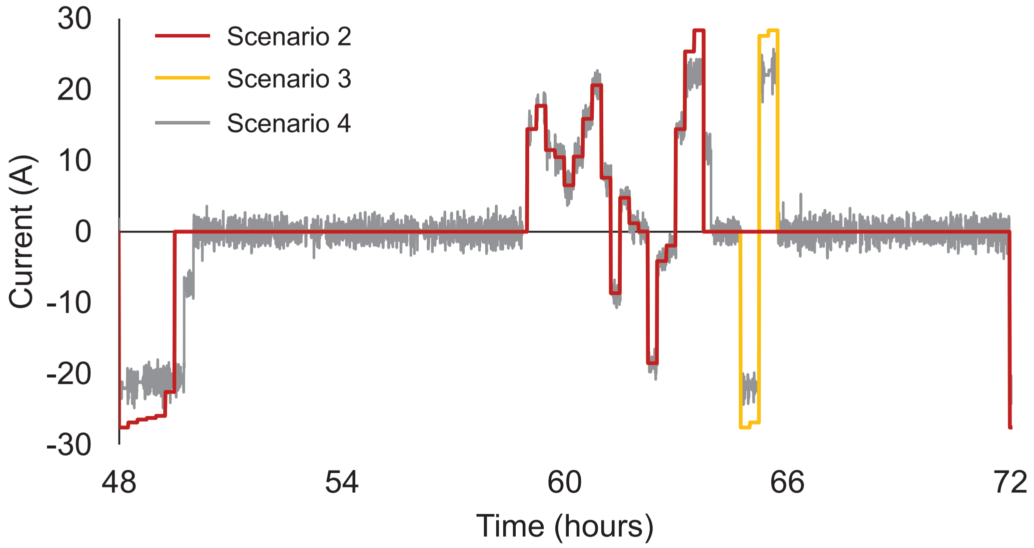

Fig. 8-16 Current going through the battery in Scenarios 2, 3 and 4

Scenarios 4b and 4c follow the same description than Scenario 4 but reducing the possible calls from the TSO to provide FRR services. Thus, in these two additional sub-scenarios there is less energy demand than in Scenario 4.

8.4.1.3 Economic analysis

The economic evaluation considers the electricity tariffs of the library from Table 8-14, but also the values from secondary markets. Two different market frameworks have been considered for the economic analysis.

As Spain, where the library is located, has no regulation on DR, neither for energy aggregation, the first framework (European framework hereinafter) considers the characteristics of the various markets described in Table 8-13 to assume a possible Spanish aggregator. In this case, payments are both for availability and utilization, supposing availability payments of 4 €/MW/hour and utilization payments equal to the payments for energy utilization in the secondary market in Spain for downward or upward regulation during the period considered (October 2017 to September 2018). This decision is in line with all the markets analyzed. Regarding FCR services, availability payments will be of 5 €/MW every hour, without utilization payments.

The second framework (Spanish actual framework hereafter) considers the Spanish FRR market although secondary markets are not yet open in the region for demand aggregators. In Spain, primary regulation is mandatory and it is not economically rewarded. All energy generators should reserve at least 1,5 % of their power for primary regulation [248]. As not all the sources in building's demand response are able to offer primary frequency control, batteries become a key element in the aggregator business. In Spain, availability payments for frequency control in FRR are higher than those considered in the previous framework and vary depending on the hour and on the day [249]. Notice that the Spanish actual framework force symmetrical market bids in contrast to the market considered in the previous case. In this framework, the aggregator has to be able to manage its offers to the TSO, keeping into account that upward and downward offers have to coincide. For this reason, availability payments of the Spanish market have been divided by two for counting the contribution of the battery that will offer flexibility just in one direction.

In both cases consumers will receive the same treatment as producers. When the TSO asks generators to reduce their production, they are paid depending on the energy price of the secondary market and, additionally, they earn money from the unproduced energy that they had already sold in the day-ahead market. So, following the same criteria, when the battery has to charge due to a call from the TSO, the consumer will receive a discount equal to the price in the day-ahead market in that hour. In this way, the TSO does not spend more money for activating consumers instead of producers and consumers are not excessively penalized for consuming energy when the energy is more expensive.

Results and Discussion

This Section will begin with the analysis of the results regarding the battery ageing to further go on with the economic study.

FRR market simulation for Scenario 3 resulted in a total number of upwards and downwards calls by the aggregator of 253 and 223 times respectively.

Fig. 8-17 shows how the frequency adjustments from the FCR services that where so clearly visible (grey) in the current profile in Fig. 8-16 are almost unappreciable on the battery voltage evolution (i.e. on SOC). This is caused basically due to the fact that the direction (or sign) of current varies so rapidly that it has almost no effect on the accumulated energy throughput and, thus, on SOC. In fact, in terms of energy, the maximum accumulated deviation from the base case (Scenario 3, in orange) is around a 0,3%. On the contrary, the differences between Scenario 2 (red), which participates in no secondary markets, and Scenario 3 (orange) are visible by peaks appearance or displacement in several moments.

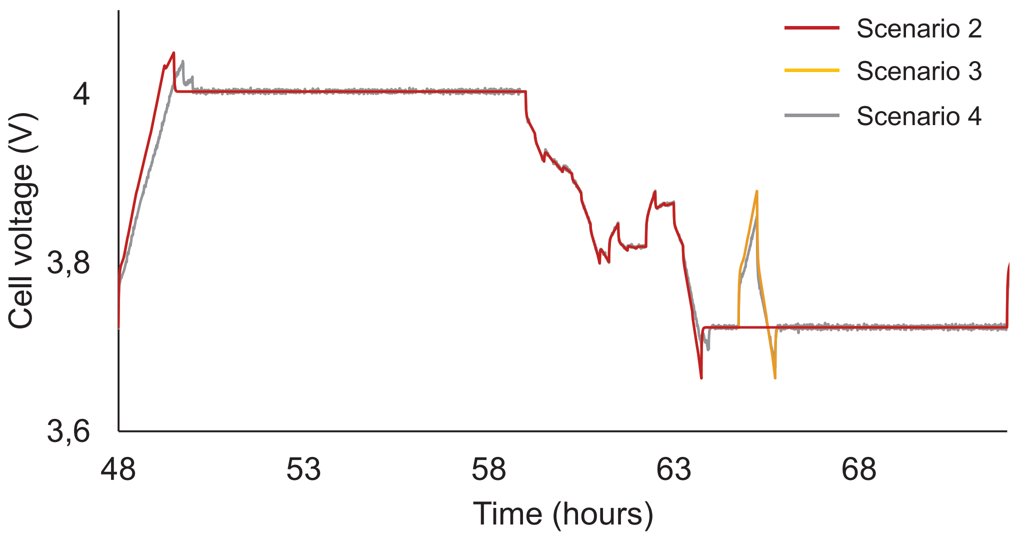

Fig. 8-17 Example of the resulting voltage of a cell in the battery during one day

Although the continuous and fast current ripples of FCR services represent, in the end, more than 15% of the total amount of energy exchanged by the battery its impact on ageing should be low as they correspond to a really small DoD [250] and batteries can improve their performance with this kind of behavior [251].

As a result of the input current (Fig. 8-16) at a constant temperature of 20 ºC (the temperature in the room where the battery is installed in the library is controlled), the ageing battery model shows appreciable differences in the SOH evolution along time (Fig. 8-18).

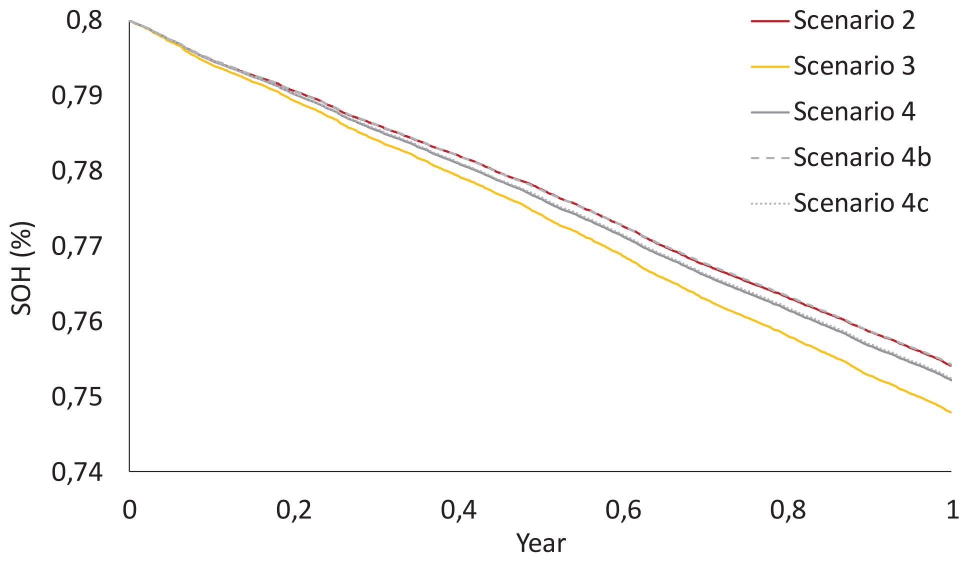

Fig. 8-18 Battery ageing (or SOH evolution) through time.

During this time lapse, the battery lost around a 5% of its capacity, being the Scenario 2 and 4b the ones with lesser ageing and Scenario 3 the one with higher ageing, as shown in Table 8-15. This represents that the Rest of Useful Life (RUL) for these second life EV batteries in stationary applications would increase for 3 to 3.5 more years if the EoL is defined at SOH 64% (that is an 80% of the beginning of the second life, which is already an 80% of the capacity of a new battery). Going beyond this limit is not foreseen as there is a risk to fall into the ageing knee, an acceleration of the ageing rate [252], and due to the fact that the internal resistance of the battery also increases substantially [209].

In fact, the participation in FRR services (Scenario 3) represents an increase on ageing of around a 13,5% in comparison to Scenario 2. Similarly, Scenario 4, participating in FCR and FRR services, also ages faster than Scenario 2 (4,2% more) but lesser than Scenario 3. Scenarios 4b and 4c, due to its fewer calls by the aggregator, age less than Scenario 4.

However, an analysis of ageing considering time as the main factor might be misleading. In fact, as shown in Table 8-15, Scenario 4 does 1,08 equivalent full cycles per day (understood as the total amount of energy divided by the capacity of the battery or cell), while Scenario 2 does only 0,91 cycles, which means that, at the end of the simulation, the battery does 393 and 333 cycles respectively.

In consequence, the higher ageing rate per cycle (or per kWh) is found in Scenario 2, which is also the one with longer lifespan, while the best performance is found in Scenarios 4, 4b and 4c, having 89% of the ageing per cycle of Scenario 2. The "Ageing per cycle" line in Table 8-15 represents the variation of ageing per full equivalent cycle in relation to the ageing obtained in Scenario 2, reason why Scenario 2 has a 100% ageing per cycle.

Table 8-15: SOH evolution and ageing resulting from the Battery model.

	Scenario 2	Scenario 3	Scenario 4	Scenario 4b	Scenario 4c
Initial SOH	0,8000	0,8000	0,8000	0,8000	0,8000
SOH after 1 year	0,7541	0,7479	0,7522	0,7543	0,7525

Difference	0,0459	0,0521	0,0478	0,0457	0,0475
Ageing increase	0.0%	13,5%	4,2%	-0,3%	3,7%
Ageing per year	4,6%	5,2%	4,8%	4,6%	4,8%
Equivalent full cycles	333	380	393	371	388
Cycles per day	0,91	1,04	1,08	1,02	1,06
Ageing per cycle	100,0%	99,5%	88,3%	89,5%	89,0%
RUL (Years)	3,5	3,1	3,3	3,5	3,4
Final eq. full cycles	1.162	1.168	1.316	1.298	1.306

This study considers that a second life EV battery such as the one presented in this study should cost between 700 € and 2.500 € according to lower bounds of 38,3 €/kWh [253] and higher bounds of 140 €/kWh (Canals Casals, Amante García, & González Benítez, 2016). Notice that these costs are considerably lower than the cost of new batteries that ranges from 300 to 500 €/kWh. Additionally, the economic analysis includes the costs from power electronics, such as the converter that charge and discharge the battery, which is assumed to be 5000 € according to market.

Scenario 1 is the starting point for the economic evaluation of second life batteries in the building, that is, the use of electricity in the library without battery. In this case, energy costs considering tariffs described in Table 8-14 rise up to 8.607 € regarding the electricity consumption and 8.706 € corresponds to the power contracted, giving a total of 17.314 € during the 352 days considered in the study.

Scenario 2 includes the use of the battery in the building without any contract with the aggregator. The amount of savings during the whole period thanks to the use of the battery are 345,3 € including taxes, of which 175,0 € come from consuming energy during valley hours instead of peak hours and about 170,3 € correspond to the increase self-consumption.

In Scenario 3, the battery will participate 214 times of the 476 (253 up and 223 down) possible calls during the period considered in the FRR market. There are 262 missed calls from the TSO that correspond to moments when the library was not available for the aggregator (903 hours during the period considered) or the call went in the opposite direction of the battery's available flexibility. Effectively, the library suffers a cost increase of electricity consumed of 20,9 € in respect to Scenario 2 including taxes due to a non-optimal building management caused by the participation in secondary markets. The difference in billing among having aggregator or not is very small because energy requested from aggregator's activation will be recovered just afterwards when the electricity price is still the same. However, in some cases, there is a cost increment whenever there is a shift of consumption between billing periods. Total incomes of the aggregator for the second life battery services were 109,7 € for energy utilization and 301,7 € for availability payments considering incomes of 4 €/MW each hour for FRR services. Payments for availability represent more than 73 % of the incomes for the aggregator.

In Scenario 4 the battery will participate 217 times during the period considered in the FRR market. In this case, as the flexibility offered to the market is 8 kW instead of 10 kW, there are 851,5 hours in which the battery can't change its pattern instead of the 903 hours of the previous case. The library's bill will increase 18,9 € including taxes. Differences in the bill among Scenarios 3 and 4 are due to a reduction in the self-consumptions, as the power available by the battery is reduced. Considering the European framework, the aggregator would gain a total of 416,5 €. In the Spanish actual framework, aggregator's profits thanks to the battery would correspond to 88,9 € for energy utilization and 429,7 € for availability in FRR markets as the Spanish market has no revenue for FCR availability. The total income is 518,6 €.

In Scenario 4b, when the battery offers flexibility just for discharge from 0h to 8h, it participates in the FRR market just 87 times during the time considered. The library electricity costs increase 16,9 € compared to Scenario 2 and payments to aggregator from the TSO in the European framework rise to 198,7 €. Considering the Spanish market framework, payments to aggregator would be 221,6 €.

Table 8-16 Economic analysis by scenario

	Total bill [€]	Energy utilization FRR [€]	FRR availability [€]	FCR availability [€]	Total aggregator profits [€]	Total library's profits [€]
Scenario 1	17314,1	0	0	0	0	0
Scenario 2	16968,7	0	0	0	0	345,3
Scenario 3	16989,6	109,7	301,7	0	411,4	653,7
Scenario 4 European Framework	16987,6	88,9	243,1	84,5	416,5	659,7
Scenario 4 Spanish actual framework			429,7	0	518,6	741,38
Scenario 4b European framework	16985,6	24,1	90,1	84,5	198,7	487,5
Scenario 4b Spanish actual framework			197,5	0	221,6	505,8
Scenario 4c European framework	16987,2	77,0	206,9	84,5	368,4	621,6
Scenario 4c Spanish actual framework			378,4	0	455,4	691,2

Finally, in Scenario 4c, the building will participate in FRR balancing services 196 times during the period considered. The battery does not participate in the market from 11 h to 15 h during summer and from 18h to 22h during winter and during 49 hours in which it is not able to offer flexibility for changing its pattern. Thus, the electricity cost is 18,5 € more expensive than in Scenario 2, but thanks to the battery, the aggregator will receive a total amount of 368,4 € considering the European market framework and 455,4 € considering the Spanish actual framework.

Table 8-16represents a summary of the economic analysis for each scenario during the days considered. For simplicity, for the calculation of the library's profits during the period considered it is supposed that the 80 % of the aggregator's gains are given to its clients. Therefore, the total library's incomes are calculated as the savings with respect to the electricity bill in Scenario 1 plus the 80% of the aggregator's revenues.

Once the effect of the participation in different markets on the second life battery ageing and the economic savings and gains that a battery produces in different scenarios is analyzed, it is worth to combine the technical and the economic analysis for understanding the best way to use a second life battery in stationary applications.

To calculate the range of the amortization costs of the overall system during the monitored year, the study considers the amortization costs of converter and battery. For the converter, an amortization period of 20 years is considered (grey bar in Fig. 8-19), while for the battery it is considered that the battery costs are applied until reaching the EoL, defined at SOH 64%. To translate this cost to the duration of the simulation the calculations were done considering the corresponding SOH variation. As an example, in Scenario 2, the battery ages a 4,6% of SOH, corresponding to an amortization cost in the range of 230 and 920 €. Finally, the profit from the library is obtained by subtracting the amortization costs of the system (uncertainty bar) to the savings of the library (orange bar) and incomes from the aggregator (yellow bar) for each scenario.

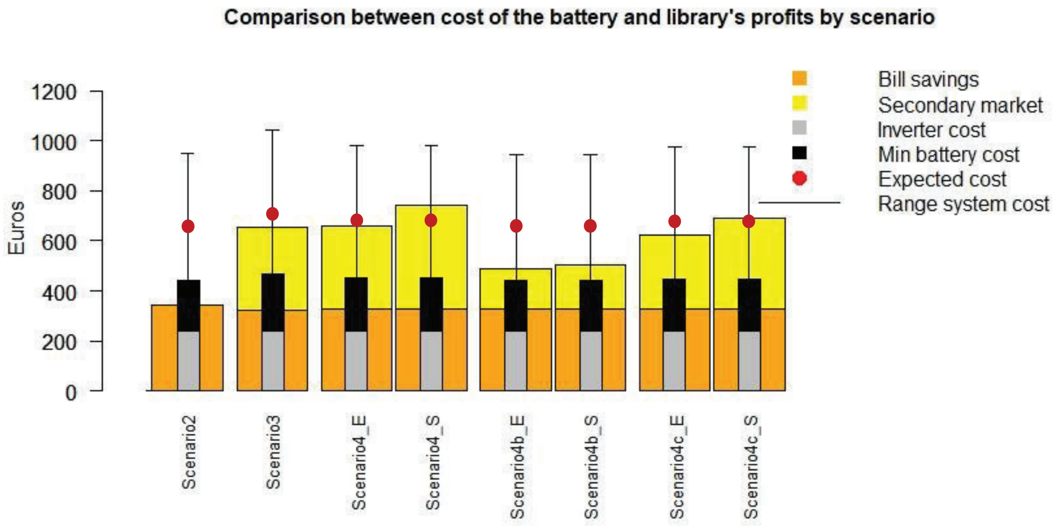

Fig. 8-19 Costs and profits by scenario

Results are visible in Fig. 8-19 showing that, effectively, batteries for self-consumption use only (Scenario 2) do not offer any economic incentive. In fact, batteries suppose an inevitable cost. The situation changes considerably in the scenarios that count on ancillary services, where profits may occur depending on the final cost of the 2nd life battery and the final market framework in Spain. It seems that Scenario 4 considering the actual Spanish framework is the best option. In fact, nowadays, the price of 2nd life batteries from 4Renergy is close to 2.300 €, but considering that other car manufacturers will enter into this market niche and that remanufacturing processes will be automatized, 2nd life battery costs could be assumed to reduce down to 1.500 € (83€/kWh) (red dot in Fig. 8-19).

Notice that, apart from Scenario 4b, in all cases the amortization costs of the system are higher than in Scenario 2, however, these costs are clearly compensated by the additional revenues from the market (basically from availability). In addition, the best option in the two market frameworks is ever to offer flexibility at all the hours of the day, as availability payments is the most important part of the incomes for secondary markets, also in this case higher amortization costs and a higher electricity bill is clearly compensated by the additional revenues.

Conclusions

The main objective of this work was to demonstrate that there are interesting markets for second life EV batteries, which are built without caring about their future premature obsolescence although EV market is in continuous growing.

This study combines the knowledge on battery ageing depending on the use with a technical and economic analysis of the secondary electricity markets in Europe and the monitoring data of a library in Montgat, Barcelona, Spain.

In the first place, this study shows that battery lifespan increases by a 35% with the incorporation of second life applications in buildings.

In all the scenarios considered with the presence of the aggregator, incomes plus savings thanks to the incorporation of energy storage systems are higher than the amortization costs of the battery plus inverter considering the optimistic lower bound of 2nd life battery price of 700 €. However, considering lesser optimistic battery costs, results change considerably and it might be rather difficult to obtain high profitability from these kind of businesses. Nonetheless, capacity payments considered in this study are rather conservative, thus, results might be more interesting in the future Spanish market.

This study showed that the ageing of battery plays a relevant role in the final results, showing that the participation in FCR markets clearly reduces the amortization costs of the battery due to a reduction of ageing per kWh delivered (ageing /cycle) maintaining the economic incomes.

Moreover, this study shows that the lower selling price of 2nd life EV batteries in comparison to new ones opens a new market niche that would be prohibitive otherwise. Additionally, it clearly states that the integration of the figure of an aggregator is necessary to run demand response services from a customer perspective.

Furthermore, 2nd life batteries could reduce the effective price of EVs and reduce its life cycle impacts.

8.5 Annex E: Case Study Tertiary and energy markets

This appendix Section presents the case study data used to test the optimization algorithms described in Section 6.3. Two different sets of data are described:

A-1 – flexumers information;

A-2 – electricity market information.

A-1 – Flexumers Information

Three types of flexumers information are considered: thermal load parameters; battery parameters and and shiftable loads.

A-1.1 – Thermal load Parameters

The thermal load parameters represent the physical and operational characteristics of the thermal zones, as described in Section 5.3.1. Thermal load parameters are the same described in Annex A. The only difference is on the type of control the aggregator is performing. While in the secondary reserve problem the aggregator could control the power output, in this case the aggregator can control the on/off status on the thermal zones 1, 4 and 5.

A-1.2 – Battery Parameters

The battery parameters represent the physical and operational characteristics of the batteries, as described in Section 5.3.2.

Table 8-17 shows the fixed or configured parameters of the five batteries participating in the secondary reserve market.

Table 8-17 Fixed or configured parameters of the five batteries participating in the energy and tertiary reserve market

	E^b [kWh]	$SOC^m, SOC0$ and SOC^M [%]	P^{Mc} and P^{Md} [kW]	η^c and η^d [%]
Battery 1	50	[0.2, 0.4, 0.8]	50	0.98
Battery 2	70	[0.2, 0.35, 0.85]	70	0.98
Battery 3	20	[0.2, 0.5, 0.9]	10	0.98
Battery 4	60	[0.15, 0.7, 0.8]	50	0.98
Battery 5	130	[0.2, 0.6, 0.9]	150	0.98

Fig. 8-20 shows the baseline of the batteries participating in the energy and tertiary reserve market. Notice that positive power means that the battery is charging, while negative power means that the battery is discharging.

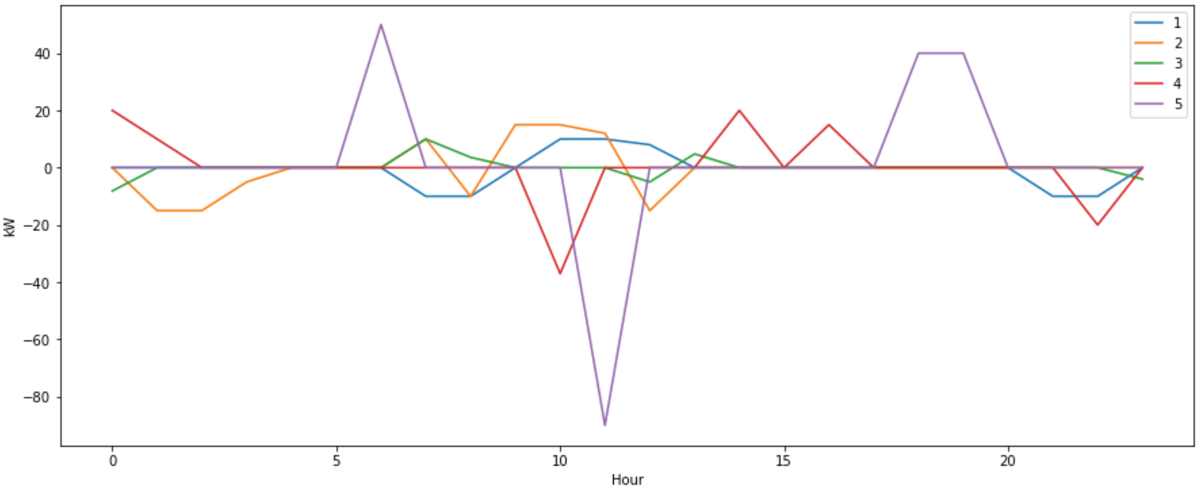

Fig. 8-20 Batteries' baseline

A-1.3 – Shiftable load Parameters

The shiftable load parameters represent the physical and operational characteristics of the loads and the user preference's, as described in Section 5.3.3.

Table 8-18 shows the fixed or configured parameters of the five batteries participating in the secondary reserve market.

Table 8-18 Fixed or configured parameters of the five shiftable loads participating in the energy and tertiary reserve market

	P^{min}, P^{max} $[kW]$	$\bar{N}_i$ [-]	T_j $[h]$	C_i^{act} [€]	$\overline{ME}$ [kWh]
Shiftable 1	[200, 400]	4	3	0	0
Shiftable 2	[100, 300]	6	4	0	0
Shiftable 3	[250, 250]	3	5	100	200
Shiftable 4	[450, 450]	8	2	0	0
Shiftable 5	[400, 400]	3	1	0	0

Fig. 8-21 shows the baseline of the shiftable loads participating in the energy and tertiary reserve market.

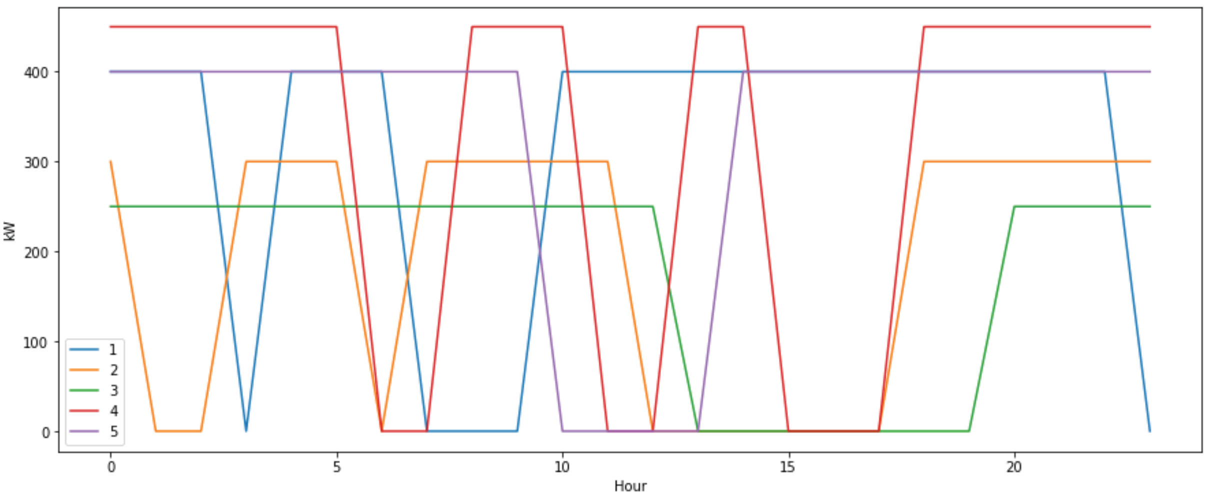

Fig. 8-21 Shiftable load's baseline

A-2 – Electricity market Information

The participation of the aggregator in the energy and flexibility markets requires the forecasting of the tertiary reserve activation prices and of the energy prices in the next intraday markets.

The market information used by the aggregator is available at the ESIOS web page [165], which collects information from the Spanish's energy market operator OMIE and the Spanish TSO's REE.

A-2.1 Activation prices

During the day ahead, the aggregator forecasts the upward and downward activation prices. The algorithm to forecast flexibility activation prices is out of the scope of this thesis. To demonstrate the reliability of the methods proposed the aggregator of the case study analyzed uses the average difference between the tertiary up and down reserve price λ_t^{eU}, λ_t^{eD} and the spot market price λ_t^{sp} to forecast the activation price. Typically, $\lambda_t^{eU} \geq \lambda_t^{sp} \geq \lambda_t^{eD}$. During 2021, the average price difference between activation and spot prices was 16 €/MWh. Table 8-19 shows the average error during the days analyzed. Such as in the secondary reserve activation price forecast, there is margin of improvements in the tertiary reserve price forecast.

Table 8-19 Performance metrics of tertiary reserve activation prices' forecast in the days analyzed

	MAPE [%]	CV(RMSE) [%]
Upward activation price λ_t^{eU}	10	17
Downward activation price λ_t^{eD}	20	19

A-2.1 Energy prices

At all hours, before bidding in the continuous intraday market, the aggregator forecasts the energy prices for all the hours of the next market session. The algorithm to forecast intraday energy prices is out of the scope of this thesis. To demonstrate the reliability of the methods proposed the aggregator of the case study analyzed uses the energy price of the last market session, assuming that it will be the same of the next session. Despite the simplicity of the forecast algorithm proposed, results are quite good due to the stability of the energy price between different market sessions.

Table 8-20 Performance metrics of intraday energy prices' forecast in the days analyzed

	MAPE [%]	CV(RMSE) [%]
Intraday energy price λ_t^{sp}	2	3

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