UNIVERSITAT POLITÈCNICA DE CATALUNYA

DEPARTAMENT D'ENGINYERIA ELÈCTRICA

Doctoral Thesis

Local Electricity Markets Design and Operation in Distribution Power Systems

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"Choose to love whoever you want:
Everything else will follow."

Saint Augustine of Hippo

"In these bodies we will live, in these bodies we will die
Where you invest your love, you invest your life"

Awake my soul by Mumford and Sons

To Maria,
Isabel, Ignasi,
Àlex
and iaia Montse

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Abstract

In the context of distributed generation growth, local grids could face operational issues. In that sense, smart grid deployment will give information to local grid operators about grid status at medium and low voltage levels for taking operational decisions on daily-basis. This thesis presents local markets as a potential solution to avoid local grid congestions and over-costs. They mainly increase the negotiation power of end-users with distributed energy resources and allow activation of flexibility at local level.

First of all, this thesis analyses electric vehicles as a potential challenge for distribution grids and electricity markets in case of uncontrolled charging as it could cause consumption peaks. At the same time, electric vehicles could be part of the solution thanks to their capability of shifting forward their consumption. The first solution presented in this thesis is a building level electric vehicle management algorithm in order to reduce energy cost and consumption peaks.

However, local grid operators need a solution to deal with aggregated level problems like high demand or high generation periods. Such kind of problems vary over time and place, and they could be difficult to integrate in regular grid tariffs. Therefore, the present thesis provides two local market designs for these problems. The first local market presented is designed for taking advantage of renewable energy producers before and after the wholesale day-ahead market without threatening distribution grids and increasing the local social welfare. However, this market implies significant regulatory changes because the local market operator should take some of the current local grid operator regulated activities.

Therefore, this thesis presents a second market design for managing portfolios of consumers, producers and prosumers, and it could be operated by retailers, balance responsible parties or aggregators for flexibility provision without regulatory issues. The work includes a description of roles, contracts and interactions of such local flexibility market, and three optimization algorithms depending on the application, complexity and portfolio scale. The first algorithm assumes limited information about each site, the second one includes such information but presents potential scalability limitations, and the last algorithm is based on a decomposition method to optimise the aggregator portfolio in a distributed way reducing the computational burden and time.

Resum

En el context d'expansió de generadors d'electricitat renovable i distribuïda, les xarxes de distribució podrien presentar problemes d'operació. A més a més, en un context de desplegament de la xarxa elèctrica intel·ligent, les companyies distribuïdores tindran un millor coneixement de l'estat de la xarxa per prendre decisions d'operació en el dia a dia tant a nivell de mitja com en baixa tensió. Els mercats locals constitueixen una possible solució per a la resolució de congestions a les xarxes de distribució d'electricitat i reduir els sobre costos del sistema elèctric. Aquests mercats també permetrien incrementar el poder de negociació dels consumidors d'electricitat a petita escala amb capacitat de flexibilitat.

Primerament s'analitza el potencial perill que poden suposar els vehicles elèctrics per a les xarxes de distribució en cas de no haver-hi gestió intel·ligent dels processos de càrrega ja que podrien aparèixer nous pics de consum. Alhora, els vehicles elèctrics podrien ser part de la solució desplaçant el seu consum a la nit. El present treball inclou un algorisme de gestió de vehicles eléctrics a nivell d'edifici per a reduir el cost d'electricitat i els pics de consum. No obstant, les companyies distribuïdores necessiten una solució per als problemes de la xarxa que podrien ser diferents segons la zona o l'època de l'any. És per això que aquest treball inclou dues propostes de mercat local per a aquests problemes.

El primer mercat local està dissenyat per a aprofitar l'avantatge dels productors d'energia renovable abans i després del mercat diari majorista sense comprometre l'operació de la xarxa de distribució. Tot i això, aquesta proposta de mercat local requeriria diversos canvis en matèria de regulació ja que l'operador del mercat local hauria de prendre algunes de les actuals responsabilitats de les companyies distribuïdores.

Seguidament, la tesi presenta un segon mercat local per gestionar una cartera de consumidors, productors i prosumidors, com una activitat més dins de les activitats de les companyies comercialitzadores o agregadores de flexibilitat. El present document inclou una descripció dels rols, contractes i interaccions, i tres algorismes d'optimització des del més simple fins al més complex. El primer assumeix una limitació en la informació disponible de cada membre de la cartera, el segon inclou més informació però presenta limitacions d'escalabilitat, i finalment el tercer presenta un algorisme de descomposició per optimitzar la flexibilitat de manera distribuïda i així reduir el temps de computació i la complexitat de càlcul.

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Nomenclature

Abbreviations

ADMM	Alternating direction method of multipliers
ALFM	Aggregated level flexibility management
ALFO	Aggregated level flexibility offer
AS	Ancillary services
BRP	Balance responsible party
CEC	Citizen energy community
CS	Charging station
CSO	Charging station operator
DAMM	Day-ahead micro-market
DAWM	Day-ahead wholesale market
DER	Distributed energy resources
DG	Distributed generation
DSO	Distribution system operator
EIT	European Institute of Innovation and Technology
FD	Flexibility device
FR	Flexibility request
HEMS	Home energy management system
ICT	Information and communication technologies
LCOE	Levelised cost of energy

LCOS	Levelised cost of storage
LFM	Local flexibility market
LV	Low-voltage
MMO	Micro-market operator
MPP	Multi-period problem
MV	Medium-voltage
OCMP	Open Capacity Management Protocol
OSCP	Open Smart Charging Protocol
P2P	Peer-to-peer
PDF	Probability distribution function
PHEV	Plug-in hybrid electric vehicle
PJ	Proximal Jacobian
PTU	Programing time unit
PV	Photovoltaic
SGAM	Smart grid architecture model
SOC	State-of-charge
SPP	Single period problem
SW	Social welfare
TE	Transactive energy
TLC	Traffic light concept
TOU	Time-Of-Use
TSO	Transmission system operator
USEF	Universal Smart Energy Framework
VPP	Virtual power plant

VRE Variable renewable energy

Indices and Sets

$\mathcal{B}^c$	Set of blocks of consumption energy, indexed by bc
$\mathcal{B}^g$	Set of blocks of generation energy, indexed by bg
$\mathcal{B}^{bat}$	Set of storage units, indexed by b
$\mathcal{C}(k)$	Set of shiftable load periods, indexed by c. It depends on each k
$\mathcal{D}^c$	Set of consumers of each node, indexed by a
$\mathcal{D}^g$	Set of generators of each node, indexed by z
$\mathcal{G}$	Set of distributed generators, indexed by g
$\mathcal{G}^d$	Subset of disconnectable distributed generators
$\mathcal{G}^i$	Subset of inflexible distributed generator
$\mathcal{G}^r$	Subset of reducible distributed generators
$\mathcal{I}$	Set of prosumer sites, indexed by i
$\mathcal{J}$	Set of segments for battery SOC, indexed by j
$\mathcal{K}$	Set of non-buffered flexible loads, indexed by k
$\mathcal{K}^{CD}$	Subset of flexible load units of type curtailable disconnectable
$\mathcal{K}^{SP}$	Subset of flexible load units of type shiftable profile
$\mathcal{L}$	Set of distribution grid lines, indexed by l
$\mathcal{N}^{\int}$	Set of storage units in the micro-market
$\mathcal{N}$	Set of distribution grid buses, indexed by m,n
$\mathcal{N}^{CCP}$	Subset of nodes connected to the main grid, indexed by o
$\mathcal{S}(v)$	Set of electric vehicle charging sessions in charging point v, indexed by s
$\mathcal{T}$	Set of periods/time slots in the planning horizon, indexed by t

$\mathcal{T}^{\pm}$ Subset of periods with up (+) or down (-) regulation

$\mathcal{V}$ Set of electric vehicle charging points, indexed by v

Optimization parameters

$A^{grid,lo}$ Lower voltage angle boundary [p.u.]

$A^{grid,up}$ Upper voltage angle boundary [p.u.]

$A_i^{bat,ch}$ Battery charging efficiency in site i [p.u.]

$A_i^{bat,dis}$ Battery discharging efficiency in site i [p.u.]

$C_{m,bg,z}^{bG}$ Energy offer cost of generator z for the energy block bg in node m [p.u.]

C_t^{dev} Deviation penalty to modify the matched power in the day-ahead wholesale market per period t [EUR/p.u.]

$C_i^{dis,ct}$ Loss of battery i lifespan for discharging energy considered as a constant factor [EUR/p.u.]

$C_{i,j}$ Marginal battery cycling ageing cost per segment j in site i [EUR/kWh]

CR_t DSO capacity limitation request per period t as the maximum consumption for all charging points [kWh]

D_k^{max} Maximum curtailment duration of the load unit k [# of periods]

D_k^{min} Minimum time duration between two curtailments of the load unit k [# of periods]

$E_{m,bg,z}^{bG}$ Energy offer volume of generator z for the energy block bg in node m [p.u.]

$E_{m,bc,a}^{bl}$ Energy offer volume of consumer a for the energy block bc in node m [p.u.]

$E_{m,a}^{B}$ Sum of all energy blocks of consumer a in node m [p.u.]

FR_t Flexibility request from DSO/BRP in period t [kWh]

N^{hour} Periods per hour [#]

N_k^{max}	Maximum number of disconnections for the load unit k during the planning horizon T [#]
O_i^{max}	Maximum battery SOC in site i [kWh]
O_i^{min}	Minimum battery SOC in site i [kWh]
$O_{i,j}^{max}$	Maximum battery SOC in segment j in site i [kWh]
$P_{b,t}^{bat,ch}$	Price to charge the battery unit $b \in \mathcal{B}^{bat}$ during period t [NOK/kWh]
$P_{b,t}^{bat,dis}$	Price in local flexibility market contract for discharging the battery unit $b \in \mathcal{B}^{bat}$ during period t [NOK/kWh]
P_k^{CD}	Price in local flexibility market contract for disconnecting the load unit $k \in \mathcal{K}^{CD}$ during period t [NOK]
$P_{g,t}^{Gd}$	Price in local flexibility market contract for curtailing the disconnectable generator unit $g \in \mathcal{G}^d$ during period t [NOK/kWh]
$P_{g,t}^{Gr}$	Price in local flexibility market contract for curtailing the reducible generator unit $g \in \mathcal{G}^r$ during period t [NOK/kWh]
$P_{m,bc,a}^{pr,bL}$	Energy offer price of consumer a for the energy block bc in node m [p.u.]
P_k^{SP}	Price in local flexibility market contract for shifting the load unit $k \in \mathcal{K}^{SP}$ one period [NOK]
$P_t^{gridBuy}$	Price at energy part of grid contract for buying electricity in period t [EUR/kWh]
$P_t^{gridSell}$	Price at energy part of grid contract for selling electricity in period t [EUR/kWh]
$P_t^{retailBuy}$	Price at energy part of retail contract for buying electricity in period t [EUR/kWh]
$P_t^{retailSell}$	Price at energy part of retail contract for selling electricity in period t [EUR/kWh]
$P_{i,t}^{buy}$	Price at energy part for buying electricity in period t in site i [EUR/kWh]

$P_{i,t}^{sell}$ Price at energy part for buying electricity in period t in site i [EUR/kWh]

$P_{v}^{CPNonSupplied}$ Price for each non-supplied energy unit (1 kWh) of the expected charging demand by the end of charging session in charging point v [EUR/kWh]

$P_{v}^{CPShift}$ Price for deferring one time period one energy unit (1 kWh) of the energy demand in charging point v [EUR/kWh]

$Q_{m,z}^{maxG}$ Reactive power upper limit of generator z in node m [p.u.]

$Q_{i}^{maxreact,bat}$ Maximum reactive power capability of battery i [p.u.]

Q_{i}^{ch} Maximum battery charging energy per time unit in site i [kWh]

Q_{i}^{dis} Maximum battery discharging energy per time unit in site i [kWh]

Q_{v}^{CPMax} Maximum power of charging point v [kW]

Q_{v}^{CPMin} Minimum power of charging point v without desconnecting it [kW]

$S_{m,n}^{maxlin}$ Apparent power from node m to n boundary [p.u.]

S_{i}^{LT} Amount of time intervals in battery lifetime in site i [years]

$T_{k,c}^{end}$ Latest possible end period for shifting the load unit $k \in \mathcal{K}^{SP}$ during time interval c [#]

$T_{k,c}^{start}$ Earliest possible start period for shifting the load unit $k \in \mathcal{K}^{SP}$ during time interval c [#]

$T_{v,s}^{CPEnd}$ Departure time of each EV in charging point v of session s

$T_{v,s}^{CPStart}$ Arrival time of each EV in charging point v of session s [#]

U^{lo} Lower voltage module boundary [p.u.]

U^{up} Upper voltage module boundary [p.u.]

$V_{k,c}^{end}$ End-period of forecasted consumption of the load unit $k \in \mathcal{K}^{SP}$ during shift time interval c [#]

$V_{k,c}^{start}$	Start-period of forecasted consumption of the load unit $k \in \mathcal{K}^{SP}$ during shift time interval c [#]
W_i^{bat}	Battery voltage charging tuning factor in site i [#]
$W_{k,t}^{CD}$	Curtailable load consumption forecast of load unit k during period t [kWh]
$W_{g,t}^{Gd}$	Forecasted generation of disconnectable generator unit g during period t [kWh]
$W_{g,t}^{Gi}$	Forecasted generation of inflexible generator unit g during period t [kWh]
$W_{g,t}^{Gr}$	Forecasted generation of reducible generator unit g during period t [kWh]
$W_{k,t}^{SP}$	Shiftable load consumption forecast of load unit k during period t [kWh]
$W_{i,t}^{l}$	Inflexible load consumption in period t in site i [kWh]
W_t^{base}	Aggregated baseline consumption in period t [kWh]
W_t^{flex}	Aggregated electricity consumption in period t after meeting the flexibility request [kWh]
$W_{v,t}^{CP}$	Baseline charging schedule of EV v in period t [kWh]
X^{expCap}	Maximum export energy per time unit [kWh]
X^{impCap}	Maximum import energy per time unit [kWh]
X_i^{exp}	Maximum electricity export capacity of site i per period [kWh]
X_i^{imp}	Maximum electricity import capacity of site i per period [kWh]
$Y_{m,n}$	Complex admittance matrix [p.u.]

Parameters ADMM

ϵ^{dual}	Dual error threshold [p.u.]
ϵ^{pri}	Primal error threshold [p.u.]

γ	Damping parameter [#]
$\lambda_t^{(k)}$	Dual variable for constrained period t in iteration k [#]
$\rho^{(k)}$	Penalty parameter in iteration k [#]
τ^{decr}	Decremental parameter to decelerate penalty parameter ρ [#]
τ^{incr}	Incremental parameter to accelerate penalty parameter ρ [#]
CT^{max}	Maximum computation time threshold [s]
K^d	Penalty for the dual error [#]
K^i	Penalty for accumulated primal error [#]
$r_t^{(k)}$	Primal error for constrained period t in iteration k [kWh]
$s_t^{(k)}$	Dual error for constrained period t in iteration k [kWh]

Optimization variables

α_m	Voltage angle of node m [p.u.]
$\chi_{g,t}^{Gd}$	Total amount of electricity generation curtailed of disconnectable generator unit g during period t [kWh]
$\chi_{g,t}^{Gr}$	Total amount of electricity generation curtailed of reducible generator unit g during period t [kWh]
$\chi_{i,t}^{buy}$	Amount of electricity bought in period t by site i [kWh]
$\chi_{i,t}^{sell}$	Amount of electricity sold in period t by site i [kWh]
$\delta_{g,t}^{G}$	Binary variable = 1 if curtailment of the disconnectable generator unit g is applied during period t, else 0
$\delta_{k,t}^{end}$	Binary variable = 1 if curtailment of the disconnectable load unit $k \in \mathcal{K}^{CD}$ ends during period t, else 0
$\delta_{k,t}^{run}$	Binary variable = 1 if curtailment of the disconnectable load unit $k \in \mathcal{K}^{CD}$ is running in time period t, else 0
$\delta_{k,t}^{start}$	Binary variable = 1 if curtailment of the disconnectable load unit $k \in \mathcal{K}^{CD}$ starts during period t, else 0

$\delta^{bat}_{b,t}$	Binary variable = 1 if the battery unit $b \in \mathcal{B}^{bat}$ is charging electricity during period t, else 0
$\delta^{bat}_{i,t}$	Binary variable=1 if battery of site i is charged in period t, else 0
$\delta^{buy}_{i,t}$	Binary variable=1 if site i is importing electricity in period t, else 0
$\delta^{sell}_{i,t}$	Binary variable=1 if site i is exporting electricity in period t, else 0
$\gamma^{SP}_{k,t}$	Binary variable = 1 if the shiftable load k begins consuming at period t, else 0
$\omega^{SP}_{k,t}$	Delivered energy to the shiftable load unit $k \in \mathcal{K}^{SP}$ during period t [kWh]
$\psi^{G}_{i,t}$	Amount of electricity produced from generating unit in period t in site i [kWh]
$\rho^{SP}_{k,c}$	Time period when the shiftable load $k \in \mathcal{K}^{SP}$ for load shift interval c begins consuming [#]
$\sigma^{seg,ch}_{i,t,j}$	Battery charging energy in time step t in segment j in site i [kWh]
$\sigma^{seg,dis}_{i,t,j}$	Battery discharging energy in time step t in segment j in site i [kWh]
$\sigma^{seg,soc}_{i,t,j}$	Amount of electricity stored in the battery segment j in time step t in site i [kWh]
$\sigma^{ch}_{i,t}$	Battery charging energy in time step t in site i [kWh]
$\sigma^{dis}_{i,t}$	Battery discharging energy in time step t in site i [kWh]
$\sigma^{soc}_{i,t}$	Battery SOC in time step t in site i [kWh]
$\sigma^{reac}_{i,t}$	Battery reactive power in time step t in site i [p.u.]
$\sigma^{ch}_{i,t}$	Amount of electricity charged to the battery unit in period t in site i [kWh]

$\sigma_{i,t}^{dis}$	Amount of electricity discharged from the battery unit in period t in site i [kWh]
$\sigma_{i,t}^{soc}$	Battery SOC of site i in time step t at the end of period t [kWh]
$\theta_{v,s}^{cd}$	Amount of demanded electricity to the EV charging point v in session s [kWh]
$\theta_{v,t}^{ch}$	Load for charging the electric vehicle in charging point v in period t [kWh]
$\theta_{v,t}^{es}$	Amount of electricity supplied to the EV charging point v in period t [kWh]
υ_m	Voltage module of node m [p.u.]
ζ^{CPFlex}	Total cost for utilizing EV CP in the planning horizon [EUR]
$\zeta^{CPNonSupplied}$	Cost for non-supplied EV CP charging [EUR]
$\zeta^{CPShift}$	Cost for shifting all EV CP in the building in the planning horizon [EUR]
$\zeta_{i,t}^{flex}$	Total cost for activating flexibility in period t in site i [EUR]
$a^{inv,ch}(\cdot)$	Battery inverter charging efficiency function [p.u.]
$a^{inv,dis}(\cdot)$	Battery inverter discharging efficiency function [p.u.]
$Dv_{o,t}^{abs}$	Absolute value of deviation in site o in period t [p.u.]
E^{mG}	Fraction of the energy generation of each block matched [p.u.]
E^{mL}	Fraction of the energy consumption of each block matched [p.u.]
$P_{o,t}^{mat}$	Matched power to exchange with the main grid [p.u.]
P_m^{pw}	Active power leaving node m [p.u.]
Q_m^{pw}	Reactive power leaving node m [p.u.]

Chapter 1

Introduction

The main purpose of this chapter is to briefly present the situation of current power systems and their potential problems caused by variable distributed renewable energy generators and electric vehicles, and suggest some solutions. In order to go straight to the point without extending the introduction chapter excessively, this chapter recommends some outstanding references for better understanding of each subject. First of all it is necessary to review the current trends to briefly introduce the context of this thesis. Additionally, forthcoming chapters contain a more detailed analysis of each topic and sub-problem, and the previous work found in the literature.

From the global perspective and according to the International Energy Agency World Energy Outlook 2018, renewable energy generation capacity is growing globally. Photovoltaic (PV) power generation technology is the most popular as its capacity addition in 2017 was 97 GW and the accumulated world PV capacity reached 398 GW by the end of 2017. That means close to a quarter of global PV capacity was installed in a single year. Moreover, wind power generation capacity increased in 48 GW and the total wind power generation capacity in the world was 515 GW by the end of 2017. Additionally, this report estimates there are 870 GW of currently under construction power plants and almost 60 % of the new capacity are renewable generation units (240 GW of PV, 170 GW of wind and 80 GW of hydropower) [1]. Therefore, we can clearly assume that in the near future the power system will have to manage more variable and renewable energy.

The natural power variability of these power production technologies and their almost null operation cost have major implications for power systems. [2, 3] explain the current electricity markets challenges, renewable power production in electricity markets and cross-border transmission system exchanges for better insight of these topics. [2] highlights the benefits and challenges of cross-border power system integration. [3] reviews many aspects including long-term investment decision challenges, electricity market limitations integrating variable renewable power production, demand response and distribution network regulation. The most relevant conclusions of this report for this thesis are:

1. A market design with a high temporal and geographical resolution is therefore needed.
2. New information and automation technologies allow small consumers to contribute to a more flexible and less costly electricity system, responding to wholesale price variations.
3. A further approach consists of treating demand response as equivalent to generation in energy and capacity markets.
4. The regulatory framework should enable distributed energy resources (DER) to participate in both local and wholesale markets.

At European level, decarbonization of the electricity system regulation has been set in motion with the rapid proliferation of distributed and renewable energy production sources. The European Union (EU) had the commitment to cut greenhouse gas emissions by at least 40% until 2030 with an expected share of 50% of renewables by 2030 [4]. Moreover, the recent legislation from the European Parliament establishes at least 32% share of energy from renewable sources in the Union's gross final consumption of energy in 2030 [5]. Additionally, European regulatory bodies defined citizen energy communities (CEC), demand response and aggregator market agent as the centre of new developments for the European internal market in electricity [5]. CECs were previously known as local energy communities (LECs). Both terms are considered equivalent within the thesis scope. The following articles of the recent legislation [5] bring indications to all Member States to regulate accordingly and the more relevant parts for this thesis are:

Article 2.11 defines CEC as a legal entity that:

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

energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders."

Additionally, Article 16.2 states:

> "16.2.(b) are entitled to own, establish, purchase or lease distribution networks and to autonomously manage them subject to conditions set out in paragraph 4 of this Article."

Finally about CECs, Article 16.3 explain:

> "(e) CECs are entitled to arrange within the citizen energy community the sharing of electricity that is produced by the production units owned by the community, subject to other requirements laid down in this Article and subject to the community members retaining their rights and obligations as final customers."

Regarding demand response, Article 2.20 establishes:

> "'demand response' means the change of electricity load by final customers from their normal or current consumption patterns in response to market signals, including in response to time-variable electricity prices or incentive payments, or in response to the acceptance of the final customer's bid to sell demand reduction or increase at a price in an organised market as defined in point (4) of Article 2 of Commission Implementing Regulation (EU) No 1348/20141, whether alone or through aggregation;"

Aggregation role is defined in Article 2.18 as:

> "a function performed by a natural or legal person who combines multiple customer loads or generated electricity for sale, purchase or auction in any electricity market."

Moreover, Article 17.1:

> "Member States shall allow and foster participation of demand response through aggregation. Member States shall allow final customers, including those offering demand response through aggregation, to participate alongside producers in a non−discriminatory manner in all electricity markets."

As a result, nowadays there is a global surge of interest in CECs managed by market-based systems providing demand response and flexibility to aggregators or other market agents. Probably one of the most popular entities developing contents about flexibility standardization for CECs, DSOs, and BRPs is the Universal Smart Energy Framework Foundation (USEF) [6].

Moreover, the EU research and innovation H2020 programme, and more specifically *'The societal challenge of secure, clean and efficient energy'*, has been a significant effort from public authorities and society in general to develop technology in Europe to mitigate climate change. Projects such as EMPOWER and INVADE among others were funded under this programme with the aim of providing new energy flexibility platforms, business models and tools to increase the amount of variable renewable energy sources in Europe.

This thesis deals with the integration of distributed energy resources in the electricity market to contribute in the objective of reducing greenhouse gasses emissions within the context of smart grids via local electricity markets as a new paradigm for scheduling resources of multiple owners and interests. This includes modelling of distributed generation, storage and electric vehicles, and considers there are technologies already implemented as grid automation, sensors, meters and decision-making platforms.

1.1 Smart grids

Smart grids [7–9] are defined in several ways but the author highlights the definition provided by the European Union Commission Task Force for Smart Grids [10]:

> "A Smart Grid is an electricity network that can cost efficiently integrate the behaviour and actions of all users connected to it - generators, consumers and those that do both - in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety. (...) A smart grid employs innovative products and services together with intelligent monitoring, control, communication, and self-healing technologies (...)"

The present section is organized as follows: Section 1.1.1 expose the reasons of the current distributed generation expansion and their price drop. Distributed generation popularization means more challenges for grid operators and therefore it increases the interest on local markets. Section 1.1.2

shows the current cost of electricity storage in batteries as an economically accessible asset in Europe. Section 1.1.3 provides basic knowledge about electric vehicles and their potential impact on power systems. Electric vehicles represent a significant energy shift from oil to electricity and their presence could increase the need of local electricity markets. Finally, section 1.1.4 presents the challenges and some current solutions for DER integration.

1.1.1 Distributed generation

Distributed generation (DG) is based on small but many generators dispersed in the territory. DG moves the production closer to consumption reducing the losses in the grid. [11] introduces the main aspects of DG technologies and their application in microgrids, electricity markets and active distribution networks.

There are two types of DG: dispatchable and non-dispatchable generators in function of their resource. Hereinafter, non-dispachable renewable generators are referenced as variable renewable energy (VRE) generators. The most popular DG technology is the photovoltaic (PV), as previously mentioned at the beginning of the introduction, and it is basically VRE because it depends on the solar radiation. However, recent developments in technology, and more complex grid constraints and market conditions, created the need of reducing power generation under certain circumstances. For instance, IEEE 1547-2018 included PV inverter inertial response capability modulating active power to the rate of change of frequency [12]. In Germany, the Renewable Energy Act (Erneuerbare Energien Gesetz EEG-2017) introduced the obligation of solar producers to install a device capable of communicating with the local DSO and controlling the installation remotely. However, installations with a maximum capacity of 30 kW have the possibility to limit the maximum PV output to 70% of the installed capacity locally and avoid the remote control.

One of the key factors for DG growth is its relative high cost-effectiveness for small scale systems and the national level economic incentives. The economic feasibility of a power generation system project can be evaluated using the levelized cost of energy (LCOE). LCOE helps to compare technologies considering all costs of these during their lifespan. The Lazard consulting group presented [13] to compare LCOE per technology for 2018. Table 1.1 shows that wind and solar PV at utility scale are cheaper options than gas combined cycle. Additionally, solar PV at commercial scale or for rooftop residential applications can be competitive in many countries for self-consumption as it allows to avoid grid costs and other charges in end-

Table 1.1: Unsubsidised levelized cost of energy (USD/MWh) comparison. Source: [13]

Renewable energy sources	**Min**	**Max**
Solar PV - Rooftop residential	160	267
Solar PV - Commercial and community	73	170
Solar PV - Utility scale	36	46
Wind	29	56
Conventional energy sources	**Min**	**Max**
Gas peaking	152	206
Nuclear	112	189
Coal	60	143
Gas combined cycle	41	74

user electricity tariffs. Finally, the report states wind and utility-scale solar PV average LCOEs have decreased 69% and 88% over ten years respectively.

Additionally, DG has received many national economic incentives as the well-known feed-in tariffs but also feed-in premium, national auctions or green energy certificates. Denmark, Germany and Spain are relevant examples about different praxis and results designing renewable power generation economic incentives [14].

1.1.2 Energy storage systems

Energy storage systems in general and electrochemical batteries in particular create new opportunities in power systems operation [15, 16]. Recent technology developments and cost reductions are the main reasons for its popularization in electric vehicles and stationary applications in households and utility-scale applications. Lazard report about levelized cost of storage [17] shows an average capital cost reduction over last five years of 28% for lithium-ion, 38% for flow-battery vanadium, and 17% for advanced lead-acid. For example, the usage of lithium-ion storage behind-the-meter for residential scale combined with solar PV costs between 476 and 735 USD/MWh. However, the same application at commercial or utility scale falls to 340 USD/MWh on average. Regarding in-front-of-the-meter storage applications, lithium-ion costs around 367 USD/MWh for grid purposes and 251 USD/MWh for wholesale markets utilizations. Unfortunately, it is difficult to know the real LCOS for electric vehicles as multiple carmakers are currently competing to offer high-performance models.

1.1.3 Electric vehicles

Electric vehicle [18–21] sales figures from last years are rising and new models are more efficient than few years ago. According to the IEA [22], the global electric car sales in 2018 were 2 million and the total fleet reached 5.1 million. In terms of market share, the global share is not significant yet but Norway has the highest annual vehicle sales share in the world with 46% of electric vehicles in 2018. Regarding energy consumption, they consumed 58 TWh in 2018 and the agency expects it will growth to 640 TWh in 2030 in the New Policies Scenario [22]. It would mean a worldwide EVs consumption equivalent to the combined French and Spanish current national consumption.

Compared from the recent past, they carry bigger batteries, and their acquisition costs per range capacity is decreasing significantly. For example, global plug-in light vehicle deliveries increased 64% from 2017 to 2018 and the total distribution over the world surpassed 2 million units in 2018 according to [23].

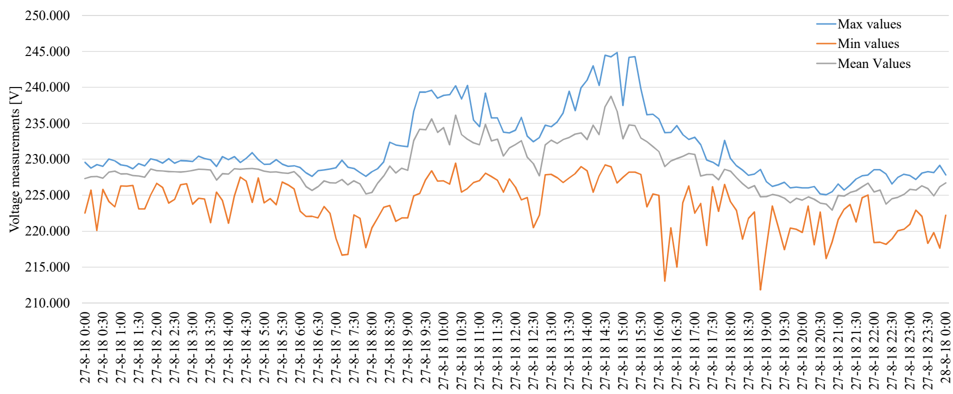
1.1.4 Integration of DERs

The integration of distributed energy resources (DERs) requires tools like smart meters to monitor energy flows, sensors at different levels, and communication technologies to interconnect grid elements. In that sense, cloud-based platforms are clearly a technology that can help power systems operation to solve these issues as it enables to use decision-making algorithms and send control signals based on optimization problems, artificial intelligence and forecasting algorithms.

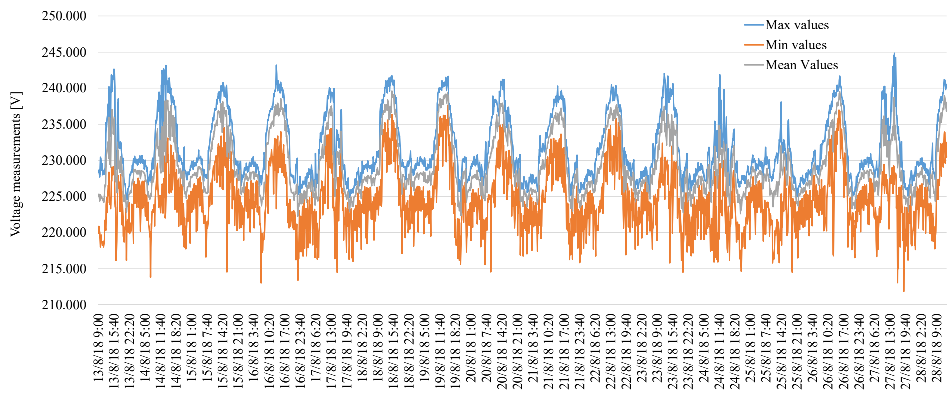
The current technical developments in distributed generation can cause bidirectional power flows in grids. Additionally, storage and electric vehicle technologies can create significant variations in household load profiles as Fig. 1.1 shows and consequently in distribution grids if this technology becomes popular with the current functionalities. This fact has major consequences in the power system, from the network planning and regulation to the daily basis grid operation.

For instance, the German pilot in INVADE H2020 project is facing voltage variations in their low voltage grids due to high PV power generation. Fig. 1.2a shows one day voltage variations above 240 V for the maximum values during the sunny hours and around 235 V for the mean values over 10 minutes measurements. This effect is not punctual and it can be repeated over days and weeks as Fig. 1.2b shows. Therefore, in scenarios

Fig. 1.1: Household load profile with photovoltaic power generation, storage and electric vehicle under an energy management system from Tesla, Inc. Courtesy of [24]



a) August, 27th 2018



b) From August, 13th to 28th 2018

Fig. 1.2: Voltage variations in a low voltage line located in the South of Germany. Courtesy of badenova AG & Co. KG.

of high presence of distributed generation, voltage values could rise above technical standard limits.

Demand side management is also key for DER integration. The European Technology Platform [25] defined the objective of DSM as:

> Enable consumers' participation in the electricity market: Demand flexibility must be exploited to offer services to the different market participants enhancing consumer flexibility and adaptability, thus providing real-time optimisation of energy flows at local and global level. To this purpose, real-time metering data

have the potential to facilitate active demand services.

Under demand response scope, EVs and storage units have a significant role managing charging processes due to their significant energy consumption and time shifting capability. Fig. 1.3 shows a representation of a distribution network with flexibility devices (FD) such as EVs, demand response and storage units in different configurations. 1 shows a MV/LV substation connected to a constrained line due to excessive energy export and low consumption. In such case, community storage unit and vehicle2building installation try to consume as much as possible energy to reduce the congestion. In contrast, 2 is a secondary substation with excessive consumption due to some uncontrolled EVs and consumption from air conditioning systems. In such case, some vehicle-2-home units in combination with centralised and distributed storage units, supply power to the grid in order to reduce transformer load. Similarly, 3 is a substation with high power demand and the vehicle-2-grid charging station is discharging vehicles and storage unit to reduce issues.

1.2 Electricity markets

Electricity markets [26, 27] are described as a very important zone in the smart grid domain. Markets are a way to organize the distribution of commodities in an efficient way when conditions enhance perfect competition between the actors. However, electricity is not a simple commodity. In order to ensure reliable and continuous delivery of significant amounts of electricity, the system needs bulk power generation plants, transmission and distribution grids and different control and monitoring functions to keep the system technically feasible. The main objective of electricity markets is to introduce competition between agents like generators and retailers and then to ensure the minimum electricity price for customers.

1.2.1 European and national level markets

Some recent episodes in European markets highlight the need of increasing flexibility. First, negative prices in European day-ahead markets are a clear incentive to shift demand during sunny or windy hours. For instance, the German EPEX day-ahead electricity market in June, 2nd 2019, had a price of -9 EUR/MWh between 2 pm and 3 pm [28]. Other more extreme episodes happened in the French EPEX day-ahead market over the Sunday June,

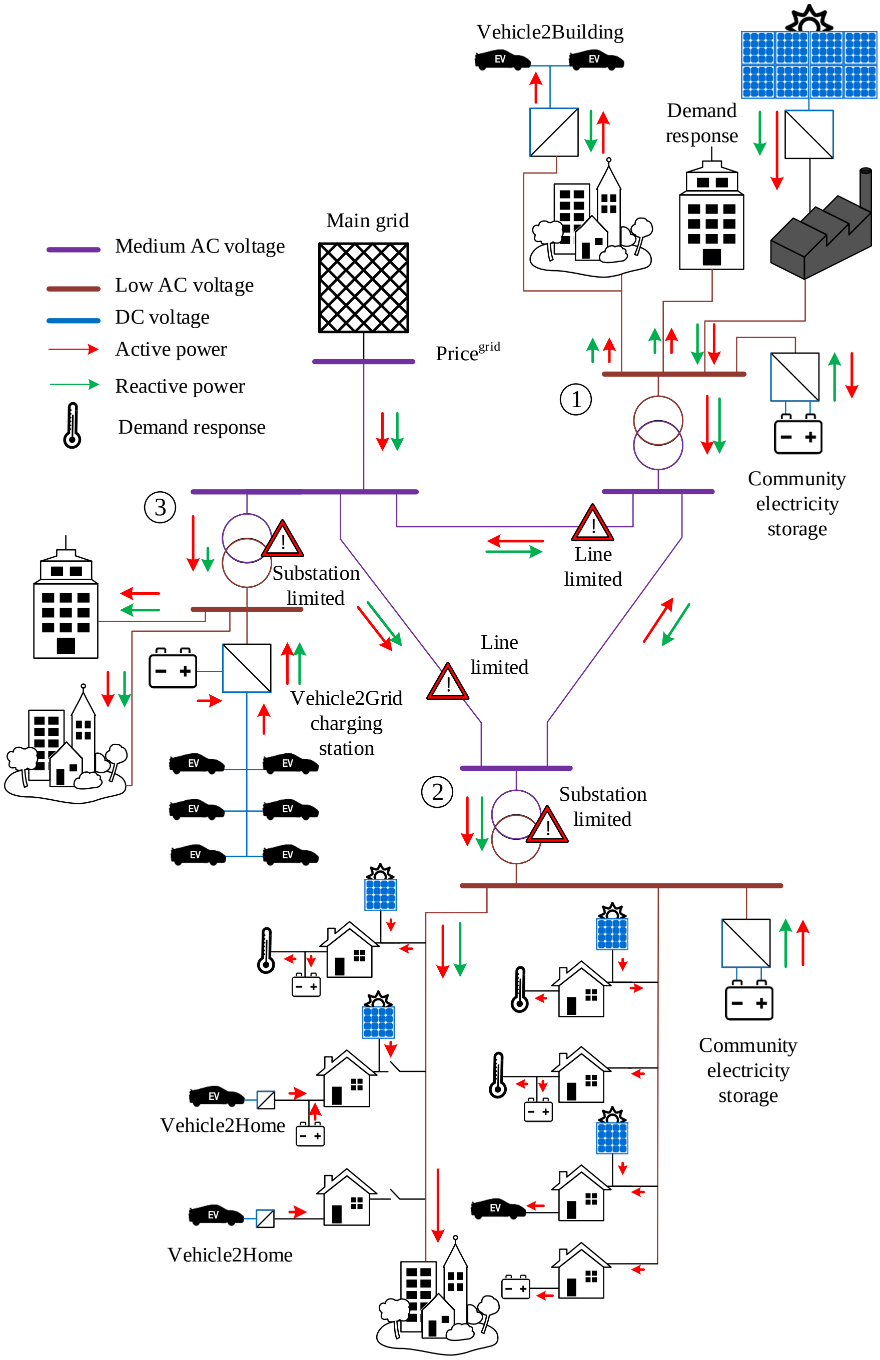


Fig. 1.3: Schematic of a distribution network with FDs and congestion issues

16th 2013 which had 6 consecutive hours with negative prices and the price between 5 am and 8 am was -200 EUR/MWh.

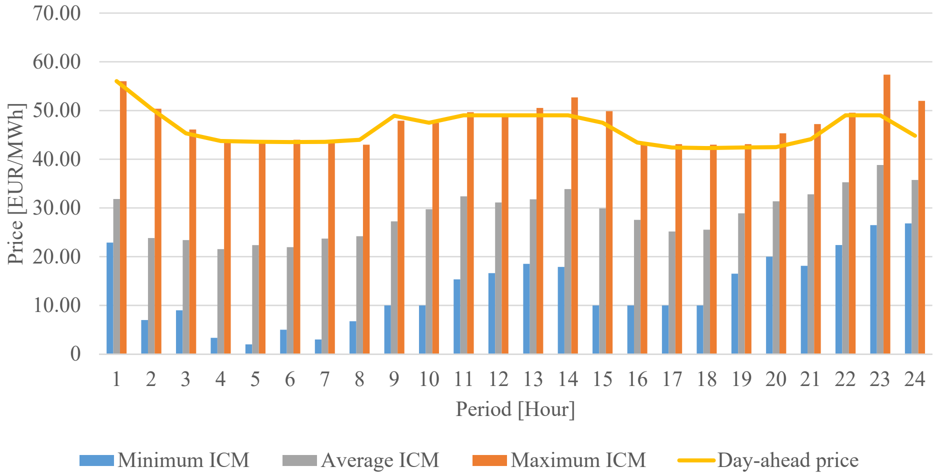
Moreover, German EPEX intraday continuous market is also experiencing high variability in prices. For instance, in May, 13th 2019, priced varied from -141.74 to 150 EUR/MWh for the period between 4:45 am to 5:00 am and the buying and selling energy volumes for that period were 464.2 and 458.9 MW respectively. Similarly, the same market reached 2.999,7 EUR/MWh for period 11.30 pm to 11:45 pm in July, 22nd 2018.

In contrast, the Spanish intraday continuous market is quite new compared to the German Intraday market, it started on June 2018, and energy agents are quite conservative making transactions because they can still bid in intraday auction sessions. One significant case of price volatility happened on the June, 8th 2019 with prices between 2 EUR/MWh at 4 am, and 57.36 EUR/MWh at 10 pm as Fig. 1.4a shows. Additionally, if you take into account the energy trading volume that Fig. 1.4b shows, you can realise that very probably retailers underestimated consumption and they needed to purchase energy in order to avoid deviation penalties. Therefore, intraday continuous market is also another potential revenue stream for flexibility sources.

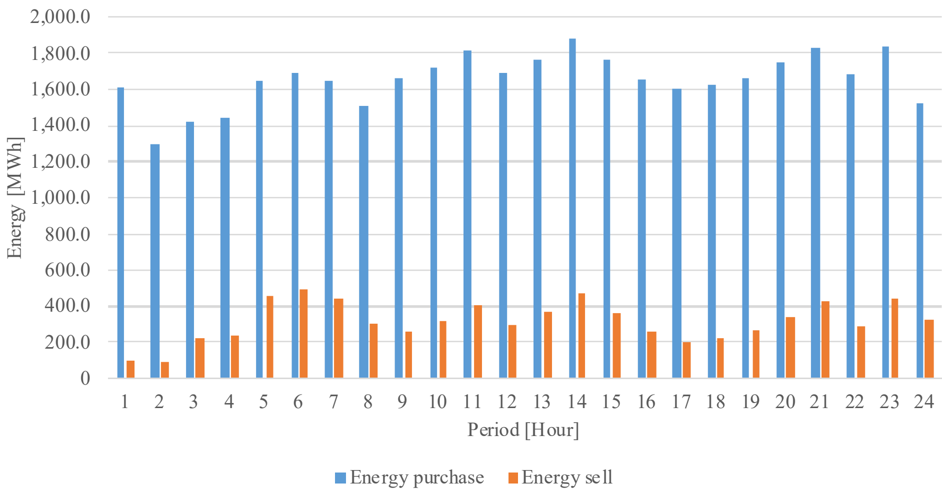
Regarding balancing prices, on May, 7th 2019 for the period between 8 pm and 9 pm, the Spanish secondary regulation market had a price of 11,498.85 EUR/MWh for down-regulation and BRP deviation penalties were above 1.200 EUR/MWh [29]. Reports about such episode are not yet available but significant wind production forecast error combined with an unexpected event in a thermal power plant, and a peak demand backwards shift created a perfect storm.

In terms of annual ancillary services (AS) cost, the Spanish case provided in Fig 1.5 shows a relation between cost and VRE production except for 2016-2018 when the TSO enabled wind power producers to offer secondary downward regulation. This change reduced drastically the Spanish operation costs. The cost peak occurred in 2013 and 2014.

In 2013, Spanish system had very low prices in the day-ahead market during the beginning of 2013 caused by high hydro-power and wind production. For instance March had 28.41 EUR/MWh and April 19.33 EUR/MWh average day-ahead market price. In contrast, the same period had unusual high technical restrictions at transmission level after the day-ahead market auctions with 2 TWh of up-regulation energy during the first phase due to high renewable power generation. This represented 27.7% of total up-regulation requests in 2013 for this service. For the same reasons, 65% of the annual down-regulation energy for solving real time constraints occurred during



a) Intraday prices



b) Intraday negotiated energy

Fig. 1.4: Spanish intraday continuous electricity market of June, 8th 2019

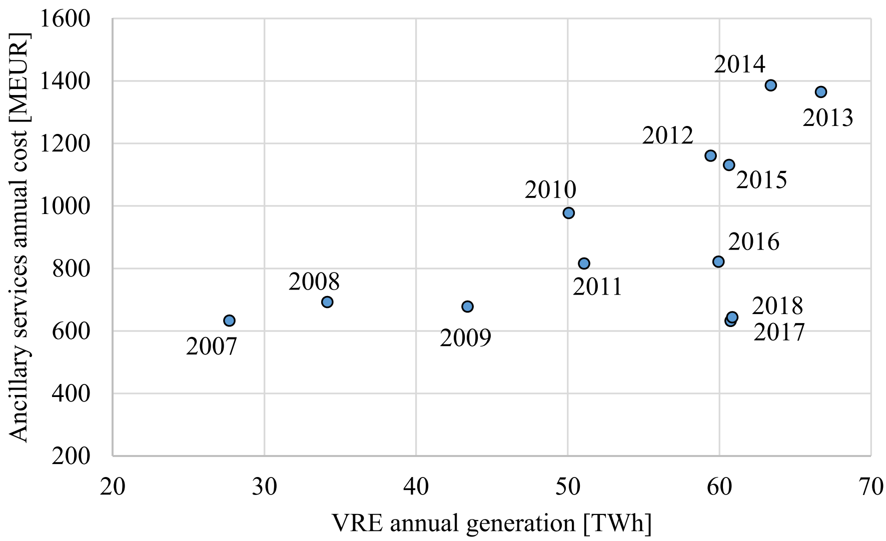


Fig. 1.5: Spanish ancillary services annual cost compared to the annual VRE sources annual production. Source: REE

March and April. The total up and down-regulation flexibility activated for solving real time constraints during 2013 was 558 GWh and 1,701 GWh respectively [30].

Fig. 1.6 shows the up and down-regulation annual energy used in the Spanish secondary regulation market. This plot shows a significant relation between VRE annual power generation and secondary up-regulation services. Mainly due to the thermal generators which supply energy when VRE production is less than expected. In terms of annual cost, Fig. 1.7 shows a less significant relation between VRE annual production and total annual cost for up-regulation. In contrast, down-regulation service is not correlated because wind power plants are authorised to provide down-regulation services since 2016 and they can help the Spanish TSO in case of excessive power generation.

Italy had a similar tendency from 2006 to 2015 with positive correlation between AS cost and VRE production. [31] highlights the cost increase from 2013 and 2015 compared to previous periods without VRE production probably due to market design. In contrast to the Spanish and Italian cases, [32] shows a reduction of AS costs by 50% in Germany from 2008 until 2015 when VRE production increased 190%. It is important to mention that Germany has more interconnection power capacity with other countries than Spain

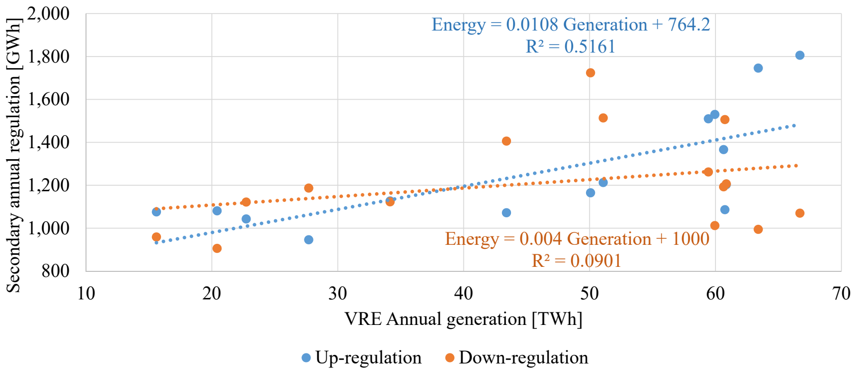


Fig. 1.6: Up and down-regulation energy used for automatic frequency response (secondary regulation) from 2004 until 2018 compared to annual VRE energy production. Data from Spanish TSO (REE) annual reports

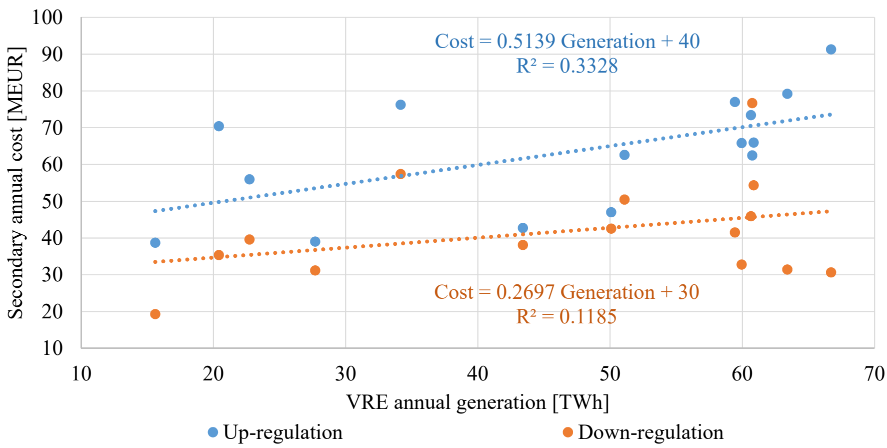


Fig. 1.7: Up and down-regulation annual cost for automatic frequency response (secondary regulation) from 2004 until 2018 compared to annual VRE energy production. Data from Spanish TSO (REE) annual reports

and Italy due to geographical reasons. In terms of cross-border energy exchanges, Germany exported/imported 82.7/31.5 TWh, Spain 12.9/24 TWh and Italy 47.1/3.2 TWh respectively [33]. Therefore, electricity markets are providing significant signals for new flexibility services in case of needing them which could eventually reduce operation costs. Additionally, some countries have not regulated demand response yet in AS. However, wholesale markets and AS are not capable of dealing with distribution level congestions as they are designed nowadays. Thus, local markets arise as a potential solution for solving MV or even LV congestions and postpone grid reinforcements.

It is difficult to say what is going to come in the power sector and electricity markets as history proved humans are really bad doing predictions like in 1889 when Thomas Edison said: "Fooling around with alternating current (AC) is just a waste of time. Nobody will use it, ever" or like in 1943 when IBM Chairman Thomas Watson said "...there is a world market for maybe five computers". In my humble opinion, if you take into account the decreasing costs of VRE and the contribution of demand response in AS, power system costs should decrease in the future. However, there are very uncertain aspects to take into account that could change everything like new market designs (if necessary) when marginal price-based electricity markets are no longer valid mechanisms for cases with vast majority of VRE. Also for example, capacity mechanisms for thermal power plants needed during weeks without much wind and sun, and the upcoming developments of storage technologies capable of short, mid and long-term energy storage are quite uncertain. Additionally, the transport sector electrification trend could represent a major change in the power sector. Therefore, the only certain thing is we need more engineers in the academia and the industry to tackle these problems and those that are going to appear in the near future.

1.2.2 Local electricity markets

As explained before, the increase of intermittent small-scale distributed generation, the empowerment of consumers and new electric loads like electric vehicles (EVs) are forcing the power system to evolve. In the past, centralised, dispatchable and predictable generation provided enough flexibility at the transmission level to balance the system. Now, the increasing amount of installed distributed renewable generation is transforming the generation side into a more variable and intermittent source of energy that needs to be managed locally. In addition, the demand side will be more active, emphasizing the empowerment and engagement of consumers. The proper management of available flexibility, both in generation and demand side, can help to compensate the lack of certainty of renewable sources.

Currently, small generators participate in wholesale electricity markets aggregatively without considering their location within the distribution network. In the future, with a high share of DER in the distribution networks, the power quality could be compromised in terms of voltage and line capacity violations. DSOs could expand the grid with redundant transformers, but demand response, storage and DER could constitute an economically more profitable way to solve grid constraints [34]. Hence, it is necessary to explore operation algorithms to increase the hosting capacity of distribution systems. One option might be that the DSO could send command signals to DER to reduce the active power injected to the grid [35]. However, this approach could compromise DSO regulated activities acting as an energy manager.

Market-based initiatives are an alternative option to deal with these situations at distribution network level. Such initiatives have recently caught the attention of policy-makers, regulatory bodies and researchers alike. Their consensus is that the current electricity market structure has limitations when it comes to integrating renewable energy into the distribution grid.

From the national market perspective, [36] presents integration limitations of the current market design for scenarios with large-scale penetration of weather-dependent generators. The forthcoming energy sector transformation with massive penetration of PV panels combined with load management has been introduced without identifying an appropriate market framework for dealing with them. [37] analyses the support schemes for renewable energies and their impact on wholesale electricity markets, and [38] evaluates the effect of intermittent renewable energy on German wholesale markets. Both references agree on the positive effects of using more flexibility to integrate renewable intermittent generation effectively.

Therefore, present thesis focuses on the usage of flexibility for solving distribution grid problems through local flexibility markets (LFM). At the same time, such flexibility provision could be useful for balance responsible parties (BRP) doing arbitrage and prosumers willing to reduce their electricity cost if the distribution grid is not constrained.

1.3 Objectives and scope

This section presents the objectives and scope of the work conducted by the author during the realisation of this thesis. Fig. 1.8 depicts a conceptual overview including all topics analysed in this thesis. This figure represents a futuristic prosumers neighbourhood with the presence of DER such as electric vehicles, batteries, thermal loads (e.g. electric water heaters), photovoltaic panels and small scale wind generators. Hereafter called flexibility devices (FDs). All FDs are connected to a communication infrastructure such as regular internet connection and they send their measurements to the aggregator local platform. Based on the collected information, aggregator executes a decision-making algorithm in a cloud-based platform and sends back control signals such as ON/OFF control for shifting EV charging processes or power setpoints for battery charging of a prosumer site among other possibilities. Given this general architecture as a thesis scope, the topics of the thesis are described below.

Firstly, it is necessary to determine if EV charges could cause complications in distribution grids building a prospective model EV charging demand and then to quantify the impact. This has to consider the stochastic behaviour EV drivers using methodologies such as Monte Carlo. It has to determine the impact on lines, transformers, and wholesale electricity markets, and optimise EV charges for buildings with charging points as shown in Fig. 1.8 in sub-problem 1.

The previous work highlights the need to provide aggregated flexibility services in order to avoid grid congestions or high charging costs. Thus, the consequent objective is to provide a local market auction algorithm capable of dealing with all previously mentioned issues: grid congestions, price variations and flexibility integration 2. However, the current unbundling does not allow to merge DSO and retailer activities in EU and there is a lack in the current literature about market-based mechanisms for aggregators providing flexibility services. 3 refers to the proposed local flexibility market design for aggregators acting as market operators scheduling FDs at minimum cost based on end-user flexibility contracts considering the new roles for each agent in the local market. Once the local flexibility market framework is set, the thesis aims to provide flexibility optimization algorithms for attending DSOs without prosumer constraints in 4. Later, sub-problem 5 includes prosumer constraints and additional flexibility services. Finally the thesis considers relevant to reduce the computational burden and time for large-scale portfolio optimization with decomposition techniques 6.

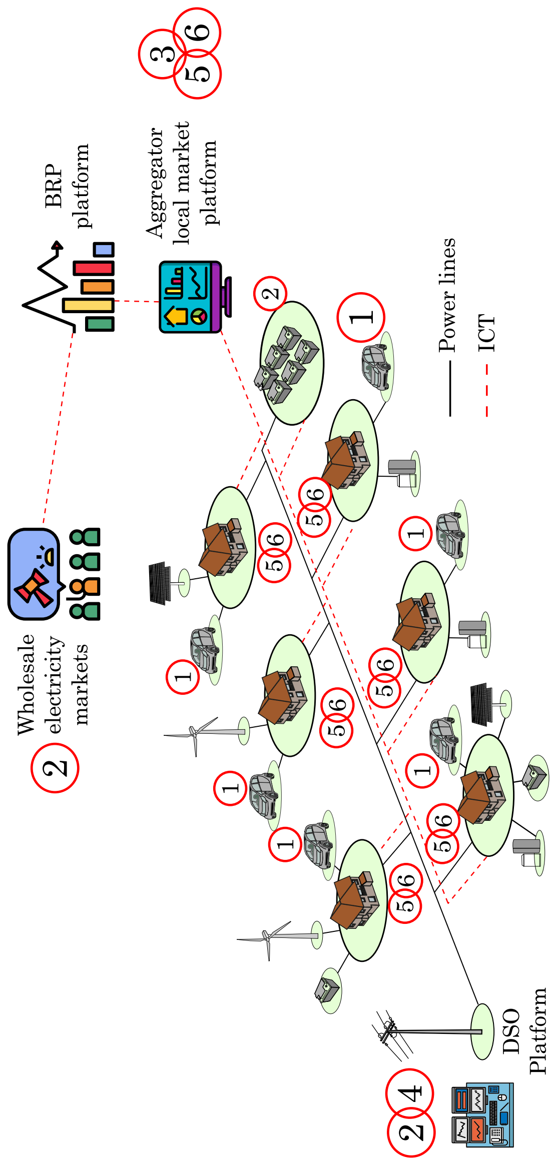


Fig. 1.8: Global view of a neighbourhood with flexibility devices connected to an aggregator local market platform interacting with the local DSO, BRP and wholesale electricity markets.

After introducing the potential problems analysed in the thesis, the objectives are enumerated below for each topic of the thesis:

1. **Analyse the impact of electric vehicles in distribution grids, electricity day-ahead markets and buildings:** Create a methodology to estimate the EV charging demand in multiple scenarios, create a methodology to analyse distribution grids and electricity markets, and design an EV charging management system for buildings in real environments with limited information access.

2. **Design and analyse a flow-based local energy market for interacting with day-ahead markets,** in order to taking advantage of price volatility without threatening the distribution grid with local flexibility assuming full information from all stakeholders.

3. **Design a local market within the current EU regulation framework for aggregators managing a portfolio of flexibility devices** from various owners with their individual costs and preferences and limited information access. In this local market, each participant end-user sets their own flexibility prices through contracts and their activation would depend on the location, availability and price.

4. **Formulate an optimization problem for the aggregator local flexibility market framework previously defined to schedule demand for meeting distribution system operator requests**. In such scenario, aggregator has the commitment of increasing or decreasing the load in a certain zone during specific periods from the local DSO to deal with grid congestions which are unknown by the aggregator where participant end-users constraints are not considered.

5. **Provide a flexibility services provision optimization algorithm for aggregators remotely managing prosumers**. This must be an extension of the previous algorithm considering participant end-user constraints. The same algorithm must decide to provide flexibility to BRPs and end-users according to the situation.

6. **Erase scalability boundaries of the previous aggregation flexibility optimization algorithm for large-scale portfolios**. The objective is to use a decomposition technique in order to reduce the computational burden and time. Such algorithm has to provide a feasible solution in less than 10 minutes.

1.4 Thesis related work and activities

This section provides an overview of the chronological activities developed by the author during the thesis period, both the ones included and non-included in the thesis document.

The predoctoral activities include EVCity, Smart Power, and Instinct projects from 2013 to 2014 promoted by the EIT InnoEnergy. EVCity project *WP1: Business & Services models to support the roll-out of electric vehicles in cities* aimed to detect what kind of local grid constraints could difficult the integration of EVs in scenarios of massive EV presence. Smart Power project - *Action 2.4 Energy markets regulation for electric vehicles encourage* was focused on national level electricity markets and EV integration. Instinct project - task 2.5.4.1 *Evaluation of EMS for VPP* aim was to assess the economic benefits of Virtual Power Plants scheduling electric vehicles considering an scenario of massive EVs presence. The outcomes of these projects were two conference papers [C1], [C2] published in 2014, one journal paper [J1] published during the early stages of the doctoral studies, and one book chapter [BC1]. Additionally, the author also contributed to knowledge dissemination about distributed energy resources in technical publications for engineers in the industry in [TR1], [TR2], and in local conferences [C16], [P-C1].

Thereafter, doctoral activities began with EMPOWER H2020 project *Local electricity retail markets for prosumer smart grid power services* (Grant No 646476) in January 2015 with the aim of designing a local trading platform and its duration was three years. During the first year of the project, work was focused on the trading platform architecture for local markets from technical point of view [TR3] in collaboration with the start-up eSmart Systems AS (hereafter eSmart), and the architecture of the local market [TR4] in collaboration with Smart Innovation Østfold (currently and hereafter Smart Innovation Norway AS (SIN)). From this work, two conference papers [C3], [C4] were published. This period included one collaboration with N. Leemput (KU Leuven) about EVs in [J4], and one collaboration with E. Prieto-Araujo (CITCEA-UPC) in [J5] about DER emulation for microgrid laboratories.

In 2016, the author moved to Norway and worked for SIN in local market design work-package of EMPOWER project. The objective was to consolidate the local market concept, its relation with the new market agent aggregator, DSOs and retailers, design local market contracts and develop trading algorithms. The work conducted during this stage was developed in close collaboration with eSmart for its implementation in their cloud platform. The result of this work was two journal publications [J2], [J3], three conference papers [C5], [C6], [C7], two EMPOWER technical reports [TR5], [TR6], two presentations in non-academic conferences [P-C2], [P-C3] and one book chapter [BC2]. Additionally, INVADE project proposal was prepared during this period resulting in a new project for further development of local markets and flexibility services at distribution grid level between 2017 and 2019.

The author moved back to Barcelona and CITCEA-UPC in 2017 to finalise his doctoral studies in local electricity markets and participating in INVADE H2020 project *Smart system of renewable energy storage based on integrated EVs and batteries to empower mobile, distributed and centralised energy storage in the distribution grid* (Grant No. 731148). INVADE tasks included the work-package leadership of dissemination and communication of INVADE project which included the corresponding deliverables and reports. Moreover, the activities included the task management for designing detailed control algorithm of flexibility management operation, and close collaboration with architecture work-package. This period resulted in the last thesis journal paper submission [S-J1], four conference presentations and posters in collaboration with other colleagues [C8], [C12], [C14], [C15], one collaboration with CIGRE WG5.24 [C13], one presentation in a local conference [P-C4], two journal paper collaborations with colleagues in CITCEA-UPC [J6], [J7], three book chapters [BC3]-[BC5], and seven INVADE technical reports in collaboration with NTNU, eSmart, Elaad and VTT [TR7]-[TR13]. Finally, the thesis concluded with three journal collaborations about energy security [J8], [S-J2] and life cycle assessment [J9].

The author was also a member of the EIT InnoEnergy PhD School and he attended to multiple courses about economic, scientific and technological intelligence, energy economics, managing innovation, and data science in institutions such as INSA Lyon, Grenoble Ecole de Management, ESADE business school, and DTU respectively.

1.5 Thesis outline

The contents of the thesis are organized as follows according to the topics and objectives explained before:

- **Chapter 2** presents the electric vehicle agent-based model for analysing distribution grids and electricity markets. Additionally, it includes the optimization algorithm for managing EV charges behind-the-meter. This work corresponds to the first thesis objective.
- **Chapter 3** corresponds to the early stage of local markets research assuming full information. This chapter aims to achieve the second thesis objective providing a flow-based day-ahead local energy market design for DER. This market assumes the presence of a new entity acting as a local market operator with all possible information regarding grid technical status and energy offers at MV/LV transformer level.
- **Chapter 4** presents the local flexibility market design for aggregators providing multiple flexibility services at the distribution network level with limited information to accomplish the third thesis objective. This chapter includes the roles of market participants, their interaction timelines, contracts between participants, and local-wholesale markets interactions.
- **Chapter 5** designs, implements and tests in an emulation microgrid laboratory an optimization algorithm for local flexibility market operations providing flexibility services to DSOs. Therefore, assuming the framework presented in the previous chapter, this work presents the minimum viable algorithm for flexibility services provision for real implementation in EMPOWER project. This chapter corresponds to the fourth thesis objective.
- **Chapter 6** extends the previous algorithm in order to include prosumer site constraints and objective function according to the fifth thesis objective. Additionally, this chapter provides a distributed optimization version of the aggregation algorithm in order to reduce its computation burden and time as the sixth thesis objective described.
- **Appendix A** enumerates the publications related and non-related to the thesis.

Chapter 2

Electric Vehicle Impact on Smart Grids and Electricity Markets

2.1 Introduction

Electric vehicles (EVs) are presented as an alternative to current internal combustion vehicles powered by fossil fuels. Increasing oil prices, greenhouse gas emissions and environmental concerns of citizens boost interest in this technology. Energy supply from power networks is required and the impact on the distribution grids in a massive EV integration scenario has to be analysed in detail [39]. Thus, studies about EV impact on power networks are needed to ensure the viability of the systems [40–42].

The EV charging demand model should allow the analysis of possible effects of this new demand supplied in present-day power networks. In order to do so, an EV charging model should include specific characteristics for each case, such as mobility, and it should allow to compare different cases. Moreover, it should consider probability distribution functions (PDF) to analyse the uncertainties of possible EV charges. In addition, this model should be designed to analyse the application of control strategies and enable their comparison.

Literature proposes models to calculate the demand with respect to vehicle, charging infrastructure, mobility, and social parameters. [43–47] use different parameters such as EV model, distance, and charging process among others to determine the EV charging demand.

2.1.1 EV Type

From the point of view of EV charging demand, EVs main characteristics are the vehicle type: Plug-in Hybrid Electric Vehicle (PHEV) or Battery Electric Vehicle (BEV), battery capacity, battery technology, EV range and energy consumption. [48] exposes an analysis about EV design considerations. Different authors only consider PHEV [40, 41, 43, 49–53]. Others only

BEV [54–58] or a combination of both [47, 59–61]. Another option is to suppose average EV models, BEV and PHEV, with average characteristics like different authors do [43, 44, 56]. [62] simulates only two representative EV models: Chevy Volt (PHEV) and Nissan Leaf (BEV) and [55] simulates Mitsubishi i-MiEV (BEV) only.

[47] proposes a stochastic model with mobility variables, but the vehicle characteristics are determined by a Gaussian distribution with standard values for the capacity, energy consumption and charging power of EVs.

The majority of papers simplify the EV model selection, but the capacity and the energy consumption are significant variables to be considered. The model presented proposes using real EV models and their technical data to define the battery capacity and energy consumption of each EV model. Moreover, the probability of each EV model is based on sales forecasting [63] to decide which EV model is more probable.

2.1.2 Battery and Charging Process

Regarding EV batteries, there are three variables linked: capacity (kWh), range (km) and energy consumption (kWh/km). [57,64] consider the battery characteristics of real models and [53, 58, 65, 66] consider average battery characteristics. Moreover, it is important to take into account the relation between the power consumed and the state-of-charge (SOC). [55] determines a relation between EV model, battery characteristics (Li-ion, 50 Ah, 16 kWh and 330 V) and its charging process.

The charging process standards of IEC 61851 [67] from Europe and SAE J17724 [68] from the USA could also change the impact in the power system. [60] compares the impact of each SAE standard. The voltage level in Europe for slow charges is 230 V and a maximum current of 16 or 20 A. In Belgium, houses have a protection up to 20 A [69] and in Spain, the common protection is up to 16 A [55]. [55] uses the power ratio of Mitsubishi i-MiEV when the initial SOC is 20% and the EV needs 4 hours to reach 100%. [70] uses level 1 (120 V–15 or 20 A) in the studio located in the United States. To compare, [71] uses 230 V and 15 A and the study is located in New Zealand. The efficiency used in the studies is around 90%, as [72] in 1983 proposed and this assumption was recently confirmed by [40, 50, 73].

Different works, such as [40,74], use constant power profiles. On the other hand, [60] consider variable power during the charging profiles. [75] propose a charging process model which links the power of the charger and SOC. [76] link the SOC and the charging time. Different authors use the specific EV charging profile of a real EV. For example, [75,77] use the charging profile of the Nissan Altra EV with a battery of 29 kWh, while [78] use a three-phase charging profile of Opel Meriva, which has a battery of 16 kWh.

2.1.3 Charging Infrastructure

Charging infrastructure parameters include the EV charging point's socket and availability to charge. The majority of works do not consider the EV infrastructure when calculating the EV charging demand. Inherent to this hypothesis is to neglect the effect of the queues at charging points by supposing there are enough charging stations, and the assumption of full compatibility between charging stations and EV connectors. Both could be reasonable in future scenarios with massive presence of EV, but could be a problem for fast chargers. [79] introduce the queue theory with exponential distribution function to simulate EV charging time and relate it to the maximum charging power of the EV.

2.1.4 Mobility

Mobility is the third key point of EV charging demand. There is a strong link between energy consumption of EV and urban mobility. For example, [80] reviewed the energy consumption in urban areas, including electric mobility.

Some authors employ the NHTS (National Household Travel Survey) to analyse the United States mobility patterns, such as [59, 70, 74, 81–83]. In the United Kingdom, studies use NTS (National Travel Survey) and UK-TUS (United Kingdom Time Use Survey), for instance [41, 84, 85]. In Germany, there is the MID (*Mobilität in Deutschland*) which [58,86] apply. The MON (*Mobiliteitsonderzoek Nederland*) is utilised by Dutch studies, as [77]. The DTU *Transport, DTU. Transportvaneundersøgelsen* is used in [87] for a case study of Denmark. In the case of Spain, there are different databases, for example *Dades Bàsiques de Mobilitat 2008* for Barcelona city [55] and *MOVILIA* for the whole Spain [88].

[65] makes use of the Deutsches Mobilitätspanel to simulate 1000 mobility of household profiles and this includes day and time of departure and arrival, travel distance, vehicle used, and destination. Additionally, [58] makes projections of EV hourly charging profiles based on MID 2008.

The present work proposes that the reason of displacement be included to determine the destination and the instant of the day to displace. Due to that, it is possible to distinguish between professional and personal mobility.

2.1.5 Social

There are social variables related to the EV driver profile that could influence EV charging demand as GDP. [81] analyse the EV charging demand considering the income, age and gender of drivers as well as the location (urban or rural). [84] use the number of members of each household and the corresponding number of vehicles based on the UKTUS database. [46] define the number of displacements, the number of houses, and the number of vehicles per house. The proposal of the present chapter is to combine these three approaches of the previous work to consider social aspects to calculate the EV charging demand.

2.1.6 Simulation Techniques

To define the characteristics of simulations, there are different details set out by each author. The first one is the data processing, after that the emulation of parameters and lastly, the driver behaviour emulation.

Considering data processing, there are different types of simulation models to emulate the EV charging demand and the most used is agent-based. This type of model considers each EV driver autonomously defining the internal (e.g., energy consumption) and external (e.g., power demand to supply EV battery) variables. The bottom-up approach simulates the system coupling all the agents of the system. Different examples of agent-based and bottom-up approach studies are [82, 89, 90]. On the other hand, the bottom-down approach simulates the EV driver behaviour with the average parameters [55, 60].

As concerns the emulation of parameters, some models use deterministic variables and others stochastic ones. The deterministic approach considers just average values of parameters and stochastic models use probability distribution functions. The Monte Carlo technique is used to simulate stochastic variables in many applications and it is also used in modeling load, EV charging demand and distributed generation to determine their variability. The majority of studies set out a deterministic approach, but some of them include stochastic variables such as [41, 55, 58, 74, 77, 84, 85]. Some of them use Monte Carlo techniques to simulate the total demand.

EV driver behaviour also influences the EV charging demand. This parameter is linked to time of day and location for EV charging, such as public stations between trips, at charging points at work or just home charging.

[91] defines user profiles related to estimated behaviour in the function of mobility, current electricity price and price forecasting. [89] uses microsim-

ulation techniques to emulate the driver behaviour. [92, 93] use MATSim (Multi-Agent Transport Simulation) and this tool allows the creation of more than a million connections between agents in transport issues. [94] uses evolutionary algorithms; [95] proposes using the Balmorel program to include distribution network, district heating, optimization, taxes and geographical data. [96] proposes including the game theory to simulate the interaction between agents and including sale of electricity with V2G service. [97] uses GPS data and EV metering to calculate the energy consumption and later to optimize the battery sizing of future PHEV.

The present work proposes combining some characteristics presented in literature. The methodology presented is a bottom-up approach to process the data with stochastic variables following the Monte Carlo formulation to emulate the parameters. And the driver behaviour is defined in function of the range anxiety, the mobility needs and the energy price.

2.1.7 Power System Impact

Possible effects on power networks caused by EVs are related to power quality or grid saturation. The majority of studies analyse the voltage drop or transformer load [46, 55]. Additionally, [40] includes Joule losses and [60] includes overloading and unbalances. [98] proposes a methodology to detect overloads in the course of a year. Moreover, vehicle-to-grid possibility is analysed in many studies such as [64, 99, 100]. Another possible impact on the power system is economic and this is reviewed in [101]. The present work analyses the distribution network in terms of the HV/MV and MV/LV transformer capacities and the voltage of each node.

2.1.8 Contribution

The state-of-the-art analysis defined seven subjects to be determined in the EV charging demand problem formulation:

- EV type and model: the majority of current models simplifies this aspect with one model or an averaged model to represent a group of models.

- Battery and the corresponding charging process: according to the literature review, the main difference found in literature is the charging process. The most common simplification is to consider a constant power but the appropriate way is to consider the relation between the SOC and the power consumed.

- Power infrastructure: the majority of articles consider the AC slow charging and the current limit depends in function on the country analysed.
- Mobility: the papers which consider it try to use the public data according to the country analysed.
- Social: the majority of the papers do not consider any economic or social variables.
- Simulation technique: the majority of papers take a bottom-down deterministic approach.
- How to analyse the impact on the power system: the majority of EV charging models avoid this issue and some of them try to optimize the EV charges to reduce some negative consequences.

The objective of this paper is to define a methodology based on agents to determine EV charging demand. The main contribution of this paper is to propose a methodology based on open data and combining social, technical and economic variables to calculate the EV charging demand and then determine the effects on the distribution networks. To do so, the parameters in literature were used separately; however, this paper proposes that all of them be combined in a single model in order to obtain more precise and realistic results. Fig. 2.1 shows the relation among the variables that are implemented in the present model. For example, EV agents have a set of constant parameters as EV model (technical), place of residence (social), GDP (economic) and others, as well as variable parameters of mobility such as distance, day of the week and others.

Finally, the result of this methodology leads to the charging process model for each EV agent, the total EV charging demand and consequently, it allows the impact on power networks to be analysed. The methodology proposed uses all sources from public data and it is applied using statistics from the city of Barcelona.

The EV charging demand model is defined as the electric demand from EVs during a certain time period, such as a day or week, to supply their batteries. EV charging demand depends on EV user driving needs and it is linked to EV characteristics and mobility of users.

The methodology proposed in this paper is the Agent-Based Modeling and Simulation (ABMS). The main strengths and applications of ABMS are listed as follows:

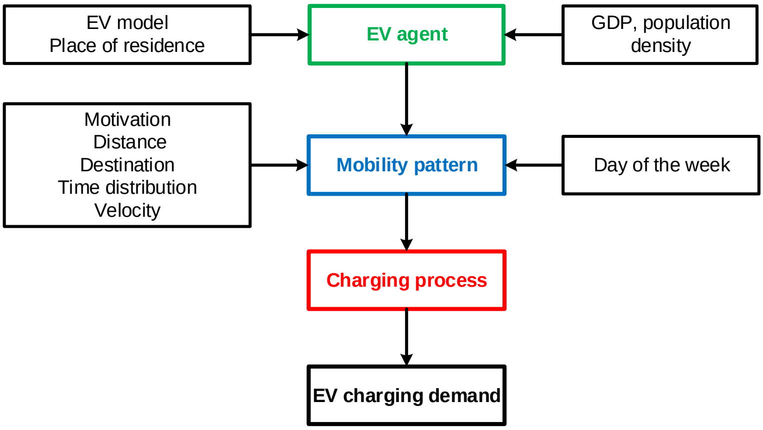


Fig. 2.1: Basic scheme of EV charging demand parameters.

- Heterogeneous individual components: EV model and mobility pattern of each EV owner.
- Flexible systems: to manage the charging demand of each EV.
- Influence of location: to consider the effects of the charging point location in the power network.
- Representation of social interactions: different types of EV owners could have different influences on the total system.

For these reasons, this methodology has been used for obtaining EV mobility patterns with an heuristic approach [102]. Furthermore, this methodology enables to simulate complex systems; for instance, load demand in power systems [45] or virtual power plants to include different types of agents [103]. Thus, agent-based modelling has been selected for this research.

In this work, the EVs are a set of agents that has been defined as autonomous entities with their attributes and their processes are dynamic and time-dependent [104, 105]. It allows defining each EV driver as an agent considering the usage of each vehicle. Each agent is simulated individually including possible interactions through the relationships between agents. Section 2.2 describes the characteristics of the agent-based model to obtain the charging demand from EVs. The impact on the distribution network is analysed in Section 2.3 and the impact on the Spanish Day-ahead market is analysed in Section 2.4. Finally, Section 2.5 presents an EV charging optimization strategy for buildings with charging points with limited information access.

2.2 EV Charging Demand Model

According to the Fig. 2.1, the parameters needed to model the EV charging demand can be clustered in three groups: the EV agent (Section 2.2.1), mobility pattern (Section 2.2.2) and the charging process (Section 2.2.3). All these parameters allow to determine all charging processes needed to reach each destination.

2.2.1 EV Agent

In the model developed, every EV agent represents an EV driver and its vehicle. The EV agent attributes are the EV model, the mobility needs, and the charging preferences. The EV agent behaviours are the trips taken (mobility), their corresponding energy consumption from their battery, the energy consumed from the electricity network to charge the battery, and the charging decision. For instance, when EV agents reach their destination, their charging process begin depending on the EV agent preferences and the energy price. The EV agent states with their corresponding variables are: waiting, driving, and charging.

Moreover, there are two other agents that influence on EV agents behaviour: the Electricity retailer Agent, who determines the electricity price for each instant, and the EV aggregator agent, who control the EV charges to reduce the electricity price. In the scenarios A, B and C, explained in the Section 2.3, there is no EV aggregator and the price is determined by the Electricity retailer agent. In contrast, in the scenario D, also explained in Section 2.3, the price is determined by the EV aggregator agent and the Electricity retailer agent does not influence on EV agents.

The main rule is that each EV agent, after each trip, takes the decision of charging in function of the battery SOC, the electricity price and, in scenario D, the signal from the EV aggregator. Moreover, before changing the state of an EV agent from waiting to driving state, it is necessary that the battery has enough energy to reach the destination. The EV agents structure, their relationships with other agents and their environment are shown in Fig. 2.2. Note that there are two environments related to the EV agents: spatial distribution and electricity network. Furthermore, the electricity market is the environment of electricity retailer agent and EV aggregator agent.

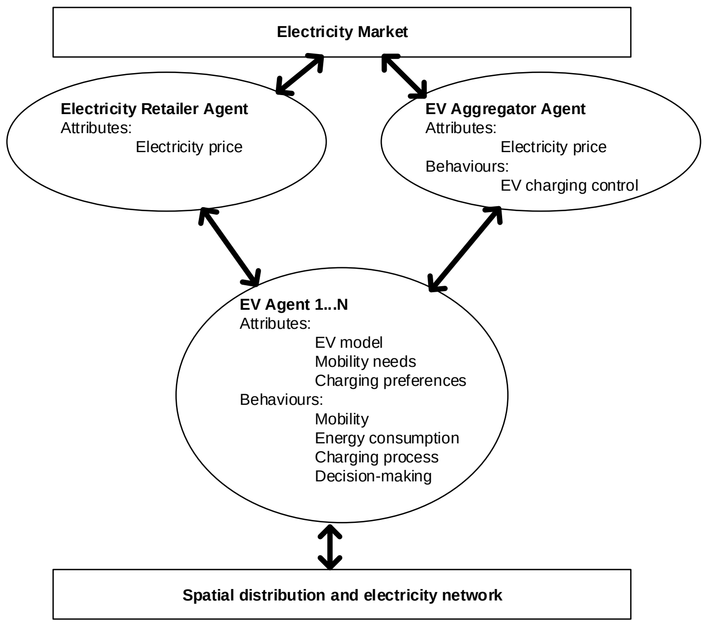


Fig. 2.2: EV agent structure.

When the simulation begins, the system computes the EV agent mobility needs and the battery SOC variation.

The first step to define the EV agents is the definition of EV agent groups (C_i) and their variables. For each group, it is necessary to define the number of agents (N), spatial distribution of influence and charging preferences. And the EV model of each agent is defined with variables EC_i, Aut_i, Cap_i, Ps_i and $Type_i$. The place of residence, defined in R_i, is considered for each agent, and this depends on the power network scenario and is modelled as a constant probability, based on public data such as [106]. R_i is linked with the charging point in home usage.

The PDF of each EV model is based on [63] data and it just considers passenger vehicles and $Type_i$. This data was filtered for the case study in relation to EV model characteristics and technical data available from auto-makers. It is shown in Fig. 2.3.

In this model it is assumed that the PHEV drive is fully electric until the end of the energy stored in the battery, when they consume gasoline as hybrid electric vehicles. Other assumptions are exhibited in Section 2.2.4.

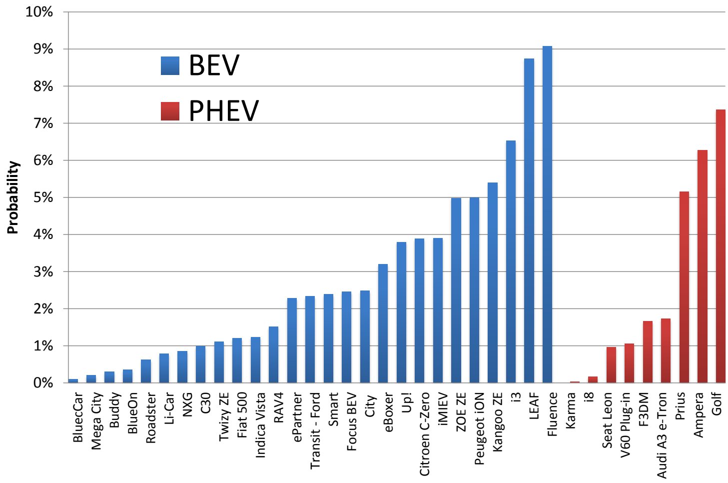


Fig. 2.3: EV model probability distribution function EV_i. Based on [63] and adapted to Barcelona-Spain and auto-makers data.

2.2.2 Mobility Pattern

Mobility variables are assigned to each EV agent in order to model its mobility behaviour. Different mobility patterns are based on open data sources. The variables considered to define a mobility pattern are defined as follows:

- **Trips per day** (S_i). The total trips are determined using a probabilistic variable which is generated through a Poisson distribution function, which is defined as [107] proposes with Poisson parameter (λ) of Eq. (2.1).

$$P(k, \lambda) = (e^{-\lambda}\lambda^k)/k! \tag{2.1}$$

  This parameter is based on the average statistic value. It should ensure at least two trips per day and is defined by Eq. (2.2).

$$S_i = 2 + \lambda \tag{2.2}$$

  In the present study analyzed, $\bar{S_i} = 3.53$ trips/day are based on [108].

- **Distance** (L_i) and **Distance per trip** (l_{ij}). They are calculated using the exponential distribution function from public reports. Fig. 2.4 shows cumulative exponential distribution functions of distance traveled per day from different countries and the relation between L_i and l_{ij} is shown the following Eq. (2.3):

$$L_i = \sum_{j=1}^{S_i} l_{ij} \tag{2.3}$$

In the case study analyzed, $\bar{L_i} = 83$ km/day is based on [109]. If $l_{ij} >$ 10 km, the trip j is considered as metropolitan considering Barcelona characteristics.

- **Destination (D_{ij}).** The model considers the reason of displacement to determine the destination. The reasons considered for the case study are based on the destination of each trip: for personal issues and for commuting. It is strongly linked to grid node, where the EV is connected in relation to social data and mobility pattern. The destination is modeled with a constant PDF according to the power network topology.

- **Day of the week (d_i)** and **Time distribution (m_{ij}).** These parameters allow knowing when an EV consumes energy as a function of the EV user's motivation to travel on a specific day. It is implemented in a PDF, as shown in Fig. 2.5 and Table 2.1 as an example applied in the case study.

- **Velocity (v_{ij}).** According to mobility data, velocity is modelled as a constant value, depending if the trip is urban or metropolitan. The average velocity from [108] and $v^{urban} = 22.2$ km/h and $v^{metrop} = 59.3$ km/h are applied.

- **Initial/Final time (t_0, t_1).** The relation between them is the average velocity (v_{ij}) and distance (l_{ij}). Each pair of time variables is grouped in the matrix Y_i as Eq. (2.4), which stores the mobility data of an EV agent.

$$Y_i = \begin{bmatrix} t_0^1 & t_1^1 \\ \vdots & \vdots \\ t_0^{S_i} & t_1^{S_i} \end{bmatrix} \tag{2.4}$$

- **Social variables**. Regarding the case study, it is necessary to take into account different variables such as Gross Domestic Product (GDP)

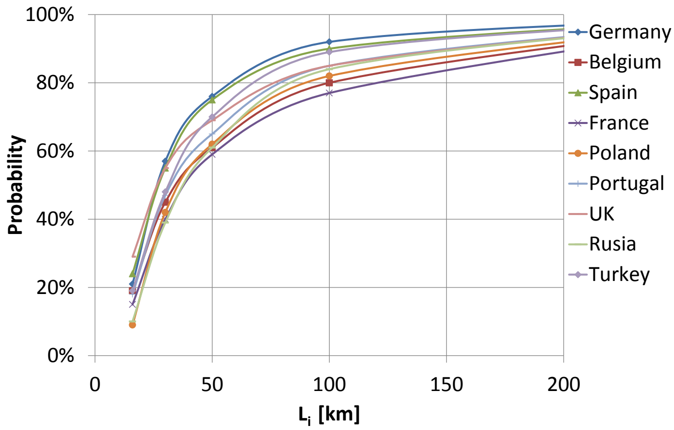


Fig. 2.4: Probability distribution function of Distance L_i [109].

Table 2.1: Time distribution considered in case study

m_{ij}	Description
1	Personal
2	Personal-Back home
3	Professional
4	Professional-Back home

and population density to determine the total number of agents (N) that could charge the EV at the same connection point. C_i definition was described in Section 2.2.1 and applied in Section 2.3.1.

2.2.3 Charging Process

The charging process considered is slow charging-AC single-phase, depending on EV model, battery capacity, SOC, Energy required to arrive to next destination and time between displacements.

All the EV models are supposed to have Li-ion batteries and the slow charging process corresponds to a typical charging curve with two periods: constant period I and descendant period II [110]. The power rate Ps_i considered for charging is 3.7 kW (230 V, 16 A) because it is commonly available in residential and commercial areas in Europe [111] and it is also used in [110]. The charging process depends on initial SOC and energy required (E^{req}) in the process. Fig. 2.6 shows the charging process of a battery with Cap_i and E^{req} of 16.5 kWh.

In this model, it is assumed that period I requires 50% of time for a full charge and period II finishes when the power output reaches 8% of Ps_i.

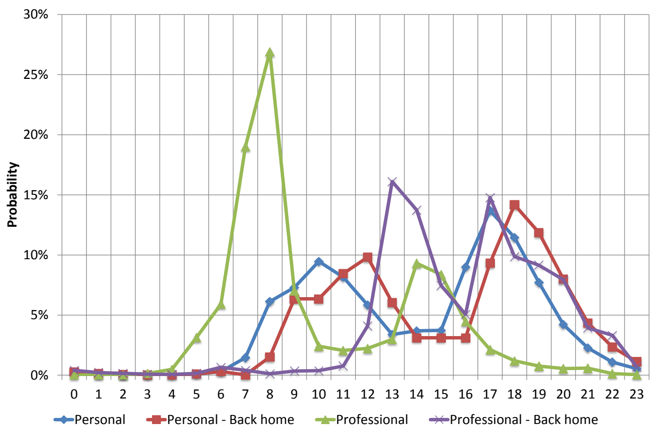


Fig. 2.5: Probability distribution function of Time distribution m_{ij} [109].

- Total energy (Battery capacity) is: $Cap = E_I + E_{II}$.
- μ and k are the exponential function parameters used in Eq. (2.7).
- Total process efficiency considered is 90% [40].

The Eq. (2.5),(2.6),(2.7),(2.8),(2.9),(2.10),(2.11) of EV charging process described before are:

- Period I is described by the following equations:

$$P_I(t) = Ps_i \tag{2.5}$$

$$E_I(t) = \int_0^a Ps_i dt \tag{2.6}$$

- Period II is described by the following equations:

$$P_{II}(t) = ke^{-\mu t} \tag{2.7}$$

$$E_{II}(t) = \int_a^b ke^{-\mu t} dt \tag{2.8}$$

where:

$$\mu = \frac{-ln(0.08)}{a} \tag{2.9}$$

$$k = \frac{Ps_i}{0.08} \tag{2.10}$$

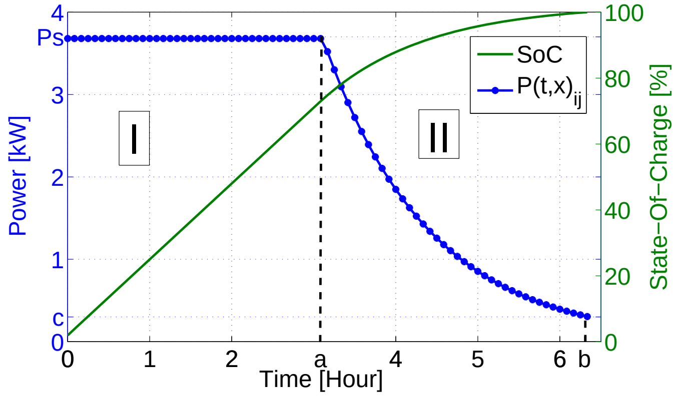


Fig. 2.6: Slow charging profile-General scheme in relation to battery capacity. Based on [110].

$$c = 0.08Ps_i \tag{2.11}$$

The initial SOC depends on the EV agent consumption. In the first simulation, the battery starts fully charged.

2.2.4 Monte Carlo Simulation

Based on Fig. 2.2, this paper proposes using the algorithm shown in Fig. 2.7 to calculate the EV charging demand in a certain power network. This algorithm is based on Monte Carlo Methodology to include stochastic variables per agent and they are: R_i, S_i, L_i, l_{ij}, D_i, t_0, t_1 and EV_i. For this reason, it is necessary to define the number of iterations (T). Furthermore, to start the algorithm, it is necessary to define the number of agents (N) that charge the EV in the network analysed. The time step used is 5 min.

The algorithm is used to define the EV agent group, the mobility variables and then the charging process for each EV agent.

2.3 Distribution Grid Impact Analysis

The proposed EV charging demand model is applied in a case study with a 37-node IEEE test feeder adapted to a typical distribution network and mobility data of Barcelona (Spain) [108]. The modelling of the case study was implemented in Matlab® and the power flow is solved by means of the Newton-Raphson method.

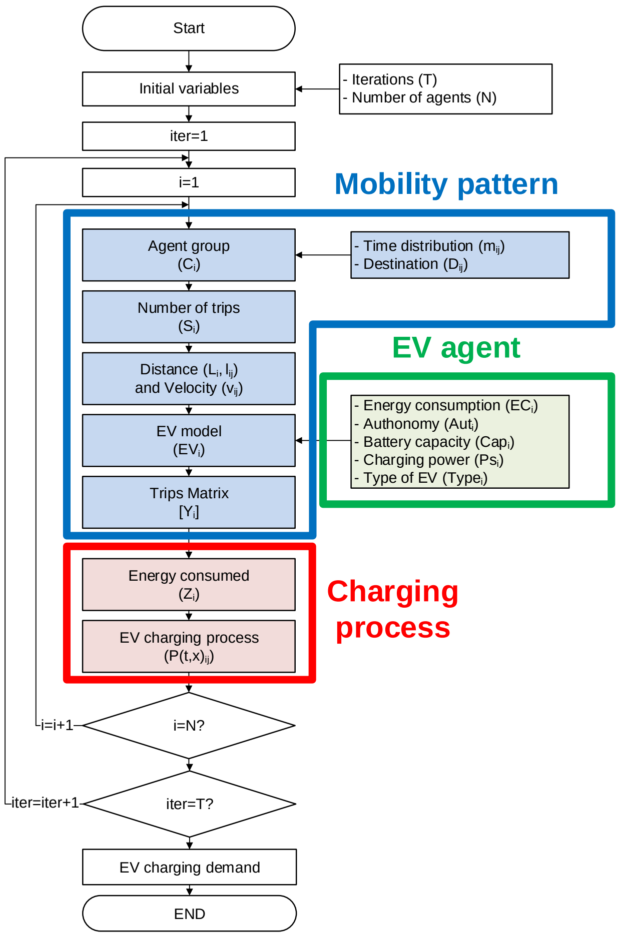


Fig. 2.7: EV charging demand algorithm based on Monte Carlo.

Table 2.2: Number of agents C_1

Zone	Nodes	Inhab./Hou.	Veh./Inhab.	Inhab.	Active Veh.
High	22–36	2.61	0.50	5016	950
Medium	3–5, 6–15	2.52	0.47	2541	448
Low	1, 2, 16–21	2.34	0.38	3288	471
				Total C1	1870

Four charging scenarios (A-D) were defined to model EV agent behaviour, which are described in the following sections. The results are the energy (Z_i) and charging demand from EVs ($P(t, x)$) and the voltage profile in the distribution network.

2.3.1 Distribution Network

This case study is an adapted MV network 37-node IEEE test feeder, which is seen in Fig. 2.8, and it applies Barcelona's mobility data. This network is adapted to a typical 25 kV MV network of Barcelona and the number of houses connected at the same MV/LV transformer [46]. In order to do that, it is necessary to consider social variables such as population density and technical regulation [112]. The maximum voltage drop permitted by the distribution system operator is 10% according to the EN 50160.

The total number of agents of group C_i is defined in relation to network topology and population density of different neighbourhoods. According to social data from Barcelona and network branches, there are three zones: high, medium and low inhabitants per house and vehicles per inhabitant density. The farthest branch is linked with the high density zone. In this way, D_{ij} of group C_1 at the end of the day is the corresponding network node. In Barcelona, 38% of vehicles are driven each day and this percentage is used to determine active vehicles [108].

Table 2.2 shows calculations to get N of group C1.

Load demand: Base load demand in this distribution network is based on system operator data [113] from national demand and it is adapted to network power capacity as 80% of HV/MV transformer power. Analysing the consumption in Spain between 2007 and 2011, load demand used in the case study is from December, 17 2007, when the maximum energy demand reached 45,911 MWh between 6 pm and 7 pm. This allows analysing EV charging increase relative to this base load.

The load presented in Fig. 2.9a is the base case, without EVs, of the

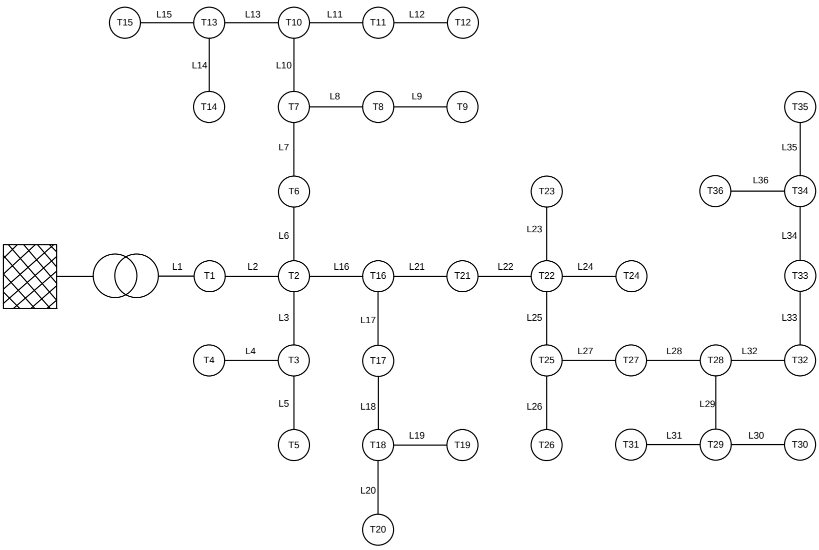
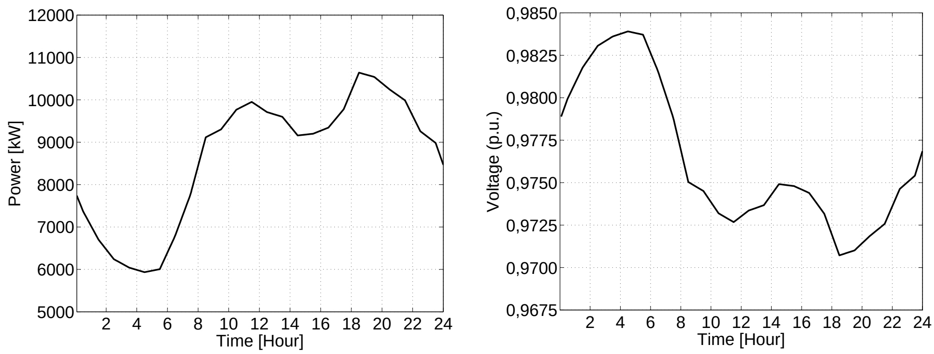


Fig. 2.8: MV network - Modified IEEE Test-feeder 37 node.

distribution system analysed. The peak demand is 10,640 kW and it occurs at 6:30 pm. The load demand of the distribution system increases during the morning (8–10 am), decreases during lunch time (1–4 pm) and increases during the evening (7–9 pm), when people come back home. The peak period is 79% higher than the valley period and the energy consumed during the course of a single day is 207.36 MWh. The voltage in the worst node is shown in Fig. 2.9b; the minimum voltage is 0.9707 p.u. at 6:30 pm and the maximum is 0.9839 p.u. at 4:45 am. The voltage follows a similar behaviour to the load demand. The lower limit of the voltage magnitude permitted by EN 50160 is 0.90 p.u.

2.3.2 Agent Profile

Six agent groups (C1–C6) were defined to consider mobility and residence. Mobility is divided between personal and professional reasons. According to the usual place where the EV is connected at the end of the day, three different areas of residence were defined: local, urban and metropolitan. Local area refers to the distribution network analysed, urban refers to the city, and metropolitan is outside the city. Urban and metropolitan agents can plug in between displacements. On the other hand, local agents can charge at any time. Table 2.3 shows the main characteristics of each group.



a) Load demand b) Voltage drop

Fig. 2.9: Residential and commercial demand without EVs.

Table 2.3: EV charging social characteristics in function of group

C_i	m_{ij}	Active Veh.	N	Area	Preferences
C1	1 & 2	1870	561	Local	At-the-end
C2	1 & 2	449	135	Urban	Between disp.
C3	1 & 2	273	82	Metropolitan	Between disp.
C4	3 & 4	41	12	Local	At-the-end
C5	3 & 4	41	12	Urban	Between disp.
C6	3 & 4	10	3	Metropolitan	Between disp.
Total		2684	805		

N is the number of EVs of each agent that charge their batteries in the case study network.

Each group has specific energy requirements for charging (E^{req}). Preferences are related to when to charge and they are described above relative to agent group definition. Regarding the E^{req} for each feasible charge between displacements, it is defined as the energy required to reach the next destination (D_{ij}) and distance (l_{ij}).

Mobility variables from Barcelona data [108] are implemented in the case study. S_i depends on agent group, d_i is the average weekday and L_i is according to [109].

2.3.3 Charging Scenarios

According to agent preferences, E^{req} and electricity market assumptions, four scenarios of EV charging demand are described, shown in Table 2.4.

Scenarios A and B consider constant electricity price for the whole day. In

Table 2.4: Table of charging scenarios

Charging Scenario	Description	Range Anxiety
A-Intensive charge	As soon as possible	High
B-Plug-and-Play	Just at home	Medium
C-Tariff controlled	Off-peak tariff	Medium
D-Smart charging	With Aggregator	Low

scenario A, EVs charge at the end of each trip due to the high range anxiety of EV agents. In scenario B, the EV agents have lower range anxiety and they charge the vehicle at home, when SOC is lower than 20% or lower than E^{req}. In scenario C it is considered that the EV agents have a Time-of-Use (TOU) tariff, special for EVs [114]. The cheapest period of this tariff begins at 1:00 am, based on the Spanish regulation [115], and then the EVs initiate the charge. The TOU tariff is an indirect control strategy to manage the EV charges. Scenario D considers one aggregator who manages all EV charges to consume the minimum power at the HV/MV transformer. This is based on an aggregator dedicated to reducing the impact in the transmission system, according to the Spanish regulation [115]. This scenario shows a direct control strategy to manage the EV charges and the aggregator offers lower electricity prices for EV agents.

2.3.4 Results

The following discussion presents the results of the four scenarios simulated. The analysis is focused on the EV demand, total demand and the voltage drop in the worst node. Due to the probabilistic design of the model, the results are variable and the plots show the variation between the maximum and minimum energy consumption. Furthermore, the plots also show the average consumption as the most probable value.

All scenarios are simulated considering that 30% of active vehicles are electric (N), based on maximum scenarios in [40,60,116]. EV_i PDF is based on [63]. What is also considered is that the EV agents with the value L_i greater than 100 km are only PHEV ($Type_i$).

The impact on power system is analysed through voltage drop located in the farthest node, which is the node 35. Fig. 2.10 shows the minimum voltage per node during the whole day and the maximum voltage drop is located in node 35.

Iterations ($iter$). The standard deviations (std. dev.) of power demand are evaluated to determine the number of iterations (T) to obtain valid results.

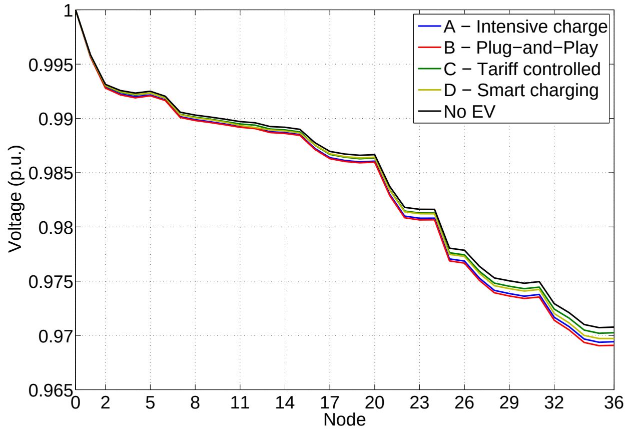


Fig. 2.10: Voltage per node.

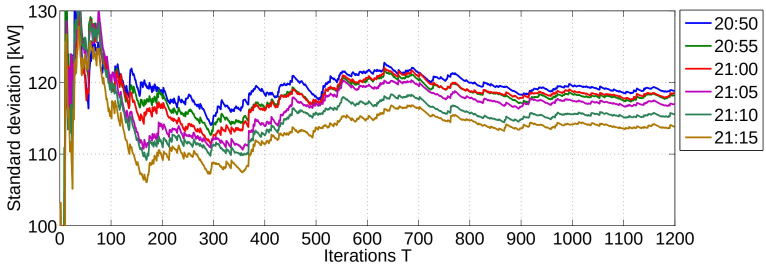


Fig. 2.11: Standard deviation variation in function of iterations T.

To do that, a simulation with 1200 iterations in scenario A for C1 group and with 30% of EVs was carried out.

Fig. 2.11 shows the std. dev. around hour 21 and it varies during the first 100 iterations significantly; it is nearly stable from iteration 200 and is constant from iteration 600. The ideal should be to do 600 iterations for all the cases, but the computing time to do it is very high and the volume of results to be stored requires a huge amount of memory. For these reasons, it is not possible to simulate 600 iterations for all the scenarios and the number of iterations has to be lower. The std. dev. varies around 10 kW from iteration 100 and from iteration 200, the results are more stable than previously. According to this, the number of iterations applied in the case study is 200. Other instances and scenarios are also checked and they comply with the std. dev. analysis. The consumption variation is also checked and it behaves similarly to the std. dev.

A-Intensive Charge

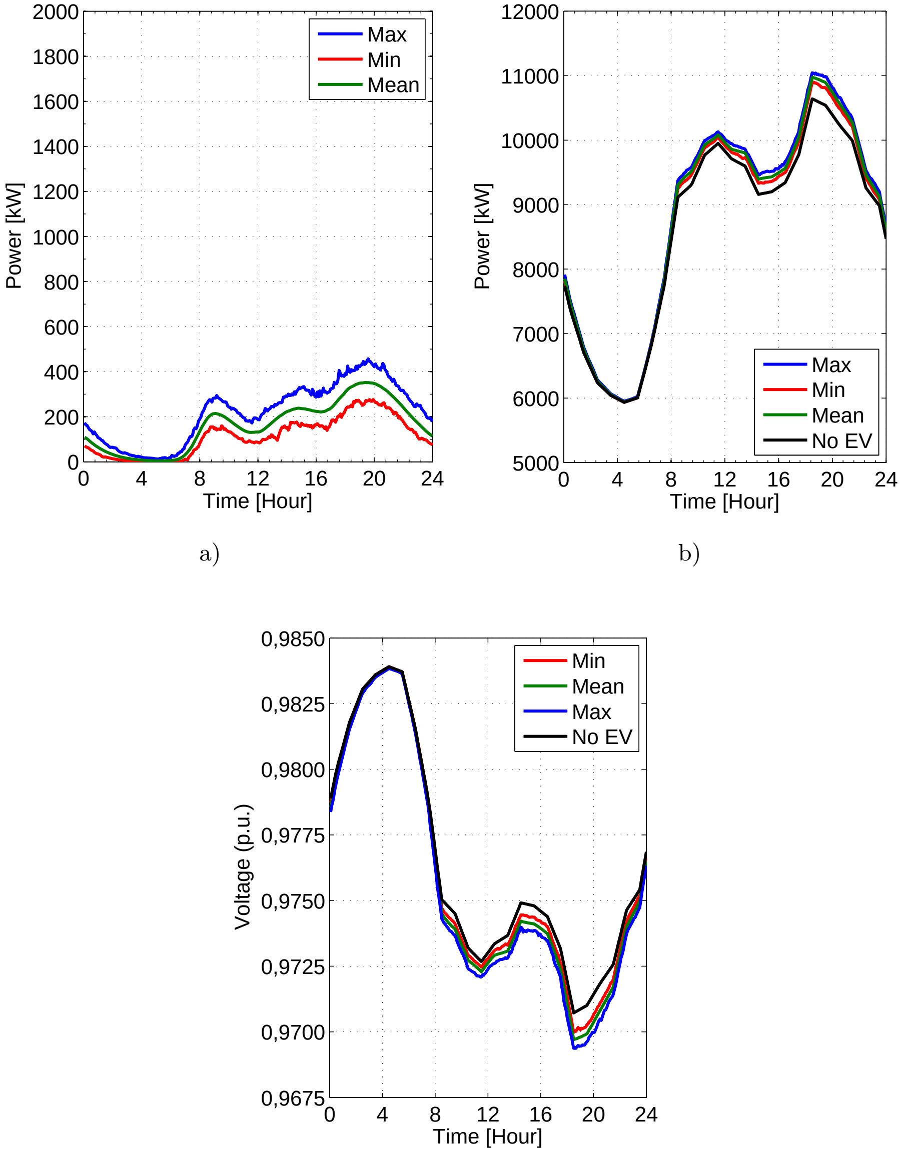
EV charging demand: As is shown in Fig. 2.12a, the EV charging demand presents two peaks with more consumption around 10:00 and 19:00. Both peaks are related to Barcelona's mobility pattern illustrated in Figure 2.5, which shows the same peaks: the peak during the morning is caused by professional mobility and the peak during the evening is caused by professional and personal back home reasons. The EV charging demand variability, the difference between the minimum and the maximum case, is significant in this scenario, and it can reach the 50% of the EV consumption as it occurs at 20:00. The EV peak demand is near to 500 kW and the total peak demand is 11.04 MW, 3.75% higher than in the base case without EVs, as Figure 2.12b demonstrates. Furthermore, the peak during the morning is coupled with the residential and commercial demand. This is reflected in Figure 2.12b, where the active power increase is steeper from 6 to 12 hours due to the EV charging demand.

Impact on power system: Figure 2.12c shows that the minimum voltage in node 35 is 0.9694 p.u. and it is 0.13% lower than in the No EV case, which is higher than the lower limit of the standard of 0.9 p.u.

B-Plug-and-Play

EV charging demand: In this scenario, the EV agents prefer to charge at home, according to the back home time distributions (m_{ij}). As shown in Fig. 2.13a, the first peak demand is lower than in scenario A because the agents do not charge at work. Moreover, the second peak demand is higher than before because the agents have not charged at work and the energy required by them is higher than in scenario A. In this scenario, the EV charging demand variability is also significant and it can reach the 33% of the EV consumption, as it occurs at 8 pm.

As Fig. 2.13b shows, this effect causes that the peak during the morning in the total demand is lower than the previous case. And the peak during the evening is higher due to the energy required and the maximum power consumed is 11,12 MW at 6:35 pm and the relative increase from the case without EV is 4.51%. Moreover, the power consumption during the night is higher than in case A, because the SOC of EV agents when they arrive at home is lower than previously.



c)

Fig. 2.12: A-Intensive charge. (a) EV charging demand; (b) Total demand; (**c**) Voltage drop.

Impact on power system: Fig. 2.13c shows that the combination of the peak from the residential demand with the EV demand causes a higher voltage drop than scenario A, due to the different behaviours of the EV agents. The minimum voltage reached during the peak demand is 0.9691 p.u., 0.16% lower than the case without EV, and higher than the lower limit of 0.90 p.u.

C-Tariff Controlled

EV charging demand: In this case, the TOU tariff causes that the EV agents begin to charge at 1:00, when the energy is cheaper. Therefore, the EV charging demand presents a peak of 1.86 MW at this moment due to the simultaneous EV charges, as seen in Fig. 2.14a. What is more, the control reduces the EV charging demand variability.

The consumption during the rest of the day is related to the energy required (E^{req}) to reach the next destination (D_{ij}) and the low SOC of each EV agent. The maximum power consumed is 10.8 MW at 6:30 pm, which means an increase of 1.5% from the original case.

Fig. 2.14b shows that this EV peak happens during the off-peak period and the total demand increase is not significant. Despite this, the power generation gradient could be a problem, which should be analysed from the point of view of the power generation and from the system stability point of view.

Impact on power system: The minimum voltage, shown in Fig. 2.14c, is similar to the original case without EVs. The minimum voltage reached is 0.9702 p.u., 0.05% lower than without EVs, and higher than 0.90 p.u. The voltage variation at 1:00 am could be a problem, which could be analysed in a transient analysis.

D-Smart Charging

EV charging demand: Fig. 2.15a shows the EV charging demand controlled by the aggregator which controls domestic EV charges. The EV charging demand is shifted to the valley period to reduce the consumption through the HV/MV transformer and to minimize the impact on the transmission system. According to this, the EV charges occur between 2 and 8 am and the variability, the difference between the minimum and the maximum case, is very small.

Fig. 2.15b shows that the total demand increases during the valley periods and the power consumption is constant at 6.6 MW. During the rest of the

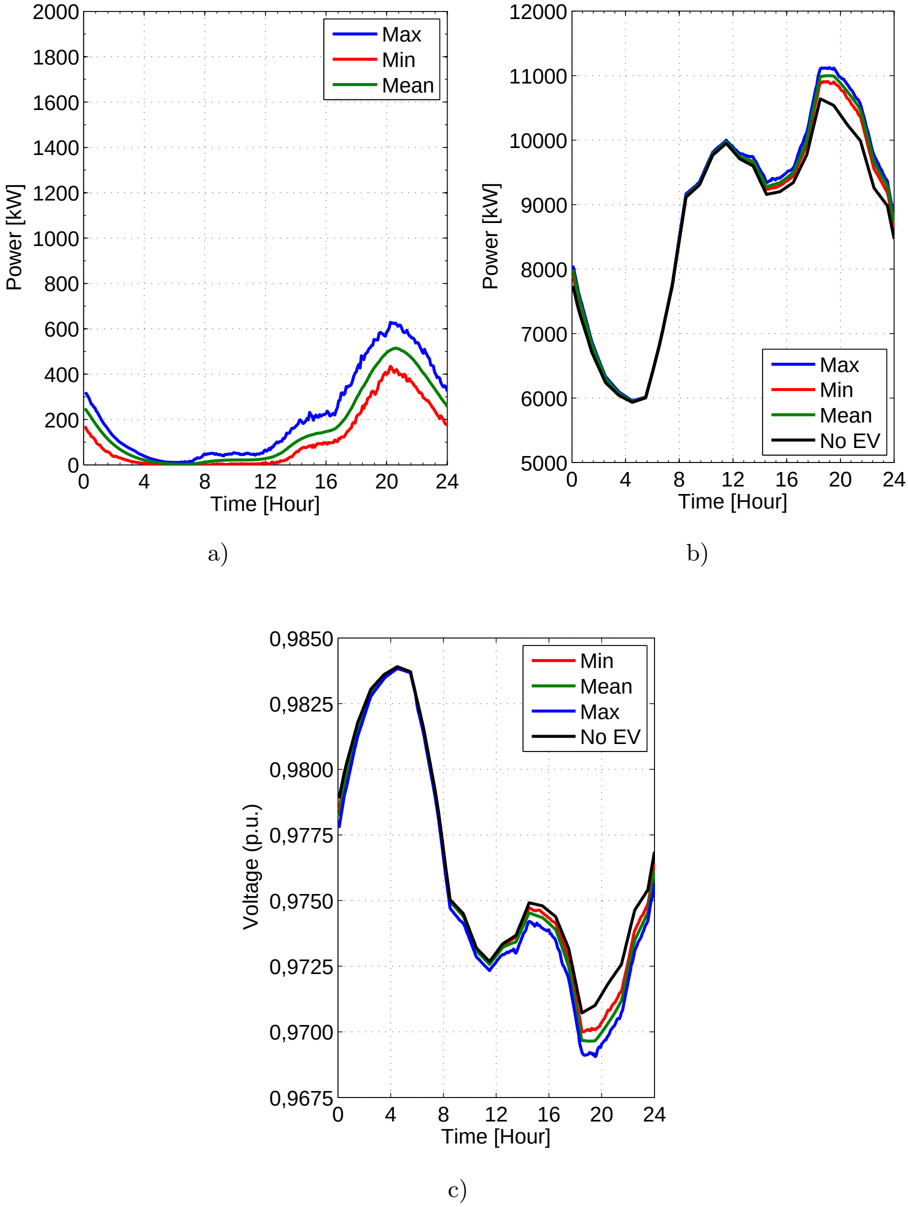


Fig. 2.13: B-Plug-and-Play. (a) EV charging demand; (b) Total demand; (c) Voltage drop.

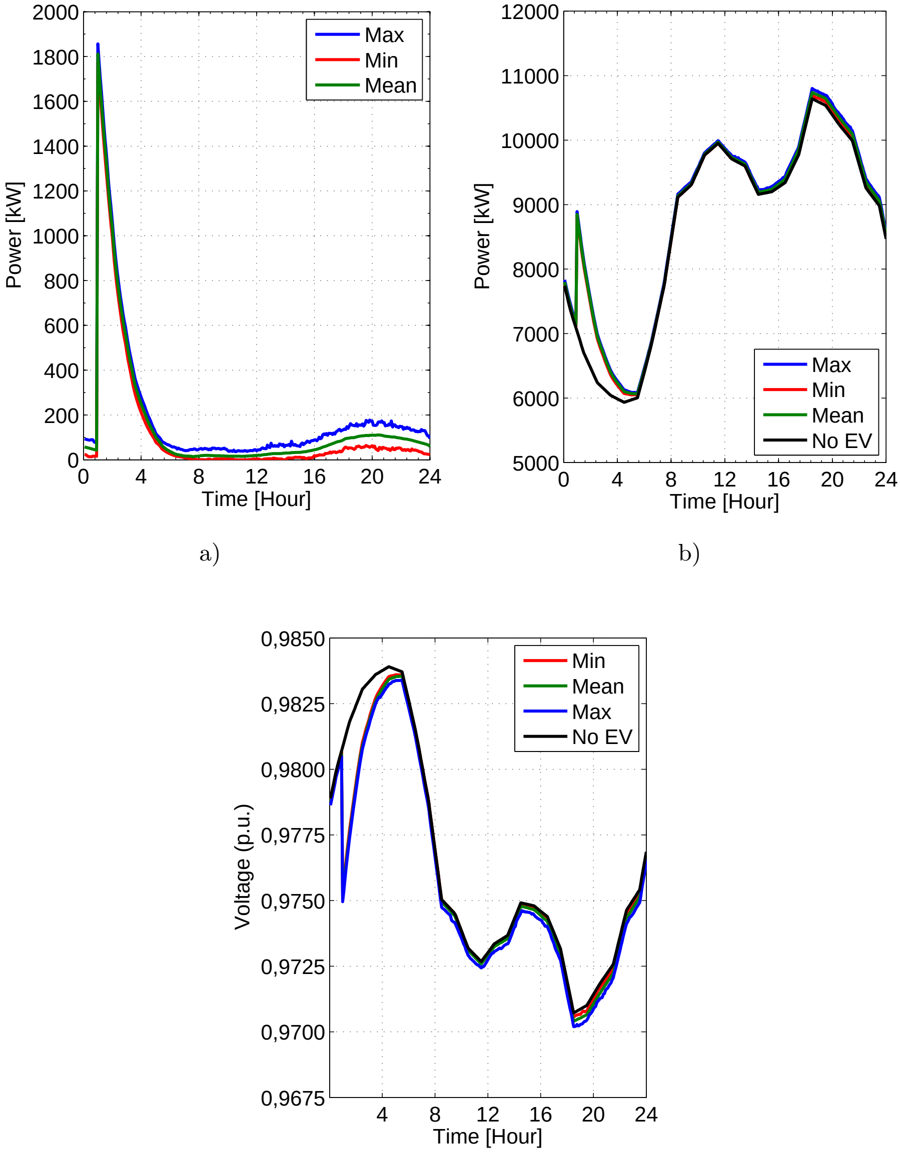


Fig. 2.14: C-Tariff controlled. (a) EV charging demand; (b) Total demand; (c) Voltage drop.

day, sporadic charges could occur, but the mean curve is near to the case without EVs.

Impact on power system: The minimum voltage is not increased by the EV charges, as is exhibited in Fig. 2.15c. The voltage during the valley period is lower than in the original case according to the total demand, but this voltage is higher than during the peak hours, and the difference between the minimum voltages is 0.02%, and the minimum value of 0.90 p.u. is not reached.

The summary of all the scenarios is presented in Table 2.5. Voltage value is the minimum and it means the maximum voltage drop.

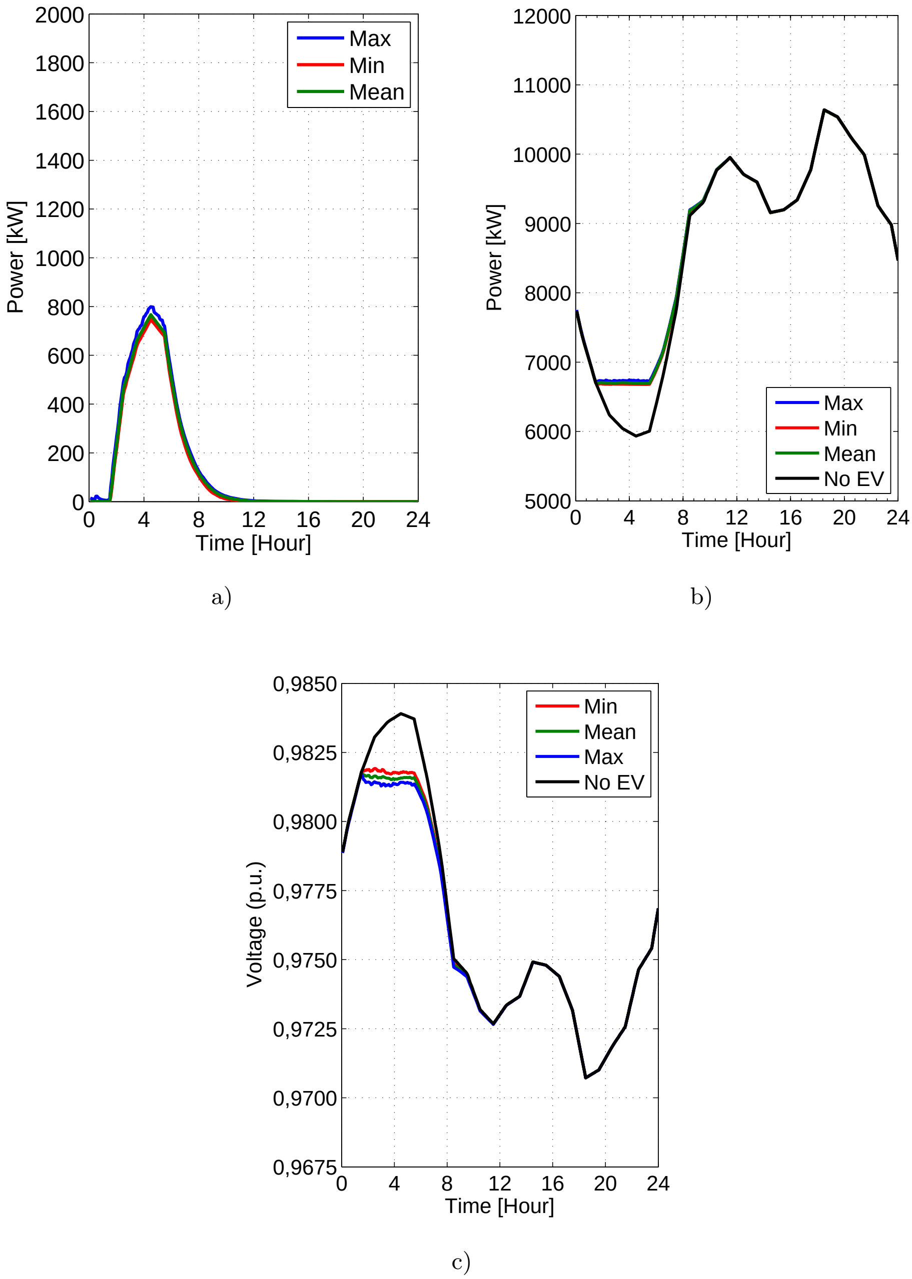


Fig. 2.15: D-Smart charging. (a) EV charging demand; (b) Total demand; (c) Voltage drop.

Table 2.5: Maximum results

Scenario	EV Demand (Max) [kW]	Peak Time	Total Demand (Max) [kW]	Variation	Peak Time	Voltage (Min) [p.u.]	Variation
No EV		6:30 pm	10,640		6:30 pm	0.9707	
A-Intensive charge	457	6:30 pm	11,040	3.76%	6:30 pm	0.9694	-0.13%
B-Plug-and-Play	628	6:35 pm	11,120	4.51%	6:35 pm	0.9691	-0.16%
C-Tariff controlled	1,857	1:00 am	10,800	1.50%	6:30 pm	0.9702	-0.05%
D-Smart charging	799	4:30 am	10,720	0.75%	6:35 pm	0.9705	-0.02%

Fig. 2.16 shows total consumption in each node and they are compared to MV/LV transformer capacity. The results show that the nodes with less capacity could reach the nominal value in some cases, but the average value is under nominal power. In the case of scenario D, total demand never exceeds the nominal capacity of transformers, which means that there is enough capacity to supply the EVs.

2.4 Electricity Day-ahead Market Impact Analysis

With the aim of assessing the regulations, to stimulate EV participation on energy markets, the impact of EV energy demand on the day-ahead market is investigated. The day-ahead market is the most important market in terms of energy negotiated. Moreover, participation is compulsory to have access to other markets.

Fig. 2.17 illustrates the dealings between the supply curve and demand curves, giving the marginal price for each MWh, and the agreed total energy. The figure also shows how the marginal price increases with 469 MWh (+1.91%) of additional demand from EVs, resulting in a price increase of +81.61% from EUR/MWh 17.07 to 31. This price increase is based on the elastic supply curve because it is based on the generation units production cost. Therefore, the price can go up with a limited demand increase.

The hourly data of 2012 for the Spanish day-ahead market are used, and the EV charging demand is added on top of the demand curve using the model explained in Section 2.2. A set of agents has been defined with different attributes, each one being an autonomous software entity. These attributes determine the way the agent behaves in the given scenario, and how they interact with the environment and other agents. The case section simulates the EV users charging behaviour of 1,094,944 vehicles which represents 10% of Spanish fleet. Using data from [109], each vehicle drives 3.1 displacements/day and 25.91 km/displacement. Therefore, using EV data from 2012, they consume 6.28 kWh/day on average per vehicle. The maximum charging power is 3.7 kW following Mode 1 IEC 61851.

Fig. 2.18 shows the EV energy charging curve during a week. In this case, it is considered that EV drivers charge at the end of each trip in public stations, at the workplace, and at home. The higher energy consumption occurs when the drivers arrive at home and charge their EV. The peak demand before noon each working day occurs when the drivers arrive at the workplace. The EV consumption at weekend days is lower than during weekdays, because the number of displacements is lower.

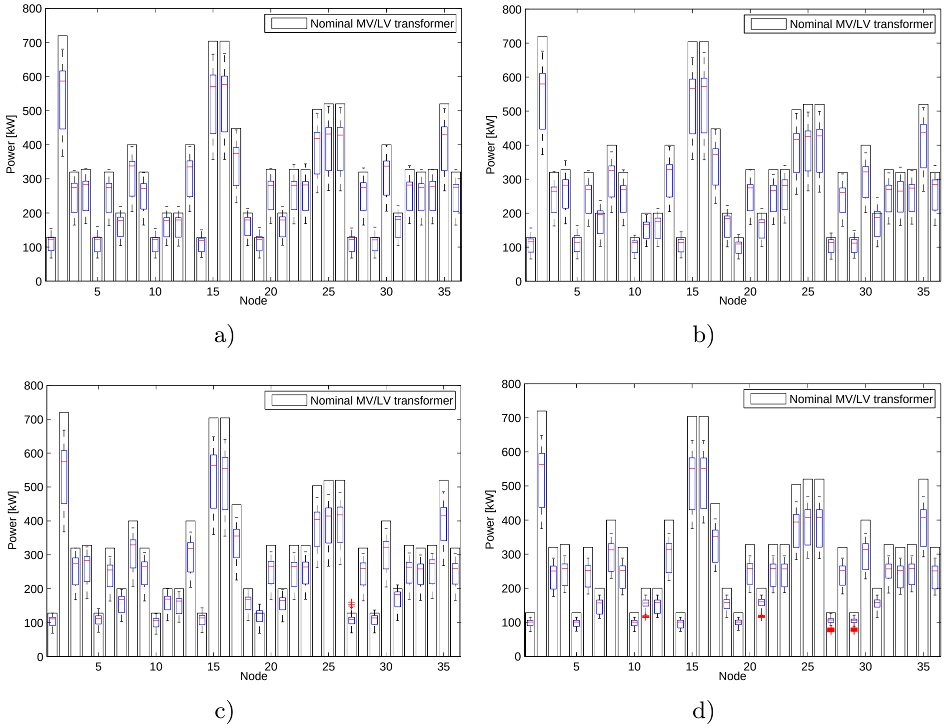


Fig. 2.16: Total demand in each MV/LV transformer. (a) A-Intensive charge; (b) B-Plug-and-Play; (c) C-Tariff controlled; (d) D-Smart charging.

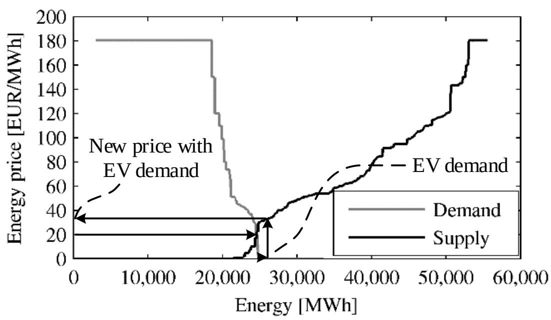


Fig. 2.17: Marginal price increase effect on March 9th of 2012 for hour 24 of the Spanish day-ahead market including EV demand

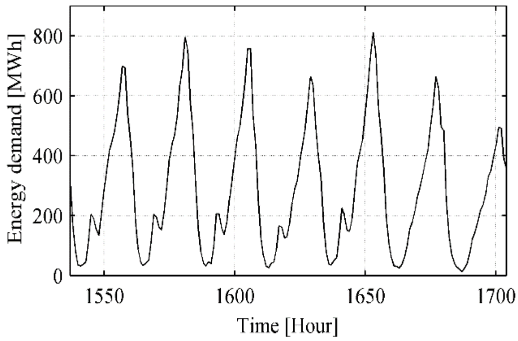


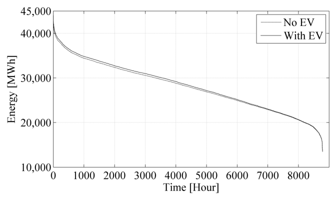
Fig. 2.18: EV charging demand load curve over a week from Monday to Sunday

Table 2.6: Impact of EVs in Spanish day-ahead market annual results

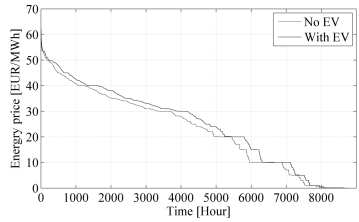
	Average price [EUR/MWh]	Annual energy trading [TWh]	Annual cost [MEUR]
Without EVs	23.62	245.42	5797.2
Including EVs	25.44	247.93	6307.9
Difference	7.71%	1.02%	8.81%

The current simulation does not consider grid constraints, complex supply offers, or risk-management to reduce deviation penalties. Moreover, the present study assumes all EV demand is negotiation in the day-ahead market. The annual results considering seasonality over a week is included in Table 2.6. However, year seasonality is not considered because there is no data available about this. Figs. 2.19a and 2.19b show the total energy purchased in the market and day-head market energy prices including EVs respectively. The most significant load increase occurs during the first 5,000 hours of the year and the maximum demand increases from 43,276 to 44,003 MWh (+1.68%) with EVs. The annual energy increase is 1.02%. In contrast, the energy price increase is more significant (7.71%), due to the shape of the day-ahead supply curves. The maximum price increase is 1.03% from 61.86 to 62.5 EUR/MWh.

Fig. 2.20 shows the impact of EVs in the Spanish day-ahead market in more detail, the analysis is focused in the 11th week of 2012, starting on March 5th of 2012. This week exposes different consequences as the wind



a) Load demand duration curve



b) Day-ahead price duration curve

Fig. 2.19: Simulated load and price of Spanish day-ahead market over a year

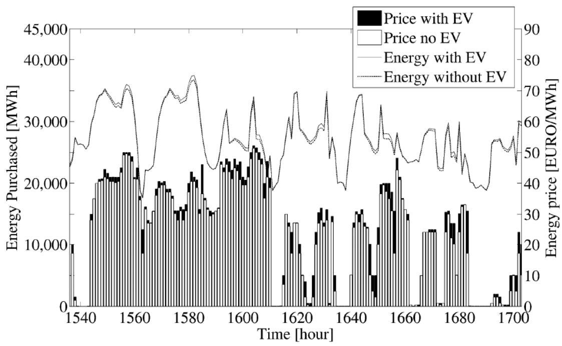


Fig. 2.20: Energy and price including EV simulation results during the 11th week of 2012

production during this week was higher than normal operation reaching 12,475 MW at 2:00 pm in March 8th, and having a market share of 37.3% at 12:00 am on March 5th. First, there are hours with zero prices even with EVs. Secondly, the price difference is shown in black bars and the highest variations do not necessarily occur during high load hours. Finally, this figure also shows the differences between the energy purchased with and without EV.

Fig 2.21 compares the EV load demand curve to the day-ahead market price increase over the 11th week of 2012. The first two days of the week show a certain proportional relation between energy and price. Nevertheless, this relation is lower during the third and fourth day of the week and clearly disappears during last three days of the week. Notice that the Spanish load curve during Fridays, Saturdays, and Sundays tend to be lower than during

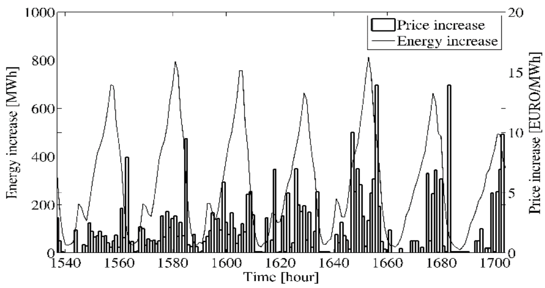


Fig. 2.21: Simulation of EV charging load curve and price increase over the 11th week of 2012

the rest of the week.

2.5 EV charging management under DSO requests in buildings

This section is focused on the management of EV charging stations in a building and it is structured as follows: Section 2.5.1 presents system description and the Dutch pilot case study, Section 2.5.2 presents the optimization problem mathematical formulation, Section 2.5.3 shows the inputs and outputs obtained and Section 2.6 includes chapter conclusions.

2.5.1 System Description and Case Study

The system considered is represented in Fig. 2.22. White boxes represent metering and sub-metering points.

The algorithm presented in this chapter is an EV flexibility management system (EV-FMS) dedicated to apply smart charging control signals for congestion management and maximum power control ($kWmax$ control) [117]. However, the stationary battery is operated locally with the purpose of reducing the peak load. However, the battery is not sufficient in some cases like in the case study and the building needs to include smart charging control. Therefore, this paper is focused on managing EVs and the battery is inflexible from the EV-FMS point of view. The FMS could include the battery in the decisions but in some cases it could be beneficial to use the local battery control. For instance, local controllers can include a specifically designed battery ageing model capable of taking better decisions than

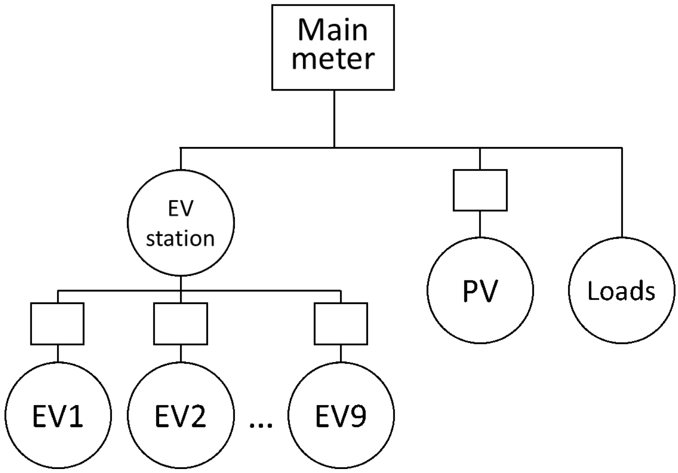


Fig. 2.22: System flexibility components considered in the building.

a third-party system taking decisions without considering ageing factors.

Simultaneous EV charging can cause grid congestions or voltage limit violations in weak or remote areas like in [118]. In such situations, the DSO could be interested in offering, through the FO, economic discounts to EV drivers if they delay or even reduce their charging load when there is grid scarcity.

Fig. 2.23 shows the sequence to prevent network congestion. The DSO measures the load on the local electricity network and based on its maximum capacity, the DSO sends out the maximum available capacity for EV charging to the Charging Station Operator (CSO). Then, the CSO redirects the available capacity to the Capacity Management System (CMO), which calculates the aggregated optimal EV charging profile for the whole charging station (CS). Based on this charging profile, the CSO can tell its charging points their maximum charging power for the next period of time.

This sequence is based on the Open Capacity Management Protocol [119] standard for exchanging information between the CSO and the DSO. The goal of this new standard is to define a protocol for smart charging electrical vehicles based on available capacity that is provided by the DSO. OCMP is a development name to the INVADE pilot project specific version of the Open Smart Charging Protocol (OSCP). This protocol will be used as input for the new OSCP 2.0 protocol to be published also by the Open Charge Alliance.

The current case study is the ElaadNL headquarter located in Arnhem,

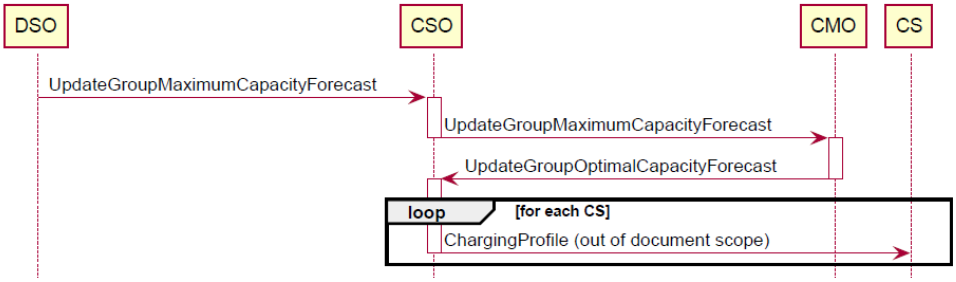


Fig. 2.23: Sequence diagram of the Open Capacity Management Protocol (OCMP) in which the DSO distributes capacity to a CSO. Source: [119]

The Netherlands. It is part of the INVADE Dutch pilots, covering the small-scale public office use case. This office building of 3.062 m^2 houses around 100 full-time employees. It has installed 4 kWp of photovoltaic panels and a central battery of 100 kWh and 200 kW. Moreover, the building has several EV charging points (CP) but only nine of them are considered in the scope. Eight CPs charge only one EV during the day and one charges two EVs.

In the considered case study, the DSO sends a maximum available capacity for EV charging of 10 kW from periods 30 to 40. At the same time, the building is limited to consume a maximum of 260 kW in total for each period, including the EVs. The generation and total inflexible load data of the studied office are obtained from ElaadNL monitoring system. The used data belongs to the 25th July 2018. This data is not open source. However, specific data for the charging sessions of the office is not yet available. To solve this, 10 alternative real charging profiles from ElaadNL are used. They are selected from the open data sets that can be downloaded from the ElaadNL platform [120]. In order to avoid the effect of energy price variability, the used energy prices are constant for the whole optimization window. In addition, this is the most common end-user energy tariff type used in The Netherlands.

2.5.2 EV flexibility management

The algorithm inputs and outputs are according to Fig. 2.24. There are two main data sources: historic time series about the main meter load and generation values, and the external data about the weather forecast, electricity prices, and charging booking if available.

This data is used in the INVADE integrated platform to generate the

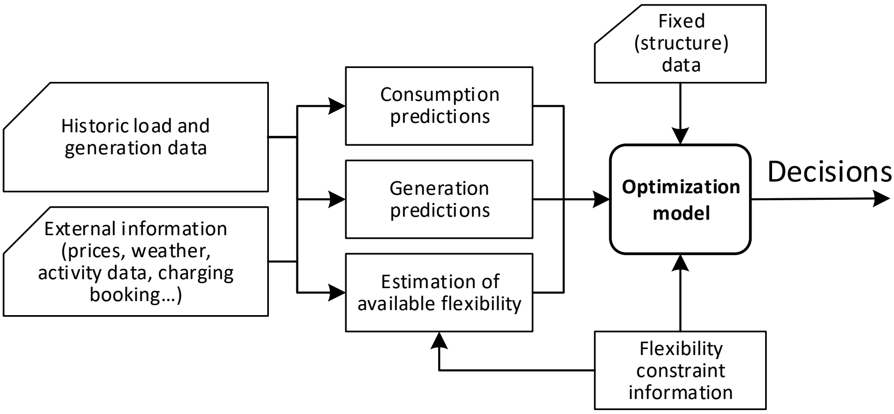


Fig. 2.24: EV-FMS algorithm inputs and outputs.

forecasted values needed in the EV-FMS. Therefore, the optimization model creates decisions and the CSO sends the corresponding control signals to each CS or directly to each CP. The EV-FMS is executed only once based on the forecast received at 12 am. The optimization horizon is 24 hours ahead.

The objective function is presented in Eq. (2.12a) and it represents the cost of buying ($P_t^{buy} \cdot \chi_t^{buy}$) and selling ($P_t^{sell} \cdot \chi_t^{sell}$) energy, and the flexibility cost (θ_t^{flex}). Therefore, the decision variables are $\chi_t^{buy}, \chi_t^{sell}, \zeta_t^{flex}$.

$$\min_{\chi,\zeta} \sum_{t \in \mathcal{T}} \left(P_t^{buy} \chi_t^{buy} - P_t^{sell} \chi_t^{sell} \right) + \zeta^{flex} \tag{2.12a}$$

$$\text{s.t.} \sum_{v \in V} \theta_{v,t}^{ch} \leq CR_t \qquad \forall t \in \mathcal{T}^+ \tag{2.12b}$$

$$\chi_t^{buy} + \sum_{g \in \mathcal{G}} \psi_{g,t}^G = \chi_t^{sell} + W_t^l + \sum_{v \in \mathcal{V}} \theta_{v,t}^{ch} \qquad \forall t \in \mathcal{T} \tag{2.12c}$$

The DSO capacity limitation request (CR_t) for the CPs is included in (2.12b) as a limitation to the aggregated consumption of all CPs for all up-regulation periods (T^+). Notice it does not consider the building consumption and the request is only referenced for the EVs. The site energy balance constraint is (2.12c) and it relates the inflexible load (W_t^l), PV generation ($\psi_{g,t}^G$) and the grid energy import (χ_t^{buy}) and export (χ_t^{sell}). It includes the set v for each CP and g for each generation unit in the same site.

The CP model and constraints are based on the assumption of the previously mentioned forecasted input parameters as the unique information available from the aggregator point of view. Forecasted values are translated into:

- EV CP status: $V_{v,s}^{CPStart}, V_{v,s}^{CPEnd}, T_{v,s}^{CPStart}, T_{v,s}^{CPEnd}$
- EV CP baseline consumption: $W_{v,t}^{CP}$

The CP for charging EVs model is modeled in Eqs. (2.13). Therefore, the total expected energy consumption per CP v and charging session n ($\theta_{v,s}^{cd}$) is calculated in Eq. (2.13a). Notice expected energy consumption is from the CP point of view and it is not necessary to consider EV battery efficiency. The total energy decided to supply to each CP v in period t ($\theta_{v,t}^{es}$) is calculated in Eq. (2.13b) and it is updated according to the previous period value and the charging control signal at period t ($\theta_{v,t}^{ch}$). $\theta_{v,t}^{es}$ is initialized at the beginning of each charging session v. Eq. (2.13c) is a disjunctive constraint to limit the CP v power control signal between a maximum (Q_v^{CPMax}) and minimum value (Q_v^{CPMin}). Finally, the total energy supplied per CP v and session n is limited to the expected energy consumption in Eq. (2.13d).

$$\sum_{t=V_{v,s}^{CPStart}}^{V_{v,s}^{CPEnd}} W_{v,t}^{CP} = \theta_{v,s}^{cd} \qquad \forall v \in \mathcal{V}, \forall s \in \mathcal{S}(v) \tag{2.13a}$$

$$\theta_{v,t}^{es} = \theta_{v,t-1}^{es} + \theta_{v,t}^{ch} \qquad t \in [T_{v,s}^{CPStart}, T_{v,s}^{CPEnd}],\ \forall v \in \mathcal{V}, \forall s \in \mathcal{S}(v) \tag{2.13b}$$

$$\frac{Q_v^{CPMin}}{N^{hour}} \leq \theta_{v,t}^{ch} \leq \frac{Q_v^{CPMax}}{N^{hour}} \vee (OR)\theta_{v,t}^{ch} = 0 \qquad \forall v \in \mathcal{V}, \forall t \in \mathcal{T} \tag{2.13c}$$

$$\theta_{v,t}^{es} \leq \theta_{v,n}^{cd} \qquad t = T_{v,n}^{CPEnd},\ \forall v \in \mathcal{V}, \forall s \in \mathcal{S}(v) \tag{2.13d}$$

Eqs. (2.14) details the costs included in the objective function Eq. (2.12a) being buying and selling costs obtained from Eqs. (2.14a),(2.14b) as the composition of the retailer contract price ($P_t^{retailBuy}$,$P_t^{retailSell}$) and the grid operator contract price ($P_t^{gridBuy}$,$P_t^{gridSell}$). The EV flexibility cost in the EV-FMS Eq. (2.14c) and it is composed by the shifting cost ($\zeta_{v,t}^{CPShift}$) and the non-supplied energy ($\zeta_{v,t}^{CPNonSupplied}$). The shifting cost Eq. (2.14d) is a penalty ($P_v^{CPShift}$) for the energy shifted from the baseline between the arrival time ($T_{v,s}^{CPStart}$) and every decision time period t. Moreover, there is a cost ($P_v^{CPNonSupplied}$) for the curtailed energy ($\theta_{v,s}^{cd} - \theta_{v,T_{v,s}^{CPEnd}}^{es}$) at departure time ($T_{v,n}^{CPEnd}$) in Eq. (2.14e).

$$P_t^{buy} = P_t^{retailBuy} + P_t^{gridBuy} \tag{2.14a}$$

$$P_t^{sell} = P_t^{retailSell} + P_t^{gridSell} \tag{2.14b}$$

$$\zeta_t^{flex} = \sum_{v \in \mathcal{V}} \left(\zeta_{v,t}^{EVShift} + \zeta_{v,t}^{CPNonSupplied} \right) \tag{2.14c}$$

$$\zeta^{CPShift} = \sum_{v \in \mathcal{V}} \sum_{s \in \mathcal{S}(v)} \sum_{T_{v,s}^{CPStart}}^{T_{v,s}^{CPEnd}} P_v^{CPShift} \sum_{T_{v,n}^{CPStart}}^{t} \left(W_{v,t}^{CP} - \theta_{v,t}^{ch} \right) \tag{2.14d}$$

$$\zeta^{CPNonSupplied} = \sum_{v \in \mathcal{V}} \sum_{s \in \mathcal{S}(v)} P_v^{CPNonSupplied} \left(\theta_{v,s}^{cd} - \theta_{v,T_{v,s}^{CPEnd}}^{es} \right) \tag{2.14e}$$

The PV generator cannot be remotely curtailed as the present framework does not allow DSO send down-regulation flexibility requests as in Chapter 4. Therefore, the PV generation variable ($\psi_{g,t}^{G}$) is equal to the forecasted PV generation value (W_t^{Gi}) in Eq. (2.15).

$$\psi_{g,t}^{G} = W_t^{prod} \qquad \forall g \in \mathcal{G}^i, t \in \mathcal{T} \tag{2.15}$$

The buy and sell decisions are limited in Eqs. (2.16a),(2.16b) respectively, due to the kWmax control to a maximum import and export capacity, and they cannot happen simultaneously Eq. (2.16c).

$$\chi_t^{buy} \leq \delta_t^{buy} X^{ImpCap} \qquad \forall t \in \mathcal{T} \tag{2.16a}$$

$$\chi_t^{sell} \leq \delta_t^{sell} X^{ExpCap} \qquad \forall t \in \mathcal{T} \tag{2.16b}$$

$$1 \leq \delta_t^{buy} + \delta_t^{sell} \qquad \forall t \in \mathcal{T} \tag{2.16c}$$

2.5.3 Simulation and results

The case study problem results in the control signals to all charging points as shown in Fig. 2.25. The charging points are listed in ascending shifting cost from 0.1 EUR/kWh in steps of 10% increase. Therefore, CP1 is shifted more periods than CP9. As the electricity price is constant, $\zeta^{EV,flex}$ is the only decision factor in this specific case study and results are easier to understand.

The DSO EV charging request constraints CPs from 30 (7:30 am) to 40 (10 am). To meet the request, CPs 2, 3, 4, 6, 7, 8 are shifted to later periods.

For instance, CP2 and CP6 are totally shifted to period 40. In contrast, CP7 and CP8 are barely reduced and CP9 is not shifted.

According to Fig. 2.26, during the periods 50 and 51 the base net load is above the limit of 65 kWh per quarter. Thus, CP1, 2, 4, and 8 are shifted or partially curtailed in the optimized result to meet the 260 kW limitation. Therefore, the optimal EV scheduling produces a constant consumption at 65 kWh per quarter between periods 42 and 58 reducing the peak load.

Table 2.7: Charging points and sessions from ElaadNL database

Charging point ID	Transaction ID	Arrival time	Departure time	Connected time [hours]	Charge time [hours]	Flexibility time [hours]	Expected energy consumption [kWh]	Delivered energy [kWh]	Shifting flexibility cost [EUR/kWh]
1	2528680	03/06/2017 9:55	03/06/2017 13:32	3.62	0.83	2.79	8.73	8.73	0.100
2	2504887	25/05/2017 9:20	25/05/2017 14:04	4.73	2.50	2.23	25.01	25.01	0.110
3	2714942	26/06/2017 9:34	26/06/2017 15:02	5.48	2.68	2.80	25.98	25.98	0.121
4	2625991	26/07/2017 9:05	26/07/2017 18:40	9.59	4.48	5.10	48.34	48.32	0.133
5	2595472	07/07/2017 6:25	07/07/2017 10:58	4.55	1.30	3.25	11.13	11.13	0.146
6	2567142	22/06/2017 7:23	22/06/2017 11:45	4.37	1.00	3.37	6.36	6.36	0.161
7	2668532	23/08/2017 7:41	23/08/2017 16:02	8.34	4.55	3.79	27.28	27.28	0.177
8	2605666	13/07/2017 7:06	13/07/2017 10:45	5.71	2.00	3.71	18.71	18.71	0.195
8	2592317	05/07/2017 11:36	05/07/2017 15:56	4.34	1.06	3.28	10.15	10.15	0.195
9	2346509	14/04/2017 10:47	14/04/2017 15:58	5.17	2.17	3.00	17.37	17.37	0.214

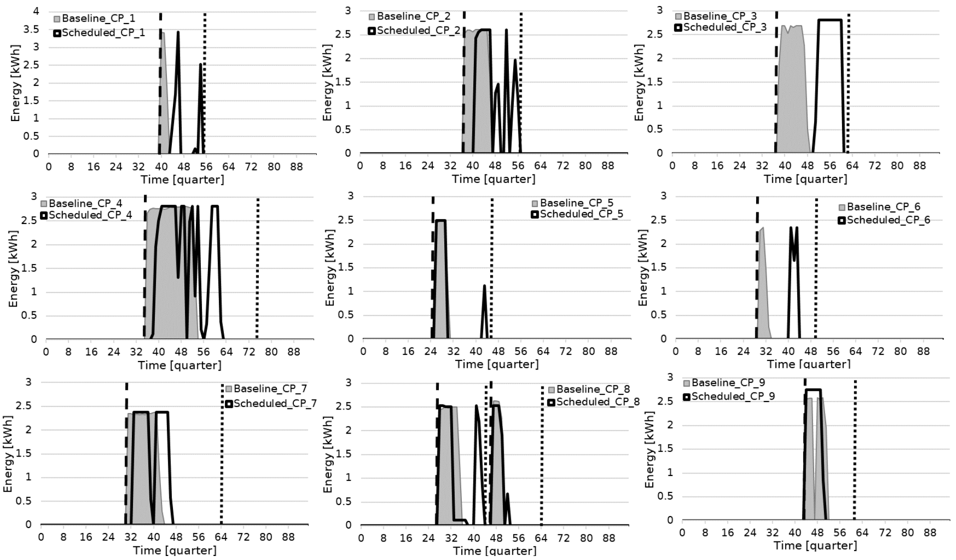


Fig. 2.25: Charging points consumption including the arrival (dashed line) and departure times (dotted line).

Table 2.5.3 shows charging points data from ElaadNL office. All profiles correspond to arrival and departure times within typical office working hours and at least they have 2 hours of flexibility time. It also shows how the decisions allow to charge the EVs completely because the non-supplied energy penalty ($P_v^{CPNonSupplied}$) is 5 EUR/kWh. The transaction ID is included for comparing results in future works.

2.6 Conclusions

The probabilistic agent-based model (ABM) obtained in this paper allows the EV charging demand to be determined, taking into account different variables of EV characteristics such as battery capacity and energy consumption of each trip, economic and social attributes, mobility needs, and charging strategies of each agent. The model developed takes into account the interaction of these variables, allowing obtaining of better accuracy in the results.

The probabilistic approach is useful to include the uncertainties related to the real behaviour of EV users, like the time distribution and energy consumed on each trip. Therefore, the model permits the determination of the impact provoked on the grid by these uncertainties.

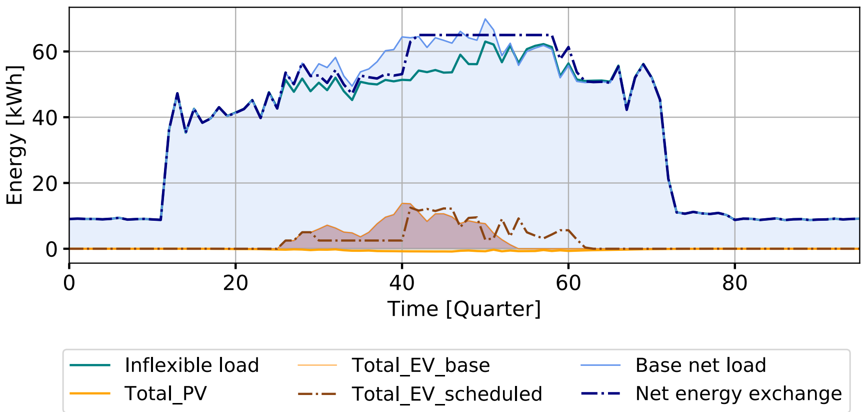


Fig. 2.26: Building load after applying the EV-FMS.

Moreover, the model proposed is a benchmark to compare case studies, such as different cities or areas in the same city. With this model, the weak regions of the grid or the areas with high EV density can be detected.

The case study presented shows that the uncertainties cause variability in the EV charging demand in scenarios without control on the EVs, as it is shown in scenarios A and B. In contrast, the consumption variability in scenarios with indirect and direct control on the EV charges, like scenarios C and D, respectively, is small.

The distribution feeder analysed in the presented case study does not have a significant impact on the smart charging strategy (D) during the off-peak period and all EV agents can charge their EV. In contrast, some MV/LV transformers could exceed their nominal power in the scenarios without control. The voltage in all the scenarios is higher than the limit of 0.90 p.u. according to the EN 50160.

Regarding EV electricity market impact, the use of EVs will have an impact on the electricity market. Simulations exposed in this chapter show how EVs can influence day-ahead electricity market price. According to that, there is a considerable opportunity for aggregators to implement controlled EV charging strategies.

Finally, the present chapter exposes a novel decision-making problem for scheduling EVs in cases of limited information access. In such cases, it is necessary to rely on forecasting tools to take decisions. Related to communication standards, OCMP standard allows DSOs to send flexibility requests referred only to the aggregated EV load within a grid connection point. EVs are very attractive to reduce building load peaks and reduce grid congestions.

The optimization algorithm presented in this paper shows a scheduling EV model considering this load limitation and the maximum consumption per grid connection. The results of the case study highlight the possibility of managing EV charges considering capacity limitations and DSO restrictions even though the limited available information. It is complicated to provide better decisions without additional data like EV battery SOC. After this chapter, the author concludes that EVs could threaten power networks and electricity markets. However, with the appropriate grid tariff EVs could autonomously decide to charge during the night and reduce their consumption during working hours.

Chapter 3

Flow-Based Day-Ahead Local Energy Market Design for Distributed Energy Resources

3.1 Introduction

As exposed in the introduction of this thesis in Chapter 1, the power quality could decrease in terms of voltage limit violations and overloaded lines in scenarios with massive penetration of VRE DG. Thus, it is necessary to explore control algorithms to deal with over-loaded distribution networks operating without capacity expansions which could increase the cost of the grid excessively.

Regarding the active control, different alternatives are proposed. The distribution system operator (DSO) could monitor the network variables and apply control signals to distributed energy resources (DER), such as reducing active generation or disconnecting consumption [35]. However, this alternative could compromise liberalization as the DSO criteria to take decisions is unclear. Other references like [121–123] assume DSOs determine the distribution locational marginal prices (DLMPs) in order to minimize the total cost of electricity consumption in the distribution network respecting grid constraints. However, this is not considered in the present chapter as the local market operator is not the DSO.

Another option is to implement an energy management system (EMS) that coordinates DER including grid constraints so the DSO needs not to worry about the grid operation. When all generators are physically close to each other, they are operated together and can be disconnected from the main grid, it is known as micro-grid [124]. EMS for micro-grids have gathered attention under the assumption that all participants share the profits and costs of the system [125]. However, the assumption about shared profits is no longer valid in systems with multiple owners spread over a distribution network, where each participant looks for its maximum profit [126]. In those cases, solutions based on market control structures are introduced. This approach is found with different names in the literature. For example, some references such as [127–129] use the term *micro-market*. The term *local market* is also used for the same approach in [130, 131]. However, the term *local market* is used for bigger systems that consider a part of the transmission system [132–134]. Moreover, the European Network of Transmission System Operators for Electricity (ENTSO-E) defined that in a local market area there are no transmission constraints between the market balance areas [135]. Hence, for the sake of clarity, the present chapter uses the term *micro-market* to define a market structure for distributed participants over a feeder of the distribution network.

A micro-market is an environment which allows all participants: consumers, producers and prosumers, to share their energy in a regime of competition on a distribution network level. In this marketplace generators send offers and consumers send bids, which are matched according to the clearing auction algorithm that also determines the energy prices.

The current section reviews the literature about micro-market proposals until the beginning of 2016. Section 3.2 exposes the structure of the day-ahead micro-market. Section 3.3 explains the clearing algorithm implemented. Sections 3.4 and 3.5 describe the single and multi-period problems respectively. Finally, Section 3.6 exposes the case study analysed and Section 3.7 shows its results.

The application of electricity micro-markets at distribution level is explored by some authors. [136] presented the necessity of prosumers to trade their energy within a neighbourhood marketplace and their model is based on the stock exchange. [137] developed a market-based control system to manage line flows considering technical limits and sending price signals to participants without a micro-market.

Regarding the participation of micro-markets in the day-ahead wholesale market (DAWM), [138] expose the possibility that different power networks can facilitate electricity trade among neighbours participating in the DAWM so that their welfare is increased.

Another proposal for a micro-market is [139] who propose a micro-market with a trading horizon of 15 minutes and with time resolution of 5 minutes using continuous double-sided auctions. This proposal, similar to [140], includes the role of the micro-market operator (MMO). Additionally, [139] explores the cost structure of market participants.

Other authors developed new market concepts, as [141] for the EcoGrid project. They implemented a real-time wholesale market operated by the

TSO to accommodate demand response in which time resolution is 5 minutes.

Compared to the state-of-the-art, the day-ahead micro-market (DAMM) designed in this paper makes the following contributions:

- The participation of micro-market in the day-ahead wholesale market is considered.
- Multi-period formulation considering battery state-of-charge (SOC) maximizing total social welfare of participants is included.
- Grid constraints are managed to increase the power quality in terms of line congestions, voltage limits and grid losses.

3.2 Day-ahead micro-market (DAMM) proposal

The DAMM is a market with the objective of organizing local resources using market-based rules to participate in the day-ahead wholesale market without compromising distribution networks.

The MMO is an independent entity with the aim of maximizing the profits of the community. It receives bids and offers from all participants, executes the clearing algorithm and supervises market operation similarly to the wholesale market operators. It is noticeable that this new entity receives information about the grid status and characteristics.

Fig. 3.1 compares the needed structure with and without a DAMM. In case of facing grid congestions, the case without DAMM requires that the DSO sends signals to each agent connected to the grid in order to maintain grid operation feasibility. Moreover, the storage unit has to send offers and bids to the wholesale market and they might not be matched. Finally, the consumers and producers participate in the wholesale market through the retailer. In contrast, the structure with DAMM allows participants to generate their offers and bids, and they send them to the MMO. The MMO sends feasible offers to the DAWM, and receives the prices and energy matched at the point of common coupling. The MMO uses prices to operate the storage unit and to decide set-points for participants. Fig. 3.1 distinguishes three zones according to the SGAM methodology: Process, enterprise and market [142].

This market design goes beyond the current energy regulation and the DAMM proposed does not consider retailers as each participant has a trading agent in order to create its prognosis, bids and offers automatically [143].

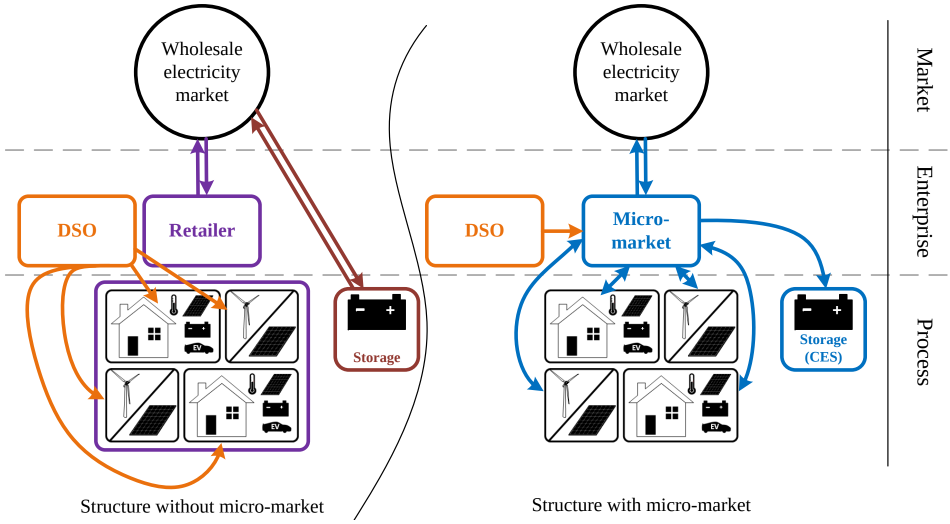


Fig. 3.1: Day-ahead micro-market structure proposed

Another important implication is that regulation needs to integrate this micro-market proposal as it is mandatory for all generators and consumers within the same grid zone.

3.2.1 Role of agents

In this chapter the DAMM requires the following roles from each agent:

Role of MMO

The MMO combines the basic aggregator role with retailer and local market operator role. Therefore, the MMO aggregates community members to take part in electricity markets. The MMO provides and controls the trading platform, executes the clearing algorithm to determine the optimal energy to export or import depending on the DAWM price based on the micro-market participants' bids and offers. Additionally, the MMO uses information about the network status and characteristics to consider technical constraints in the micro-market clearing algorithm which is exposed in the following section.

Role of DSO

In this proposal, the DSO has a limited responsibility; It sends the grid information to the MMO, who includes them in its clearing algorithm. Otherwise, the DSO only verifies that the technical constraints are satisfied.

Role of participants

Generators, consumers and prosumers have to trade for the energy that they consume or produce. They have to send offers, receive auction results and to fulfil the energy settled. Participants could take advantage of automatic trading agents.

Role of the storage

In this proposal, the centralized storage units are controlled by the MMO to maximize the social welfare of the micro-market community charging or discharging the battery. This assumption is based on the concept of community electricity storage (CES) unit introduced in [144]. This paper assumes that the CES unit is owned by the community and the benefits are shared between participants. Charging and discharging costs such as the round-trip efficiency and equivalent ageing costs are not considered as benefits for the community. No specific remuneration is considered for the CES unit in this work.

3.3 Micro-market Clearing Algorithm

The algorithm proposed in this paper is shown in Fig. 3.2. The algorithm can be divided in two steps, one executed before the DAWM takes place and the steps taken afterwards. Two mathematical models are proposed: The single period problem (SPP) and the multi-period problem (MPP).

- The SPP is responsible for finding the optimal power exchanged with the main grid given a market price for each period. As the prices are not known in advance, the SPP is executed with different price scenarios to generate piece-wise offers and bids. The micro-market is considered a price-taker.

- The MPP is to be executed after the DAWM when prices are already decided. Then, the CES unit can be operated to take advantage of price differences between periods, but we may have to pay deviation costs due to difference between the power matched in the market and the power delivered eventually.

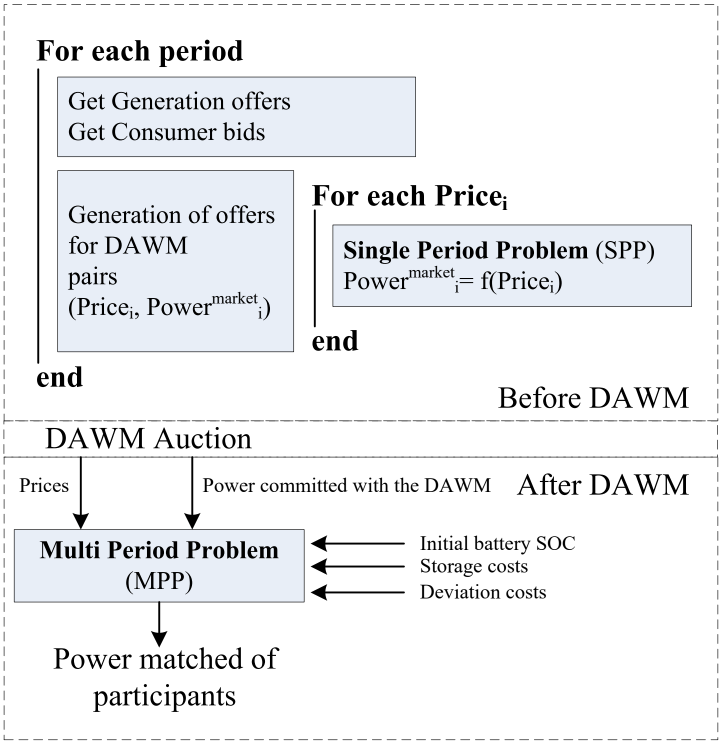


Fig. 3.2: Day-ahead micro-market algorithm

The deviation cost is assumed in this work to be 15% of the DAWM price as an average value in the Spanish market.

Once the power matched is decided, the micro-market price cannot be determined based only on matched auction curves because the following phenomena can appear:

- The energy exchanged with the main grid is paid at the DAWM price no matter the micro-market result.
- There is a price gap between the last matched offer and bid.
- There are deviation and storage costs that have to be considered.
- Nodal prices can be different if technical constrains are active in the optimal solution.

Considering the phenomena exposed previously, micro-market rules to set the price in each case have to be defined. According to the rules implemented, renewable energy generators may be promoted or consumers can pay less for their energy.

3.4 Problem Formulation SPP

In this section, parameters and variables names include superscripts while sub-indices refer to the sets over those parameters or variables are defined.

3.4.1 Network

Given a set of nodes $\mathcal{N}$ and a set of lines $\mathcal{L} \subseteq \mathcal{N} \times \mathcal{N}$ and given two indices $m, n \in \mathcal{N}$, the network impedances can be characterized with a complex matrix called admittance matrix. Let $Y^{mod}_{m,n}$ and $Y^{\alpha}_{m,n}$ be the modules and angles matrices from the admittance matrix expressed in a polar form. Apparent power in lines are bounded by $S^{maxlin}_{m,n}$. Voltage modules and angles are bounded by $U^{lo}, A^{grid,lo}, U^{up}, A^{grid,up}$.

The variables under decision are voltages and angles at each node constrained by:

$$U^{lo} \leq v_m \leq U^{up}, \quad A^{grid,lo} \leq \alpha_m \leq A^{grid,up} \qquad \forall m \tag{3.1}$$

Active and reactive power leaving each node is presented by P^{pw}_m, Q^{pw}_m. Active and reactive power flowing from node $m \to n$ are defined as $P^{pw,lin}_{m,n}$ and $Q^{pw,lin}_{m,n}$. Those variables are constrained over the set $\mathcal{L}$ with the following equation:

$${P^{pw,lin}_{m,n}}^2 + {Q^{pw,lin}_{m,n}}^2 \leq {S^{maxlin}_{m,n}}^2 \qquad \forall m, n \tag{3.2}$$

The equations that relate voltages and angles with powers are the well-known power flow equations.

$$\underline{\mathbf{S}} = \underline{\mathbf{U}} \cdot \underline{\mathbf{I}}^* \quad \underline{\mathbf{I}} = \underline{\mathbf{Y}} \cdot \underline{\mathbf{U}} \tag{3.3}$$

3.4.2 Consumers

Consumers send bids to the MMO, those bids are step-wise cost functions of energy with the maximum price which those consumers are willing to pay.

Given a set of blocks of energy $\mathcal{B}^c$, a set of consumers for each node $\mathcal{D}^c$ and given two indices $bc \in \mathcal{B}^c, a \in \mathcal{D}^c$ the offers are defined by the energy quantity, $E^{bL}_{m,bc,a}$ and the price associated to that energy $P^{pr,bL}_{m,bc,a}$. Moreover, the sum of all blocks of energy is $E^{L}_{m,a}$ and the total reactive energy is $Q^{L}_{m,a}$. The power factor of consumers is assumed constant for any matched power.

The decision variable for the consumers is the fraction of the energy of each block matched E^{mL} constrained by:

$$0 \leq E^{mL}_{m,bc,a} \leq \frac{E^{bL}_{m,bc,a}}{E^{L}_{m,a}} \qquad \forall m, bc, a \tag{3.4}$$

Notice that in section 3.4.5 reactive power consumed by the load will be related to $E^{mL}_{m,bc,a}$.

3.4.3 Generators

Generators send offers to the MMO. Their offers are blocks of energy with the cost of that energy, which is equivalent to a piece-wise linear cost function. It is assumed that the MMO can send reactive power planning to the generators.

Given a set of blocks of energy $\mathcal{B}^g$, a set of generators for each node $\mathcal{D}^g$ and given two indices $bg \in \mathcal{B}^g, z \in \mathcal{D}^g$ offers are defined by an energy quantity $E^{bG}_{m,bg,z}$ and the cost associated $C^{bG}_{m,bg,z}$.

Reactive power is bounded by $Q^{maxG}_{m,bg}$. The decision variables for generators are the power matched E^{mG} and reactive power Q^{G} and are constrained by:

$$0 \leq E^{mG}_{m,bg,z} \leq E^{bG}_{m,bg,z}, \quad -Q^{maxG}_{m,z} \leq Q^{G}_{m,z} \leq Q^{maxG}_{m,z} \tag{3.5}$$

3.4.4 Common Coupling Point

The common coupling point can act both as a consumer or generator depending on the needs of the micro-market. It is assumed that there are no bounds in power. Given a subset of grid-connected nodes $\mathcal{N}^{CCP} \subset \mathcal{N}$ and an index $o \in \mathcal{N}^{CCP}$ the decision variables of the CCP are P^{CCP}_{o}, Q^{CCP}_{o}. The price of the DAWM is defined as C^{CCP}. This parameter is unknown, so different scenarios are computed.

3.4.5 Node Balance Equations

The equations that relate all previous elements are known as the node balance equations. Those equations are

$$0 = -P_m + \sum_{bg} \sum_{z} E^{mG}_{m,bg,z} - \sum_{bc} \sum_{a} E^{mL}_{m,bc,a} \cdot E^{L}_{m,a} + P^{CCP}_m \qquad \forall m \qquad (3.6)$$

$$0 = -Q_m + \sum_{z} Q^{G}_{m,z} - \sum_{bc} \sum_{a} E^{mL}_{m,bc,a} \cdot Q^{L}_{m,a} + Q^{PCC}_m \qquad \forall m \qquad (3.7)$$

3.4.6 Objective function

The social welfare for a single period is defined as the sum of the generators and consumers surpluses, following [145].

$$\begin{aligned} f^{DAWM}_{obj} = & -\sum_{m} \sum_{bg} \sum_{z} E^{mG}_{m,bg,z} \cdot C^{bG}_{m,bg,z} \\ & + \sum_{m} \sum_{bc} \sum_{a} E^{mL}_{m,bc,a} \cdot P^{bL}_{m,bc,a} - \sum_{o} P^{CCP}_{o} \cdot C^{CCP} \qquad (3.8) \end{aligned}$$

3.5 Problem Formulation MPP

For the MPP formulation, the SPP model is defined over a new set of time periods $\mathcal{T}$. Additionally, the energy storage and the deviation cost models are included, and the objective function is modified. Consider the index $t \in \mathcal{T}$ for the following definitions.

3.5.1 Energy Storage

The energy storage unit considered in this paper is a battery. We may have several storage units but only one per node. Given a set of storage units $\mathcal{N}^s \subseteq \mathcal{N}$ and an index $i \in \mathcal{N}^s$ the battery is defined by a useful capacity considering the safe operation range of the battery O^{max}_i, an efficiency applied to the discharged energy A^{dis}_i, reactive power capability $Q^{maxreact,bat}_i$ and maximum active power Q^{ch}_i,Q^{dis}_i for both charge and discharge processes respectively.

Additionally, storage units have an operation cost due to their loss of lifetime $C^{dis,ct}_i$. In this case this function is considered as a constant relation with the energy discharged in the objective function.

The initial state-of-charge is defined as $\sigma_{i,0}^{soc}$. The decision variables for the energy storage units are their absorbed or generated power $\sigma_{i,t}^{ch}, \sigma_{i,t}^{dis}$, the state-of-charge of the battery in each period σ^{soc} bounded by 0 and O_i^{max}.

The active $\sigma^{ch}, \sigma_{i,t}^{dis}$ and reactive power $\sigma_{i,t}^{reac}$ of the battery converter and their limits are:

$$-Q_i^{maxreact,bat} \leq \sigma_{i,t}^{reac} \leq Q_i^{maxreact,bat} \qquad \forall i,t \tag{3.9}$$

$$\sigma_{i,t}^{ch} \leq Q_i^{ch} \delta_{i,t}^{bat} \qquad \forall i,t \tag{3.10}$$

$$\sigma_{i,t}^{dis} \leq Q_i^{dis} (1 - \delta_{i,t}^{bat}) \qquad \forall i,t \tag{3.11}$$

The equations that define the battery behaviour are the SOC relation:

$$\sigma_{i,t}^{SOC} = \sigma_{i,t-1}^{soc} + \sigma_{i,t}^{ch} A_i^{bat,ch} - \frac{\sigma_{i,t}^{dis}}{A_i^{dis}} \qquad \forall i,t \tag{3.12}$$

3.5.2 Market Contract

After we have a matched power $P_{o,t}^{mat}$ to exchange with the main grid from the DAWM, we can choose not to deliver or consume that power at the expense of paying a penalization cost C_t^{dev} depending on the market price.

The absolute value of the deviation $Dv_{o,t}^{abs}$ is defined with the equations:

$$Dv_{o,t}^{abs} \geq P_{o,t}^{CCP} - P_{o,t}^{mat} \qquad \forall o,t \tag{3.13}$$

$$Dv_{o,t}^{abs} \geq P_{o,t}^{mat} - P_{o,t}^{CCP} \qquad \forall o,t \tag{3.14}$$

Dv^{abs} and C^{dev} will be included in the objective function to compute the deviation costs.

3.5.3 Objective Function

When the energy storage is considered, we want to maximize the sum of social welfare over all periods, even if some participants may be disadvantaged in certain periods. The objective function also includes the deviation costs and the operation and maintenance cost of the battery.

$$
\begin{aligned}
f_{obj}^{CES} = - \sum_t \sum_m \sum_{bg} \sum_z E_{m,bg,z,t}^{mG} \cdot C_{m,bg,z,t}^{bG} \\
+ \sum_t \sum_m \sum_{bc} \sum_a E_{m,bc,a,t}^{mL} \cdot P_{m,bc,a,t}^{bL} \\
- \sum_t \sum_o P_{o,t}^{CCP} \cdot C_t^{CCP} \\
- \sum_i \sum_t \sigma_{i,t}^{dis} \cdot C_i^{dis} - \sum_t \sum_o Dv_{o,t}^{abs} \cdot C_t^{dev} \quad (3.15)
\end{aligned}
$$

Notice that, E^{mG} and E^{mL} are variables because the usage of the CES unit may alter the power matched of the micro-market's participants.

3.6 Case study

In this section, the case study is presented. It includes photovoltaic (PV) producers, prosumers with rooftop PV panels and consumers without generation connected to a meshed distribution network. The demand is assumed elastic because consumers may have demand-response capability or remotely controllable electric vehicles. For the MPP, five periods of one hour are studied to illustrate the micro-market behaviour.

The micro-market results are compared to the case without DAMM in order to assess its benefits. When there is not a micro-market, power matched in the DAWM might violate some grid constraints. In this work it is assumed that in those cases the DSO monitors the grid. When the DSO detects violations, applies power curtailments sending an active power reduction signal to all generators until the violation is corrected. This signal is a relative reduction of power and it is the same for all generators.

Fig. 3.3 shows the energy offered by all PV generators, the maximum energy demanded by micro-market's participants, and the DAWM price. During the initial periods the micro-market has energy surplus and during the last hours energy deficit. Moreover, the grid price is cheaper during initial periods than final periods.

3.6.1 Network model

In order to show the DAMM operation, the case study analysed is a 4 node distribution network with a high penetration of renewable generation shown

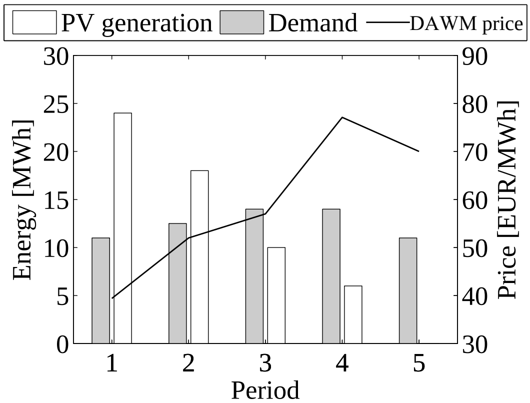


Fig. 3.3: Case study data

in Fig. 3.4. The CES unit is connected to node 4 with a charging/discharging capacity of 1 MW and ±1 MVar, 3 MWh of useful energy capacity and 85% of full cycle efficiency.

As it has been mentioned earlier, the grid is only under-sized for peak generation power, not for the consumption; the line between bus 1 and 2 has 12 MVA capacity which constraints the power exchange with the main grid, the other lines cannot export the full power of renewable generation of G3 and G4 which is 12 MW peak each one.

3.6.2 Simulation cases

The present chapter compares three different scenarios in order to see the advantages of the DAMM combined with CES units.

1. **Without DAMM**: DER units are aggregated for the participation in the DAWM without considering the grid. During the operation, corrections needed to avoid grid violations are determined by the DSO's distribution management system.

2. **With DAMM**: DER units are aggregated for the participation in the DAWM considering the grid.

3. **With DAMM and CES unit**: This case shows the effect of the battery unit on the participants' social welfare.

Table 3.1: Reduction signal for case 1

Period	1	2	3	4	5
Reduction signal	0.6	0.7	1	1	1

Table 3.2: Social welfare of each period and simulated cases

Period	Simulation case		
	1	2	3
1	1,446.1	1,576.7	1,599.2
2	1,713.9	1,848.3	1,881.5
3	1,813.2	1,815.1	1,817.3
4	1,591	1,593.2	1,661.1
5	842.3	843.6	861.8
total	7,406.5	7,676.9	7,820.9
Δ (%)	0	3.651	5.595

3.7 Results

Results are presented In this section for the three cases simulated. Table 3.2 shows a social welfare (SW) comparison. During the first periods considered there is a great amount of renewable generation and, as the grid is above its capacity, the renewable power cannot be exported to the main grid without overcharging lines 1-2, 4-2 and 3-2. Without a micro-market, the DSO is forced to reduce power of all generators as it is shown in Table 3.1. If the reduction of generation makes it not possible to satisfy all consumption, the main grid acts as slack bus. This is less profitable than considering the network during the clearing algorithm execution. In the last periods, when there is little renewable generation, the micro-market benefits without a battery are not significant.

When a CES is considered, the overall SW is increased. In this simulation it is forced that the battery ends with the initial SOC to avoid free energy injections. The battery is capable of increasing the SW in all periods, and not only in those periods where it acts as generator. In order to understand the battery participation, the period 2 is studied in more detail for the case with micro-market and CES and shown in Fig. 3.4.

As the Fig. 3.4 shows, during period 2 the CES unit stores energy and produces reactive power locally to increase the active power transmission capacity. Furthermore, lines between nodes 2-3 and 2-4 are near to their limit and for this reason, G3 and G4 are reduced from their maximum power.

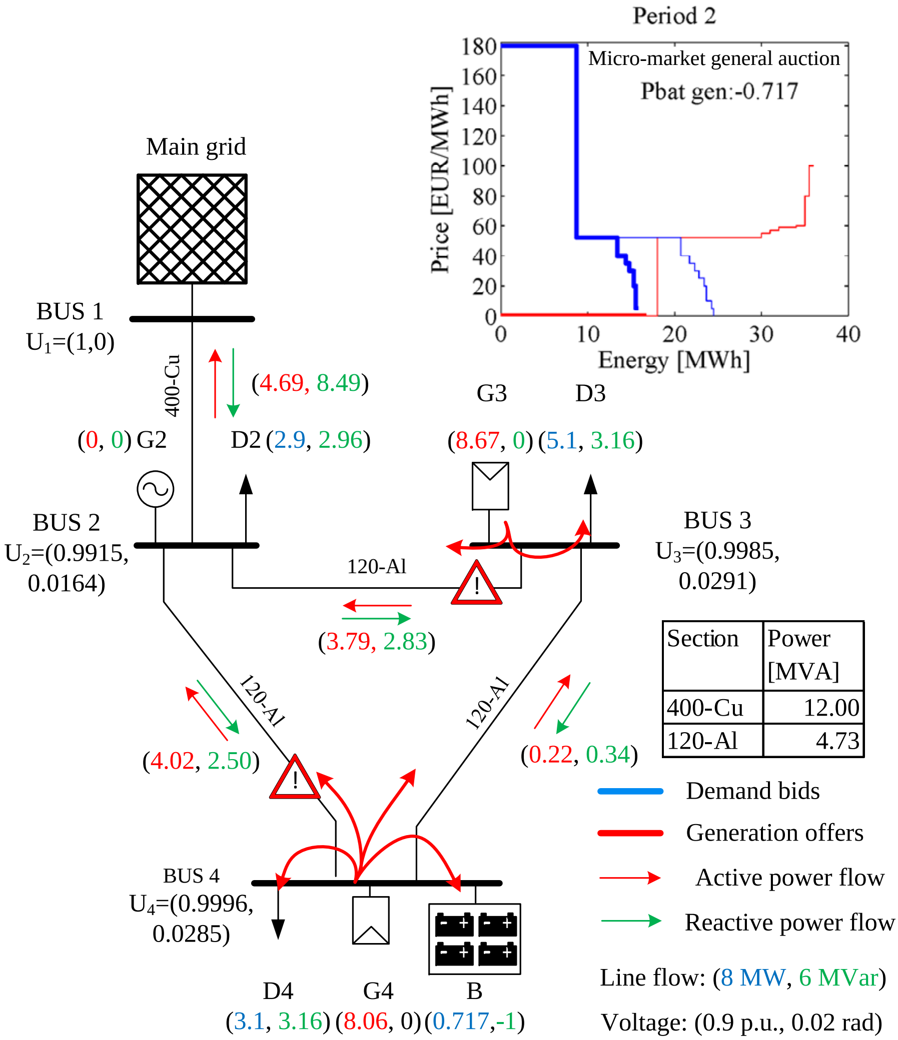


Fig. 3.4: Period 2 results for case 3

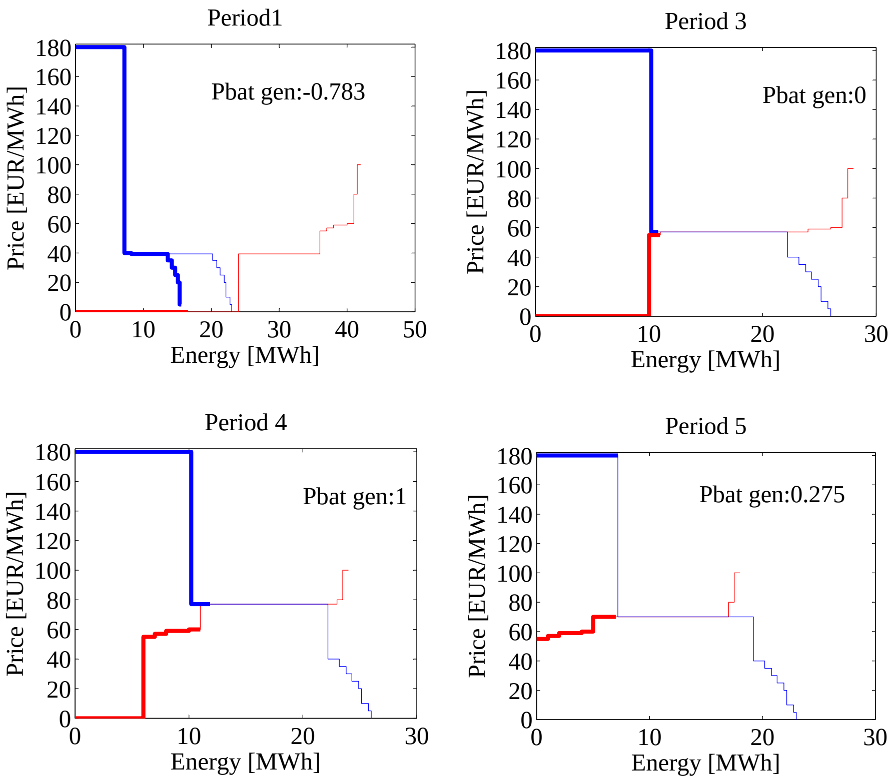


Fig. 3.5: Auctions for case 3

Fig. 3.5 shows the auction curves for the other periods. During periods 1 and 2 not all renewable generation can be matched and the battery stores energy. In contrast, the battery does not act during period 3 because the DAWM price is lower than periods 4 and 5. During these periods the battery delivers the energy stored to reduce the power consumed from the main grid.

3.8 Conclusions

In this chapter a micro-market is introduced to manage DER. With the increase of renewable distributed generation the current network can be under-sized. If the network is not considered for the participation of DER to the DAWM, power quality can be compromised and eventually power can be curtailed in a non-optimal way. The micro-market structure presented ensures competitiveness among agents considering social welfare in its clearing algorithm. The micro-market proposed can help both ensure the network constraints and increase the social welfare, especially when VRE DG is high. Moreover, a CES unit can be added to improve the performance of the micro-market, and it can effectively increase the social welfare.

Chapter 4

Local Flexibility Market Design for Aggregators Providing Multiple Flexibility Services at the Distribution Network Level

4.1 Introduction

LECs and CECs are an emergent trend with the aim of engaging end-users in a sustainable energy future after the recent regulation from EU Parliament as introduced in Chapter 1. Currently there is not a detailed CEC definition yet as they can be organized in different ways. As stated in [146], LECs are citizen-led renewable energy cooperatives, housing associations, foundations or charities, which are not commercial actors, but produce energy meant for self-consumption, mainly by solar PV panels and wind turbines. Additionally, [147] analysed LECs in The Netherlands, and their common characteristic is their intention to prioritize community benefits. However, it is not clear if an LEC should be under the same DSO or BRP's portfolio in all cases or not. Every Member State will have to develop the specific regulation based on the EU Parliament directive [5]. In this context, BRPs are responsible for balancing demand and supply for a certain group of metering points according to Eurelectric [148]. Either way, end-user aggregation would constitute an opportunity to create flexibility exchanges regardless of the LEC characteristics. Hence, the concept of local flexibility markets (LFM) as a market-based mechanism to manage demand response at the LEC level for multiple objectives is adopted in the present work.

In contrast to wholesale-focused solutions, literature until 2017 presented different price settlement methodologies and energy transactions mechanisms for local markets. [149] reviews different concepts of local trading, enabling technologies and required frameworks. Additionally, [150] elaborates on a survey about different market-based control methodologies for DER. In terms of price settlement, [151] presents two types of electricity auctions: uniform price and discriminatory auctions at the neighbourhood level. In contrast, [139] presents a continuous double-sided auction to settle energy prices and [136] shows a stock exchange-based model with discrete fixed time slots.

Moreover, in terms of energy transactions mechanisms, [152, 153] analyse a local market platform controlled by a central entity that minimizes the operation cost for each household trader. Similarly, [139] present a distributed market-based control that divides the grid into nodes and uses zero-intelligent automatic agents to maximize the profits for each household. In that case, the market operator is in charge of executing the energy auctions for maximizing total market surplus. [154] presents a LFM model based on auctions without studying the flexibility services from the local market. [155] describes a LFM for bidding in the day-ahead and intraday markets without considering interactions between local market operator and the TSO. In contrast, [156] formulates the NRGcoins as a virtual currency for energy injected into the grid that is traded between prosumers and pure consumers based on blockchain technology. In this approach, the DSO acts as a local market supervision entity.

The main difference between [156] and the LFM proposed in this chapter is the regulatory approach. On the one hand, the LFM operator supervises the local trading, aggregating flexible resources and selling flexibility services to third parties. In the case of aggregators being a BRP at the same time, it can access wholesale markets for trading corresponding energy surplus or deficit. However, NRGcoins is a parallel market not related to the retail business. Moreover, NRGcoins uses the DSO as a supervision entity instead of the aggregator as proposed in this LFM approach. Therefore, NRGcoins may not fit in the European liberalized regulatory regimes that do not allow DSOs to participate in energy trading-related businesses.

A shortcoming that may arise from demand response activities in LFM is the risk for fault occurrences. The reason is the generators' operation on a wide output range to increase elasticity. There should be a balance between elasticity and risk, which might lead to an increase of the system cost. It should be further analysed at the global system level, covering TSO and DSO domains, so as to assess the risks and associated costs of flexibility from demand-side activities in smart grids. Chapter 5 of [157] describes the relation between demand response activities and VRE production uncertainty, and [158] provides a framework for reliability and risk assessment in demand response activities for capacity procurement at the distribution level, which could be implemented to determine the benefits of demand response schemes.

In contrast with the previous peer-to-platform transaction mechanisms, [159, 160] describe peer-to-peer (P2P) negotiation systems. The main advantage of P2P is to avoid the need for a central entity. However, this approach could result in low negotiation power when selling flexibility services to bigger stakeholders, such as BRPs, DSOs or TSOs. Furthermore, individual market players like prosumers would not have access to wholesale markets depending on their size and national regulations.

The peer-to-platform approach offers some advantages for trading flexibility in contrast to the classic P2P approach. First of all, decisions on local issues are made centrally, and they are supervised by the aggregator. Thus, the aggregator has a complete LEC status overview and can make decisions to benefit the LEC as a group, and not every participant individually. This could be a disadvantage in some specific situations. For example, prosumers with thermal flexibility could be activated frequently, which may result in a significant loss of comfort and causing a drop of user acceptance being a flexibility contributor to the LEC. Nevertheless, prosumer economic rewards should be higher than their opportunity cost, and they can request higher payments. The most beneficial decision should be analysed case by case.

Regarding flexibility services, [34, 161] analyse the usage of demand response for DSO services using a centralised platform. In contrast, [159, 162] describe a P2P mechanism to attend to DSO requests. Furthermore, [163] highlights different flexibility market frameworks across Europe, being mostly based on a centralised approach. At the BRP level, [164] proposes a centralised platform system to provide flexibility services to BRP, participating as a market actor within the European Energy Exchange Spot Market. The P2P approach has not been considered yet to provide flexibility services to BRPs, a centralised approach currently being the main application. In [165], flexibility market-based schemes are defined for TSO-DSO coordination. This work is a deliverable of SmartNet H2020 European Project that is currently being developed. There, two LFM are detailed: a Local Ancillary Services (AS) real-time market, to consider balancing and congestion management services for DSO and TSO. DSO operates the local market to solve distribution grid problems and then aggregates the remaining flexibility offers to TSO markets. The second model is a common TSO-DSO AS market model, which is also based on a real-time dispatching. It is based in a local market operated by the DSO, but satisfying the needs for both TSO and DSO. It is worth noting that only one flexibility customer is being considered on the previous literature references, and so, they do not take into account the grid status when flexibility services are dispatched. However, the DSO as local market operator could present contradictions with the market liberalization and the sector unbundling of the European power system.

The present chapter provides several insights and novelties in terms of flexibility services. Firstly, it is based on a centralised approach for flexibility services providing, with the new market agent, the so-called aggregator. The aggregator manages the flexible loads to provide services to DSO and BRPs, the TSO being out of the scope at the present time. Secondly, to be able to manage these flexible loads, this paper proposes the traffic light concept (TLC) explained below, allowing the coordination between flexibility customers and DSOs. In the LFM that is being presented, the role of the aggregator and the consideration of the grid status under the TLC concept permits the interaction between more than one flexibility customer and allow one to dispatch flexibility services transparently.

Furthermore, the centralised LFM approach requires less computation devices per FD because they do not need to install local intelligent devices to make decisions in each flexible asset or house. All FD could be forecasted in the centralised platform, and optimization operation algorithms could take into account uncertainties in a more efficient way than with a distributed LFM. Thus, the centralised concept alleviates the burden on each trader, supports pool-oriented flexibility exchanges and provides the aggregator with essential information pertinent to future and past assessments.

The contribution of this chapter lies in the design of an LFM operated by an aggregator who manages flexible devices with direct control for providing multiple services in distribution grids with DER to different stakeholders. The aggregator uses an Information and Communication Technology (ICT) trading platform, from now on called the aggregator platform. The design includes a description of objectives, contracts and role details, among other issues.

In this chapter, the author presents a selection of the results on local market design and operation that has been developed in the EMPOWER Horizon 2020 project [166] and the initial findings of the Horizon 2020 INVADE project [167].

Section 4.2 provides a general overview of the local market and delves into the local market concept describing the objectives, roles, contracts, wholesale-local market interactions and their timelines. Section 4.3 explains the LFM in detail, and Section 4.4 shows a simulation test case that compares three scenarios to prove the convenience of the TLC. Finally, Section 4.5 introduces a discussion about the current regulatory barriers, and

Section 4.6 presents the main specific conclusions of this chapter.

4.2 Local Market Overview

An LFM is an electricity trading platform to sell and buy flexibility within the LEC. In order to run the LFM, an aggregator provides a trading platform for sharing information, exchanging flexibility and scheduling flexible devices. The aggregator acts as the local market facilitator for the LEC. This implies that the aggregator takes actions to increase local market interactions, in order to ensure enough liquidity.

LFMs are voluntary, and they represent a market-based energy coordination framework. Their main contribution is to monetize the flexibility sold within the community. LFMs enable the P2P flexibility transactions at a certain level. However, the LFM includes an aggregator as a central entity, which supervises the LEC in terms of electricity production and consumption, settlements and contract fulfilment. Therefore, LFM creates a peer-to-platform business model. This is similar to several other network-based markets as described in [168].

[169] describes the early stages of the Smart Energy Service Provider, the local market structure and relationships and its platform. [170] defines four new business models of flexibility creation based on interviews and industry research. Additionally, the Smart Grid Coordination Group [171] specifies the general framework for flexibility markets at a high level. This chapter presents the concept of the LFM based on previous references. Henceforth, aggregator is the title used in this chapter to follow its definition included in the Clean Energy for All Europeans proposal of measures [4]. In the present context, smart energy service provider and aggregator are considered as synonyms.

4.2.1 Concept

In this chapter, the author presents multiple geographically-distributed and voluntary LFMs managed by aggregators as a complement to the current wholesale markets. Following our understanding, aggregators could be flexibility managers selling to third parties like BRPs and DSOs. Additionally, aggregators could control end-user flexibility to reduce their electricity bill during periods without third party requests. Therefore, our vision of aggregators includes energy service company functionalities to increase the benefits of using the aggregator platform. Aggregators could be current BRPs or energy retail companies adding new functionalities in their daily

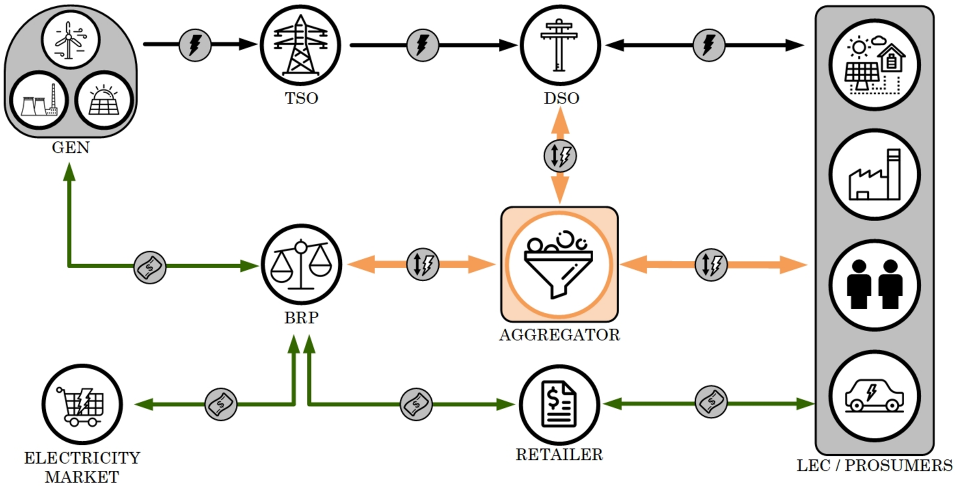


Fig. 4.1: Local flexibility market overview. LEC, Local Energy Community.

business. This chapter is mainly focused on the aggregator functionalities, but includes some specificities of BRP being an aggregator at the same time.

As shown in Fig. 4.1, the aggregator supervises local market operations with the aim to maximize profits for its LEC members. The cooperation between LECs and aggregators could increase their negotiation power with BRPs and DSOs.

An aggregator can generate new earnings offering flexibility to DSOs, BRPs and prosumers themselves. For example, each LEC connected to the same DSO within the same BRP portfolio could have its own LFM managed by an aggregator. In this case, this aggregator could offer flexibility services from LECs to the BRP and the DSO at the same time. However, our approach is not limited to LECs. An aggregator could manage customers out of LECs, as well. For example, a group of customers under the same DSO could offer services for grid congestion management. Similarly, customers under the same BRP could offer flexibility to reduce deviation penalties, for instance. However, an LEC could have more benefits from the LFM and gain stronger negotiation power than customers individually.

This chapter explains flexibility services, the roles and responsibilities for local market stakeholders, trading processes, high-level operation algorithms for flexibility activation and the relation between local and wholesale markets. Additionally, the presented framework includes the individual-collective flexibility usage dilemma, which has not been included previously. LECs will face controversial situations when some individuals could profit optimizing individually rather than maximizing community welfare. Under the LFM umbrella, community members can establish internal reward mechanisms to partially compensate adversely-affected members. Finally, the present chapter highlights the benefits of the local flexibility market framework to coordinate actions in situations with different flexibility requests at the same time.

The local market proposed in this chapter has been designed considering the current European regulatory framework, and hence, some aspects of this design may not be applicable for other regions. However, it is assumed that the energy regulation allows prosumers to sell flexibility, and the regulation provides a clear definition of flexibility at the distribution level. In the European context, up-regulation flexibility at the transmission system level refers to more generation or less consumption and vice versa for down-regulation. For example, [26] in the academic context and the Danish TSO Energinet [172] in the commercial sector follow this criterion. Based on that, the LFM follows the same principle. However, this chapter does not include a regulatory review. Additionally, this chapter assumes that distribution system operators are allowed to buy flexibility from distributed resources for grid operation purposes.

Finally, this work follows the flexibility and baseline definitions proposed by the the Expert Group 3 (EG3) [171]. An agreed consumption and generation baseline is needed for all involved actors to have a common reference when doing the settlement process. In this framework, the aggregator calculates the baseline, and it is accepted by the DSO and BRP in case there is not a regulated entity for this task. However, the recommendation from the INVADE project for future regulatory proposals is to create a separate and regulated entity to define baselines. This new entity should not have any incentive to over-predict or under-predict the energy assets' performance.

4.2.2 Objectives

The LFM ambition is to develop a local market place to encourage local generation and active participation of prosumers to exploit the flexibility that they can provide, for the benefit of all LEC members and stakeholders. The LFM objectives are listed as follows:

1. Promote the installation of distributed renewable generators.
   (a) To create an attractive and competitive trading platform that forges incentives to buy energy from local and renewable resources.

   (b) To cater to increased investment in distributed renewable resources.

2. Support the trade of end-user flexibility for the benefit of the DSO and its operations.
   (a) Managing grid bottlenecks.
   (b) Providing power curtailments under request.
3. Support BRP in wholesale markets.
   (a) In day-ahead markets.
   (b) In intraday markets.
   (c) In balancing markets.

4.2.3 Flexibility Services

Two sources have been identified as key references to define the flexibility services. One of them is the Universal Smart Energy Framework (USEF) [117,173], which delivers one common standard on which to build an integral market for the trading of flexible energy usage. The second source is the conclusions and advice regarding flexibility implementation from the EG3 about regulatory recommendations for smart grid deployment [171]. They are normally classified as a function of the flexibility customer, namely DSO, BRP and prosumers.

DSO Services

The DSO requests correspond to the amount of flexible resources needed to operate the distribution grid within the safe operation zone. The INVADE project is focused on the following services that the ICT platform can provide to the DSO, and they are:

- Congestion management: to avoid the thermal overload of system components by reducing peak loads where failure due to overloading may occur.
- Voltage/reactive power control: to use load flexibility as an option to avoid exceeding the voltage limits.
- Controlled islanding: to prevent supply interruption in a given grid section when a fault occurs.

BRP Services

Aggregators can help BRPs to balance their portfolio and commitments in wholesale markets. Flexibility sources could be used for managing forthcoming imbalances due different reasons like forecasting errors or for minimizing BRP electricity costs. Flexibility services to BRPs could be:

- Day-ahead portfolio optimization: to shift loads from a high-price time interval to a low-price time interval before the day-ahead market closure. It enables the BRP to reduce its overall electricity purchase costs.
- Intraday portfolio optimization: to enable value creation on the intraday market, equivalent to the day-ahead market.
- Self-balancing portfolio optimization: to reduce imbalance by the BRP within its portfolio to avoid imbalance charges. The BRP does not actively bid on the imbalance market using its load flexibility, but uses it within its own portfolio.

Prosumer Services

Finally, flexible assets behind the meter can be used to minimize prosumer electricity costs. An aggregator can implement some home energy management algorithm in the aggregator platform. [174] reviews and compares algorithms for different applications. USEF listed the following potential flexibility services to prosumers [117]:

- Time-of-use (TOU) optimization: to use flexibility from high-price intervals to low-price intervals.
- kWmax control: to reduce prosumer consumption peaks within a predefined duration.
- Self-balancing: to use the price difference for consuming, producing and selling electricity favourably.
- Controlled islanding: to maintain electricity supply behind the meter during grid outage situations.

Multiple Service Compatibility

The services offered to BRP, DSO or final customers/prosumers can be requested at the same time, and requests could be contradictory between them.

For this reason, it is necessary to classify flexibility requests according to a certain criterion. Our basis is the TLC applied to power systems introduced by the German Association of Energy and Water Industry (BDEW). The BDEW [175] described the need for aggregators to receive certain information about the current grid status and how the TLC can contribute to that.

Following the TLC approach, this chapter assumes that grid operators announce if the grid is under threat or not codifying the grid status into three levels: green, amber and red. This information would be used for prioritizing flexibility services.

- Green state: This is the normal operating state in which the grid does not face threats in the near future. Under the green state, the LFM operates freely. Then, the grid operators may not request flexibility services, and BRP or prosumer services have the highest priority. BRP and prosumer services would compete by price in the LFM.
- Amber state: This indicates the state where grid operators actively engage with the LFM in order to prevent the grid system from becoming saturated and entering over the red state. Under this state, a grid operator has the highest priority and may request flexibility services. It is a temporary state until the grid operation becomes safe again.
- Red state: The grid operator needs to take control of LFM interactions in a certain area where a grid constraint has occurred. Under this state, the grid operator can override existing contracts in the LFM and execute dedicated emergency actions through the aggregator in order to re-stabilize the system.

Table 4.1 shows flexibility services possible in each grid state indicated with X, and Fig. 4.2 compares regularity, flexibility services and grid status priority. In red and amber states, the aggregator offers its available flexibility to the DSO to solve or avoid problems in the grid, which should only occur on a few specific occasions. These services have higher priority than other flexibility requests, and consequently, these are supposed to be highly rewarded. The DSO is responsible for the identification of the grid state and necessities to inform aggregators about them. Controlled islanding service at prosumer premises can also be performed in the red state.

Table 4.1: Flexibility services to be offered in each grid state by local energy communities.

Flexibility Customer	Flexibility Service	Grid State		
		Green	Amber	Red
DSO	Congestion management		X	X
	Voltage/reactive power control		X	X
	Controlled islanding		X	X
BRP	Day-ahead portfolio optimization	X		
	Intraday portfolio optimization	X		
	Self-balancing portfolio optimization	X	X	
Prosumer	TOU optimization	X		
	kWmax control	X	X	
	Self-balancing	X	X	
	Controlled islanding			X

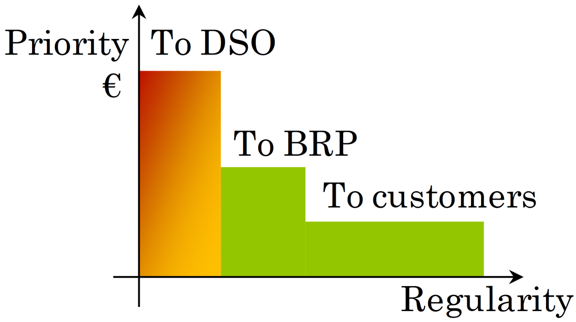


Fig. 4.2: Traffic light concept applied to the flexibility services and customers.

In the amber state, surplus flexibility, which is not used to avoid grid problems (DSO services), can be utilized to satisfy some BRP and prosumer services if they help to relieve the grid. For instance, self-balancing BRP portfolio optimization can be used during the amber state if the BRP request is in the same direction as the DSO request. However, day-ahead and intraday optimization services could compromise flexibility sources needed for real-time grid operations. Similarly, kWmax control and prosumer self-balancing could be useful if the DSO need is to reduce energy consumption or production.

On the other hand, flexibility in the green state can be offered to the BRP or to prosumers interchangeably. Here, services to the BRP (portfolio optimization for instance) and to the final customer have to compete for the same available flexibility. Before flexibility is offered to other customers in an aggregated way, a prosumer can use its own flexibility for in-home or building optimization. As a first approach, services to the BRP may be less frequent, but highly rewarded compared to the services to the final customer, which are always present by default if no other flexibility request is in place.

4.2.4 Roles and Responsibilities

The main participants in the LFM are an aggregator, DSOs, BRPs and LEC members (consumers, producers and prosumers). The LEC members in the LFM are attracted from neighbourhoods and organized by an aggregator. Participation in the LEC is purely voluntary. In the future, members of the same neighbourhood could choose between different LECs. Interactions between LECs are not considered in this chapter. The aggregator and

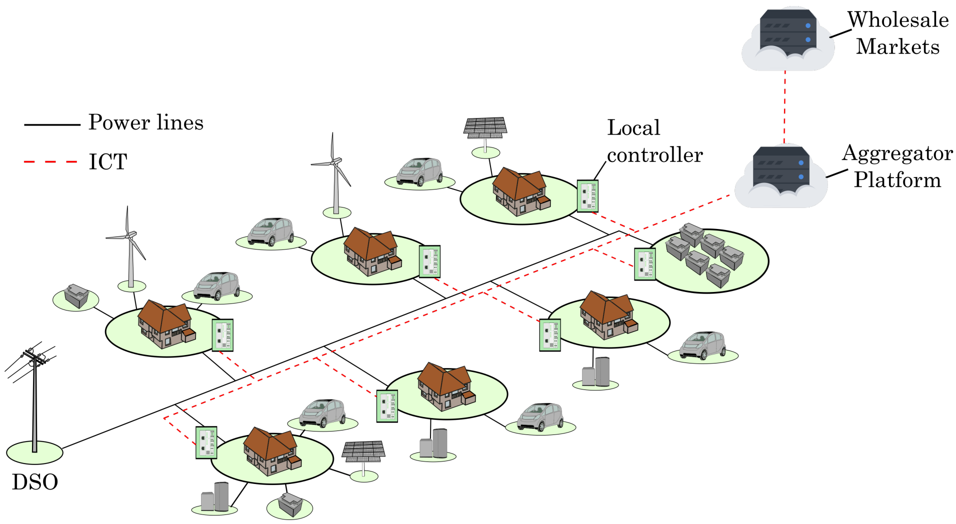


Fig. 4.3: Local energy community example connected to the aggregator platform.

the governing body of the community can also decide on certain rules and requirements that must be satisfied before membership can be granted.

Fig. 4.3 shows an example of a small LEC with different types of community members, such as households with photovoltaic generators, storage units and demand response from water heaters and electric vehicles. The LEC could be managed for different purposes like maximizing the renewable energy usage or the economic profitability. This could be decided by the LEC, and the aggregator could offer different optimization approaches.

All flexible members with distributed energy resources need to have a local controller. It has to monitor electricity consumption and production of each flexible device. Moreover, the local controller should be capable of receiving control signals from the aggregator platform for each flexible device. As stated before, the local controller does not necessarily include intelligence to make decisions locally.

The LEC members and prosumers in the LFM are responsible for:

- Fulfilling the established contracts.
- Providing the required information about flexible resources.
- Installing local control devices connected to the aggregator platform.

The various roles of aggregators are listed as follows:

- Local market operator: to organize flexibility exchanges and maintain the trading platform.
- Risk manager: to manage all risks such as energy deviations and technical failures.

Additionally, an aggregator could represent LEC members in wholesale markets in the case of it being a BRP at the same time.

For the reason that the DSO cannot publish grid status transparently for privacy and security reasons, the aggregator is not aware of the grid constraints. Therefore, the LFM could disturb the distribution grid operations in certain situations. To avoid potential dangerous circumstances, the aggregator could communicate and share consumption and generation plans with the DSO during such cases. Section 4.3.4 digs into the DSO-aggregator interaction timeline. In addition, the LFM offers to the DSO the possibility to interact with the aggregator in the case of flexibility need. These new aggregator functionalities could constitute an update of the DSO and BRP business models.

4.2.5 Aggregator Platform

The aggregator platform must facilitate all processes associated with creating an on-line community of consumers, prosumers and producers. The overall life-cycle process for a community member consists of the following distinct steps:

- Recruitment: includes all processes related to attracting users, signing in and profile creation.
- Commissioning: includes all activities related to introducing equipment technical data into the platform and checking their veracity.
- Engagement: includes all the processes related to defining contract prices and renewal processes. Moreover, engagement also involves the member so that they become active LEC members.

- Exchanges: includes all processes related to verifying and monitoring flexibility trades and exchanges.
- Settlement: defines the total amount of flexibility activated and requested. It produces the delivery note to be sent to LFM participants.

4.3 Local Flexibility Market

In the LFM, the aggregator controls its members' flexible resources such as loads, generators, EVs and batteries during certain time intervals and rewards them according to their flexibility contract activation prices. Flexibility contracts for loads, EVs and batteries are explained in detail in [176]. The LFM defines flexibility plans according to allocated and reserved flexibility for future needs, respectively.

The goal of the LFM is three-fold:

- Complying with DSO requests to prevent grid overloads caused by consumption or generation from community members or others connected to the same grid. Thus, the LFM allows the DSO to prevent grid damages and postpone grid reinforcements.
- Compensating BRP deviations due to forecasting errors or other issues to reduce deviation penalties for the BRP in wholesale markets. The aggregator uses the ICT platform to send flexibility control signals to compensate LEC deviations if the deviation penalty is higher than the flexibility costs.
- Complying with prosumer needs. In the case of no external request, the aggregator can activate flexibility to reduce electricity cost individually.

The following sections describe the LFM in detail.

4.3.1 Contracts

All LFM participants need to have a contract with the aggregator. Nowadays, consumers can have separate or unified contracts with the BRP for consuming and producing electricity depending on the national regulations. Additionally, the LFM adds a new contract for activating flexibility. They settle an activation price for every flexibility asset, and they can include additional constraints like permitted activation periods or the number of flexibility activations per day. These contracts can be renewed periodically every month, week or day depending on participation levels. The aggregator issues all contracts and offers a brokering, clearing and price settlement service.

The LFM contracts are introduced below:

- Aggregator-DSO contract: This defines the information shared, message exchanges, actions, timetable, responsibilities of each partner and the rewards for each service provided by the aggregator.
- Aggregator-BRP contract: This is the same as the aggregator-DSO contract, but for providing balancing flexibility services.
- Aggregator-prosumer: This defines the flexibility reservation and activation prices, time constraints and penalties for failures to meet contractual obligations.

The prosumer's contract reservation price stipulates the cost paid by the aggregator for periods during which the aggregator can manage flexibility devices. The activation price stipulates the fee when the aggregator activates demand response. Contract details could differ case by case.

4.3.2 Flexibility Portfolio Balance

The fundamental guiding principle for aggregator operations in the case of exchanging flexibility with external agents is represented by the function (4.1) following the goals explained previously:

$$E^{\Delta} = f(E^{REQ,DSO}, E^{REQ,BRP}, E^{REQ,Prosumer}) \tag{4.1}$$

The E^{Δ} function is the flexibility that the aggregator has to provide, and this function is composed by external requests from agents like DSOs ($E^{REQ,DSO}$) and BRPs ($E^{REQ,BRP}$). Additionally, the prosumer flexibility need ($E^{REQ,Prosumer}$) is considered, as well. In principle, if there is no external flexibility requests, the prosumer need prevails. Moreover, prosumer needs could be more beneficial than the external offers in some specific cases. When external agents request up-regulation, it is defined as positive ($E^{REQ} > 0$) and negative for down-regulation ($E^{REQ} < 0$).

Depending on the flexibility regulation direction, simultaneous external requests can be complementary or contradictory. In the case of allowing multiple flexibility services, the aggregator has to follow a certain criterion.

The criterion applied in the case study shown below follows the TLC explained before. Therefore, the DSO requests always have higher priority than others in the case of opposite requests.

In the case of contradictory requests, the aggregator should pay a penalty to the BRP for increasing its deviation. However, the DSO economic reward for the flexibility must be higher than the BRP penalty.

In contrast, if the BRP and DSO requests have the same direction, the aggregator applies the biggest request. In the case that the DSO request is bigger than the BRP request and it is in the same direction, there are no penalizations because the BRP will not pay a deviation penalty to the system. This is based on the assumption that the BRP requests make its portfolio deviate in favour of the power system balancing, helping the TSO to keep generation and consumption equilibrated. In that case, the BRP only pays for the energy consumed, but without penalty. That is applicable in most of the European electricity markets at least.

Finally, in the case that the BRP request is higher than the DSO and they are in the same direction, the aggregator applies the BRP request as it does not cause trouble for the DSO. Nevertheless, the DSO only pays for the amount requested, not for the activated flexibility.

The E^{Δ} function can be decomposed into the following flexibility providers:

$$E^{\Delta}(t) = E^{STO}(t) + E^{FL}(t) + E^{FG}(t), \tag{4.2}$$

where $E^{STO}(t)$ is the flexibility available from storage units for charged energy ($E^{STO}(t) > 0$) and discharged energy ($E^{STO}(t) < 0$), $E^{FL}(t)$ is the flexibility available from loads for up-regulation ($E^{FL}(t) < 0$) and down-regulation ($E^{FL}(t) > 0$) including EV and $E^{FG}(t)$ is the flexibility available from generators for up-regulation ($E^{FG}(t) < 0$) and down-regulation ($E^{FG}(t) > 0$).

4.3.3 Local and Wholesale Markets' Interaction

The LFM could interact with wholesale markets depending on the implemented services. BRP services could provide flexibility to reduce electricity costs while day-ahead and intraday markets are open. Additionally, aggregators could provide additional benefits trading in balancing markets. Fig. 4.4 shows the parallelism between local and wholesale markets. Flexibility markets are limited to short-term wholesale markets for simplicity. The potential value of distributed flexibility in capacity markets is out of the scope.

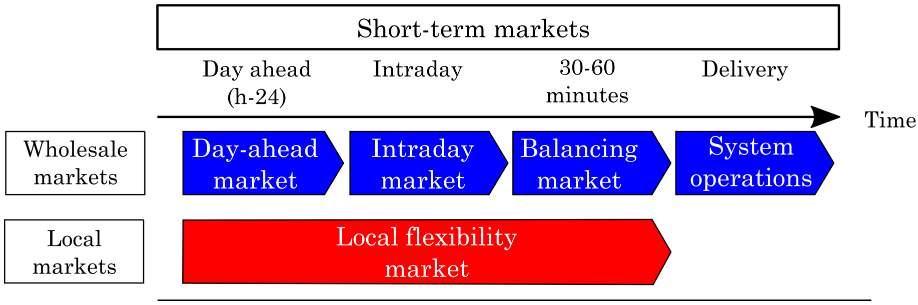


Fig. 4.4: Wholesale and local market relation in the short term. Adapted from [3] including local markets.

4.3.4 LFM Timeline

The actions executed in the LFM are represented in Fig. 4.5 as an example. It is divided in two main parts: operations needed to schedule flexible resources and the flexibility settlement process. It contains the case where the BRP and the DSO can request flexibility at the same time. For simplicity, the flexible resource represented in this figure is a single battery, but it applies to a portfolio of different flexible assets. Scheduling tasks can happen days, hours or minutes ahead of the final delivery. This figure is open to be adapted to different cases. The action sequence of LFM is listed as follows:

First of all, it is necessary to carry out the operation process a certain time ahead of the actual energy delivery or consumption, and it is as follows:

- The DSO receives grid metered values from its SCADA or similar systems. This information is used by a grid congestion detection algorithm to quantify the flexibility to requests in the forthcoming periods. If it is needed, it sends a flexibility request (Flex. request) to the aggregator.
- Similarly, the BRP receives the portfolio forecasts and estimates the future unbalances using an internal algorithm. If it is needed, it sends a flexibility request number i to the aggregator.
- The aggregator receives all flexibility requests and establishes a prioritization according to the grid status. This includes the compatibility of multiple requests for the same period. If there is no flexibility requests, the LFM algorithm will optimize for the individual benefit of every LEC member.

- Before scheduling flexibility, the aggregator checks the availability of every flexible asset like the battery unit b using the local controller.
- Once the aggregator knows the available flexible assets, it schedules them to meet the external requests, and it produces the flexibility plan (Flex. plan) containing all management signals for the request i to be sent later on.

Once the operation management signals have been applied, the settlement process audits what happened during every period. This process certifies that the flexibility has been activated. For example, it checks the metered values at the flexible device level. The settlement process is as follows:

- The aggregator platform receives metered values about flexibility activated during request i from local controllers.
- The aggregator calculates flexibility activated during operation.
- The aggregator settles contracts with the BRP, the DSO and flexible assets according to flexibility contracts.
- The aggregator sends delivery notes and bills to the BRP and the DSO with the effective flexibility activated.

4.3.5 LFM Algorithm

The flexibility plan is the LFM optimization problem of scheduling flexible resources. The aggregator executes this process sequentially during the operation day in order to adjust the baseline with new foresight and requirements as explained in Section 4.3.4. Time resolution could be 5, 15 or 30 min, depending on the case. The optimization problem could include temporal constraints from batteries, EVs and space heaters such as the battery state of charge or building thermal inertia. Therefore, the planning horizon could be the entire operation day or even two days in advance. However, multiple LFM operation algorithms can be designed depending on flexibility services and requests. In this algorithm, end-users settle a price in their flexibility contract for activating demand response. This work does not focus on all possible LFM optimization approaches as it does not affect the general LFM design.

The LFM algorithm is an optimization problem that minimizes cost involved in scheduling flexibility devices to meet required flexibility. It can be

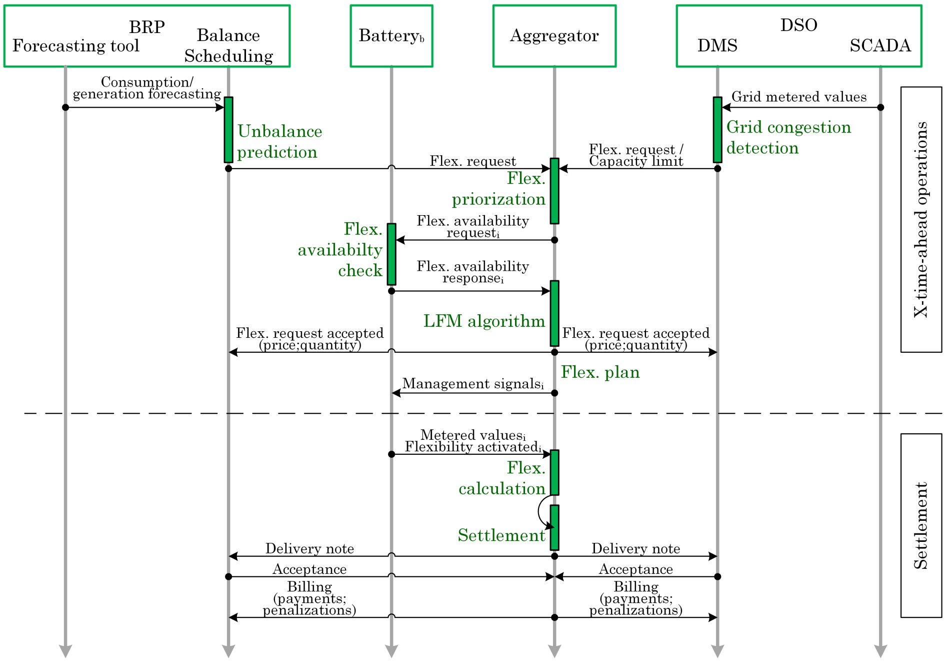


Fig. 4.5: LFM, Local Flexibility Market timeline example.

formulated in two different approaches. The first approach could formulate the objective function as a maximization welfare function, and the flexibility auction could be a single-side auction between flexibility providers and the aggregator requesting flexibility. Fig. 4.6 shows an example of a flexibility auction for a single period. In this example case, the DSO requested a consumption curtailment and presented a bid accordingly. Moreover, different offers from flexible assets for up-regulation are sent and included in the auction.

The corresponding offer curve is generated according to their activation fees if they are reserved during this period, and also considering their available estimated power curtailment capacity. The offer curve is sorted in ascending order to prioritize the least expensive offer instead of the most expensive one. The flexibility offer curve is composed of different EV disconnection offers from different EVs at the same price. Later on, a group of Electric Water Heaters (EWH) is included as up-regulation sources. They are aggregated at two price levels according to their flexibility contracts. Finally, a group of batteries offers their up-regulation capability at the highest price. In this case, all EV, all EWH and some batteries are used to fulfil the

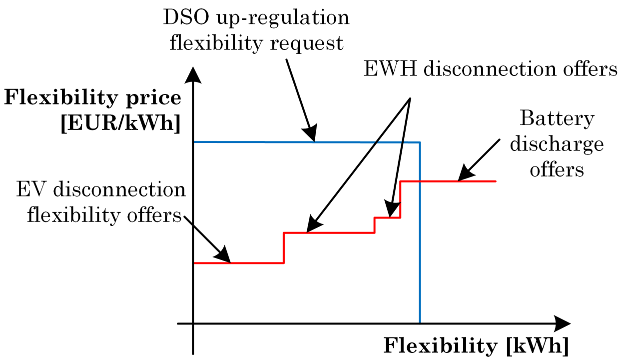


Fig. 4.6: Local flexibility market auction example.

DSO request.

The auction approach is transparent in order to clearly show which flexible devices are the least expensive for every period. However, it could present difficulties in being implemented. For instance, the offer formulation from every flexibility contract of EVs and batteries could be too complex to generate automatically because their flexibility capacity is linked to their state-of-charge.

In contrast with the auction formulation, the problem can be formulated as a multi-period minimization cost objective function for an aggregator allocating the least expensive flexibility offers. This approach facilitates the inclusion battery and EV time-based constraints, and the information from flexibility contracts can be easily included in the objective function. For instance, [176] formulates an LFM algorithm for meeting DSO requests at minimum aggregator cost as a multi-period optimization problem, and it was implemented in the EMPOWER H2020 project [166].

Fig. 4.7 shows the algorithm high-level flow diagram, the general inputs and outputs together with the potential required functionalities. The first step is to forecast the energy consumed and produced in the aggregator portfolio. This is done using historic consumption and weather data, among others. This forecast must distinguish between flexible and inflexible resources. Additionally, it is necessary to estimate the status of flexible assets considering their physical and contractual constraints. All this information is introduced in the optimization problem, and it returns the flexibility plan explained before. This process can be repeated every time there is a new event in the forecasting system or an external agent creates a new flexibility request.

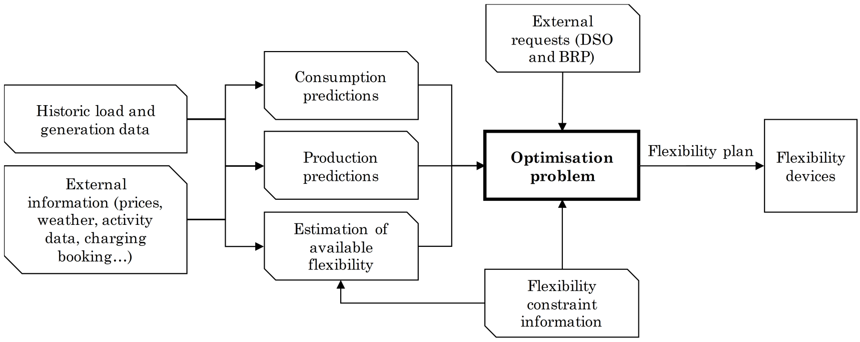


Fig. 4.7: Local flexibility market algorithm.

4.4 Simulation Test Case

The following simulation test case aims to show the application of the LFM under different situations. In this case, the aggregator provides flexibility services to the DSO for congestion management and to the BRP for self-balancing portfolio optimization. The case study and all input parameters to the optimization problem are the same as in [176]. Fig. 4.8 shows the flexibility requests applied to the same case study and they constitute three comparative scenarios:

- Scenario 1: The DSO and BRP request flexibility in different periods; the DSO requests down-regulation during midday; and BRP requests down- and up-regulation during the night.

- Scenario 2: The DSO and BRP request flexibility in the same periods and in the same direction. During midday and midnight, both need down- and up-regulation, respectively.

- Scenario 3: The DSO and BRP request flexibility in the same periods but in opposite directions. The DSO and BRP request down- and up-regulation, respectively.

Applying the optimization problem presented in [176] in the same case study to the previous flexibility requests, Fig. 4.9 shows how the loads, batteries and generators contribute to fulfil the requirement. Disconnectable loads contribute to up-regulation during the evenings; generators can be disconnected during mid-day to provide down-regulation; and batteries and shiftable loads can contribute in both directions.

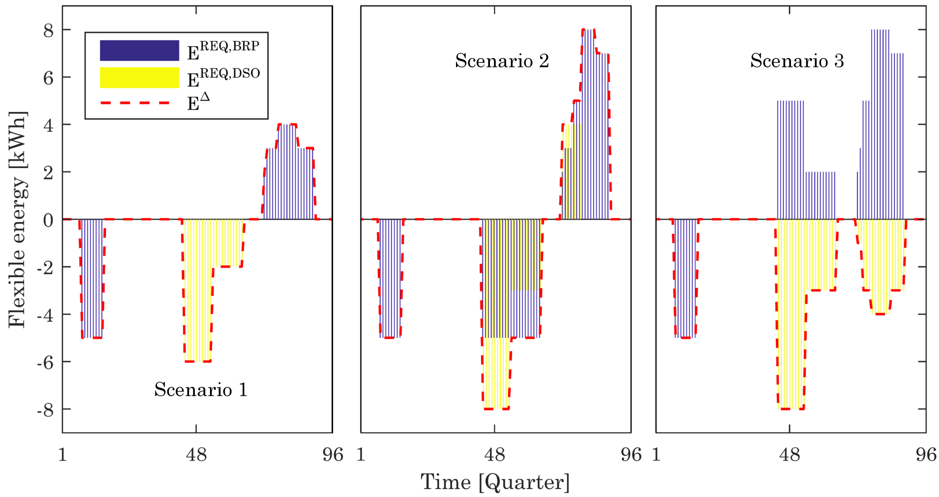


Fig. 4.8: The DSO and BRP flexibility requests in the three scenarios.

All scenarios could be profitable for the aggregator depending on the flexibility contracts and the DSO and BRP flexibility fees. The analysis of the aggregator profitability is out of the scope and could depend on the case study.

4.5 Discussion

In the context of massive distributed energy sources' installation, especially photovoltaic panels on rooftops, electric vehicles and distributed batteries, coordination mechanisms are needed. Additionally, variable renewable energy production requests flexibility mechanisms to secure operation of the power system.

The local flexibility market proposed in this work has important implications for energy policy and regulation. First of all, aggregators should have new consumption and generation data every quarter-hour or hour to favour local flexibility markets deployment. Another policy implication is about the conflict resolution between DSOs and aggregators when the flexibility requested by the DSO is not enough to prevent a grid outage. This could be due to a flexibility deficit requested by the DSO or a lack of flexibility provided by the aggregator. In order to resolve their dispute, the regulatory energy agency should be capable of auditing flexibility requests and activa-

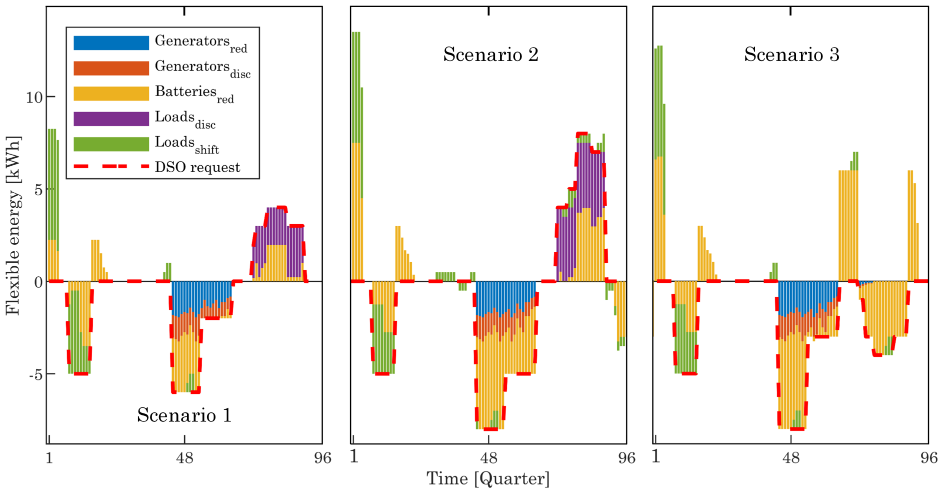


Fig. 4.9: Test case results from the three scenarios.

tions to clarify who was responsible for the damage. Therefore, standard communication protocols are needed to supervise DSO-aggregator interactions. Thus, flexibility penalties included in DSO-aggregator contracts could be easily settled. Additionally, this implies a common understanding about the way to measure flexibility activations, which is not standardized nowadays.

Moreover, future local flexibility market implementations could attract multiple aggregators competing to provide flexibility to the same DSO. The DSO would then get an additional role as a market provider enabling competition for flexibility in a similar manner to current tertiary reserve markets. This new DSO role should be analysed carefully and included in the DSO regulated activities jointly with the grid operator role. Otherwise, another entity could take the local market operator role. This discussion is out of the scope of this doctoral thesis and left for future researchers of local markets.

Finally, TSOs could be flexibility buyers, as well, including demand response from aggregators as an asset for ancillary services. In that situation, the aggregator could become an agent that offers flexibility to the TSO. In the case of activation, the aggregator should use the LFM as a market-based mechanism to allocate flexibility devices and meet the TSO request. However, this chapter is focused in the distribution network domain.

4.6 Conclusions

The present work proposes a market-based framework to manage multiple flexibility services. This framework is the LFM, and it is a platform-based mechanism to clearly distinguish priorities in smart grid-dominated scenarios with an aggregating central entity. This framework is an implementation case of the USEF standard including prosumer services. The novelty of this LFM remains in the individual-collective flexibility usage and the provision of multiple services to prosumers, DSOs and BRPs simultaneously.

This framework has been introduced by the EMPOWER H2020 project [166], and the DSO services have been partially and successfully tested. This project was mainly focused on the technical viability demonstration in the local market. INVADE H2020 [167] aim is to implement BRP and prosumer services in real test-pilots, to improve DSO services and estimate stakeholders' economic viability for flexibility.

This chapter elaborates on the principles of LFMs for multiple flexibility buyers. It is focused on defining services, contracts, market timelines and operation algorithms. The proposed trading platform is generally designed to be scalable, adaptable and customizable in order to suit the diverse conditions and regulations.

The chapter delves into the intricacies of operating a local flexibility market in conjunction with wholesale markets and stipulates the rules for planning and operating the LFM. In particular, the interactions between DSO-BRP-aggregator-LEC-prosumer have been outlined and described. The trading model applies to multiple facets of flexibility-related trade, and this chapter has studied most of the associated technical aspects including optimization issues required for the aggregator operations and a simulation of a case study.

To conclude this chapter, multiple questions remain open such as the minimum viable LFM size. The LFM needs enough liquidity to ensure a certain competition level to attract new LEC members. Another question is the local market economic profitability for all involved stakeholders. Both questions could depend on each case. Nevertheless, future studies should analyse reference scenarios and regulatory regimes to demonstrate local market viability.

Chapter 5

Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources

5.1 Introduction

Focusing on distribution grid operational challenges from DERs integration, the evolution driven by smart grids is shaping a scenario with new energy exchanges. In this context, new actor and roles are materialising within the power system leading to new operational procedures. A representative example is the appearance of the prosumer concept, which combines the consumer, storage and local level generator capabilities. These capabilities enable electricity and economic transactions in the so-called local electricity markets [169], also known as micro-markets in some studies [129, 177] or local flexibility markets as the previous thesis chapter 4. In the near future, an energy exchange scenario can be envisioned with several geographically allocated local markets. Such markets managing flexible resources can address high penetration of DER at distribution grids [177].

Recently published literature provides a wide variety of definitions of the flexibility in power systems [178, 179]. In this paper, the following definition is adopted: Flexibility expresses the extent to which a power system can modify its electricity production and consumption in response to variability, expected or otherwise [180]. Additionally, upward regulation is defined as increasing generation or decreasing demand, and downward regulation means decreasing generation or increasing demand. Moreover, [181] classified flexibility effects on power systems chronologically as short-term, mid-term and long-term categories. The present work is focused on the short-term flexibility in the range of hours or minutes ahead.

According to the Smart Energy Collective alliance definition [6], the role of aggregator consists of accumulating flexibility in active demand and supply. The aggregator seeks the lowest costs to meet the energy demand of his portfolio taking the costs for capacity usage into account. In this context, aggregation activities are considered within the scope of the smart energy service provider (SESP). SESP can also offer other services in the field of insurances, energy efficiency audits or similar. In the present chapter, SESP and aggregator are considered synonyms. Additionally, [182, 183] defined four flexibility customers: DSO, BRP, TSO, and prosumers. DSO and TSO are interested to purchase flexibility to manage grid congestions and reduce upgrading grid costs. BRP and retailers can use flexible resources to manage their portfolio and reduce deviation penalties and operation costs. Finally, prosumers can use their flexibility capabilities to reduce the electricity bill.

This chapter is focused on flexibility in distribution grids with high penetration of VRE production and other distributed resources such as storage systems. Additionally, their variability can pose issues in grid operation due to voltage fluctuations, limiting the grid hosting capacity to integrate DG [184, 185]. Redundant transformers can avoid operating the grid close to its voltage limits, but the required expenses are considerable leading to the necessity of finding alternative solutions like storage [186] and demand response [34]. Furthermore, if some loads, DG and batteries connected to distribution networks could operate according to grid necessities, DSO would manage networks avoiding these power quality issues. Hence, a LFM for distribution grid operation could provide the required trading environment avoiding additional investments.

The contents of this chapter are structured as follows. Section 5.2 includes the literature review about distribution grids with high penetration of DER. Section 5.3 describes the system under analysis and its architecture to identify the main actors and their interactions with the SESP. The optimization problem defined in this work, detailed in section 5.4, is executed by the SESP to determine the system operation scheduling. The case study exposed in section 5.5 shows the simulation results which are validated in a scaled experimental platform in Section 5.6. Finally, chapter conclusions are drawn in Section 5.7.

5.2 Literature review

Following the recent contributions on the distribution network operation with high penetration DER, this section compares different solutions proposed in the literature. In order to compare different methodologies, [159] classifies distribution-level energy management approaches in four categories: Top-down switching, centralised optimization, price-reactive and transactive energy systems. The present analysis is focused in two categories: local markets with a centralised approach and transactive energy systems. Classical demand response programs using a top-down switching methodologies and price reaction approaches are not included in the comparison because they use one-way communication systems considering end-user as a passive actor.

5.2.1 Centralized local flexibility market approaches

Previous proposals presented approaches like virtual power plant (VPP) that aims to emulate the behaviour of conventional generators aggregating DER [187, 188]. First of all, [187] reviewes the aggregation approaches of DER comparing VPP with incentive-based indirect control systems. [188] distinguishes between commercial and technical VPP. Commercial VPP facilitates DER trading on wholesale markets and technical VPP provides services to support transmission system operation. Different authors proposed scheduling algorithms for VPP [189–193] Nevertheless, VPP are not end-user focused and they do not provide the framework for participants willing to be active traders with certain negotiation power. Alternative proposals like local markets and transactive energy systems are following the EU recommendation to put consumers at the heart of the energy markets by ensuring that they are empowered and better protected [4].

Comparing similar local market-based proposals to the present work, [194] exposes an optimization problem formulation to reduce the energy cost in energy community scheduling distributed energy resources (DER). [195] presented an optimization problem for BRP day-ahead portfolio management to compensate load and supply forecasting deviations. Finally, [155] operated an LFM to bid in wholesale markets. These three proposals are addressed at providing flexibility services to the BRP for portfolio management without receiving DSO requests. Finally, [196] presents a case study for using flexibility to reduce the electricity bill from the prosumer perspective.

Previous works about constrained distributed grid operation like [197, 198]. They compare different frameworks for managing flexible resources to reduce network peaks but the corresponding operation formulation is not included. [199] analyses the impact of flexibility on distribution grids without specifying the operation optimization problem. [200, 201] present a similar problem using demand response but they assumed that activation decisions of each device are made by the DSO. Based on the queries to different

European DSO in EMPOWER project, DSO are currently not interested in taking such decisions and they are more inclined towards simpler approaches without many interactions as in [202] and the previous thesis Chapter 4.

In contrast and from the DSO point of view, [161] proposes a fix rate local flexibility market for managing flexible demands as a long-term planning tool for DSO. This aims to solve the expansion problem allocating flexibility needs and including grid expansion costs to alleviate grid constraints.

Moreover, [203] presents an optimal power flow algorithm to manage grid congestions using flexible resources. A similar approach is presented in [204] who considered that the DSO publishes the transformer capacity. Moreover, their proposal included a multiple aggregators per transformer case assuming their availability to share information. However, not all consumers connected to the same distribution transformer have to be members of the same BRP and different BRP could not be interested to share information. Presumably, these two proposed algorithms are not applicable in the current European regulatory framework due to the current unbundling principle: there is a legal separation between network management and commercial activities [205]. Therefore, aggregator, SESP and BRP are not allowed to know the grid parameters either grid status. That makes the inclusion of grid congestion constraints in the optimization problem not feasible in Europe. Moreover, DSO are not allowed to schedule flexible resources affecting the BRP portfolio balance.

In contrast in this thesis, aggregator/SESP receives DSO requests without knowing grid status information to solve grid congestion problems in the daily basis. In order to attend its demands, aggregator controls flexible assets using the LFM explained in chapter 4.

5.2.2 Transactive energy approaches

Local markets are central platform-based systems which can be contrasted with similar approaches like transactive energy (TE) systems. The U.S. Department of Energy's Gridwise Architecture Council defined TE in [206] as a set of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter.

[207, 208] proposes a TE for managing constrained grids where DSO and retailers negotiate to settle the congestion price. [207] presents a initial stage of a multi-period network-constrained TE method to integrate EV in distribution networks. The proposal evolved and [208] requests a new agent called distribution-independent system operator to coordinate DSO and retailer's interest and operational conflicts but this new agent requires a new regulatory framework. Additionally, retailers need information about end-user grid bus connection and it could be not permitted in real implementations because it is considered confidential information by many DSO. Finally, the proposed methodology is very communication intensive because DSO and retailer iterate several times to find a feasible solution. In contrast, the present work proposes that the DSO is the first mover requesting flexibility and the SESP reacts based on this without any iterative process.

Other TE proposals are more user-focused and they rely on the assumption that every prosumer can trade its energy with a local intelligent controller or agent according to [159]. However, balance responsibilities of every TE trader are not considered. At least, all transactions should happen in the same BRP portfolio. Moreover in the TE approach, communications are based on prices and energy quantities in a two-way negotiation. Therefore, consuming and producing devices communicate their energy preferences in terms of price and energy volume. Additionally, [209] presents a methodology based on reverse auctions with multiple agents for local transactions and this framework is tested by simulation and in laboratory environment.

5.2.3 TE and LFM comparison

This subsection compares benefits and drawbacks of TE and local markets for meeting DSO requests. The local market is a central platform-based system and it fits partially in the centralised optimization category with direct control signals. Nevertheless, flexibility contracts signed by end-users for each flexible device in local markets give them a strong decision power on local issues like TE do. Flexibility contracts specify available periods, cost per device and specific characteristics like control type.

Moreover, the system-level reaction is known when a response is triggered in centralised market-based methods [159], which is requested by DSO to ensure the appropriate response to attend their demands. In order to comply with DSO requests, TE user-focused approach could be less attractive for DSO because there is no central entity responsible for meeting the DSO request, and multiple negotiations are needed.

The main drawback of centralised approaches for meeting DSO needs is the scalability limit due to the communication system requested. Nevertheless, constrained situations will occur exceptionally and the communication system will be used occasionally. Additionally, the DSO problem will be located to a specific area and the communications requirements will be proportional to that.

Furthermore, the centralised platform approach with a single LEC manager for negotiations with the DSO offers a simpler and more easy to implement congestion management system than TE. Moreover, aggregator as central entity can limit the maximum prices offered from flexibility sources to ensure stable flexibility prices. Finally, the platform-based does not need automatic trading agents as it is based on flexibility contracts.

5.3 Local flexibility market description and architecture

This section focuses on the local flexibility market description and architecture of the system under analysis. The main components, actors and their functions enabling the coordinated operation and control through the SESP are presented. In order to facilitate a clear definition of the relationships between all the involved agents, components and their interactions, the system architecture definition is based on the smart gird architecture model (SGAM) developed by the standardization agencies CEN, CENELEC and ETSI to provide a common reference framework to develop smart grids [210].

In contrast to the previous studied works, this chapter presents a novel and innovative development of a local flexibility market-based operational problem of SESP, aggregator or BRP to attend DSO requests scheduling FD at short-term time range for real and feasible implementation in EMPOWER H2020 cloud platform under the current European regulatory framework. This problem formulation assumes existence of flexibility contracts as inputs from end-users. The LFM operation problem formulated here is based on the market architecture and rules, and the new BRP agent called SESP defined in [169]. Other activities related to the BRP operations in wholesale markets are not covered in this chapter.

Furthermore and according to the TLC from the German Association of Energy and Water Industry (BDEW) [175] and its application in [211], the present problem formulation is designed for situations where the DSO determined a yellow light situation in a grid zone and it wants to go back to the green light status. Thereafter, the DSO asks the SESP to apply corrective actions in exchange for economic compensation previously established on their contract. During yellow light situations, the DSO needs have maximum priority to avoid over-voltages or transformer over-loads and prosumers or aggregator priorities are not considered.

The centralised approach is to increase the DSO confidence in the LFM ensuring that all participants will collaborate to recover the green light sta-

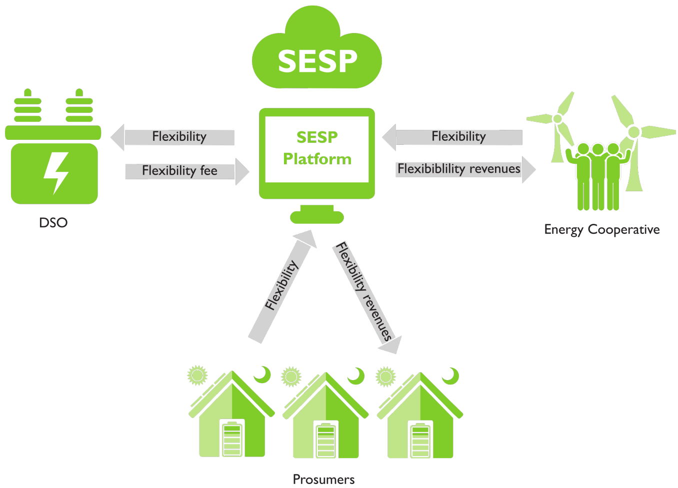


Fig. 5.1: Local flexibility market agents overview. Based on deliverable 2.2 of EMPOWER H2020 project [216]

tus. The SESP interacts with external agents like DSO and FD through its cloud-based trading platform, that has been designed and developed in the EMPOWER H2020 project [212–215]. The solution presented in this work for the grid constrained management problem is tested by simulation and validated in a laboratory environment.

5.3.1 Local flexibility market

Based on previous chapter 4, an LFM is an electricity trading platform to sell and buy flexibility in geographically limited areas like neighbourhoods and small towns. The SESP is the local market platform provider and community aggregator. At the same time, the SESP can be a BRP from the regulatory point of view because it could bid in wholesale markets. In order to run these markets, local traders need the SESP Platform for sending information, trading for flexibility, and scheduling actions.

Fig. 5.1 shows an LFM with four kind of agents:

- The DSO purchasing flexibility and giving the corresponding economic compensation.
- The SESP as market platform provider receiving flexibility offers and requests.
- Energy cooperatives and prosumers sending flexibility offers.

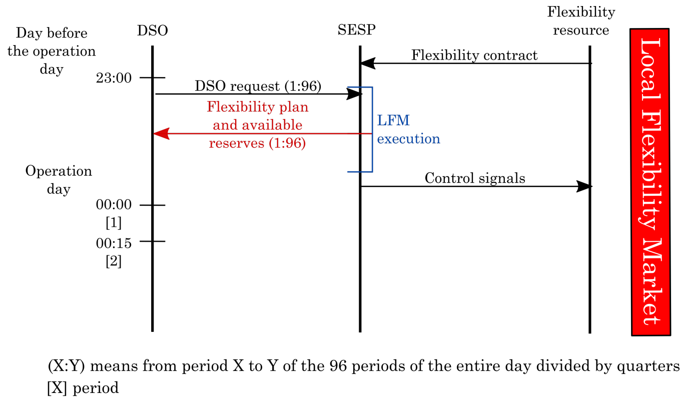


Fig. 5.2: Local flexibility market timeline. Based on deliverable 6.3 of EMPOWER H2020 project [202]

Energy cooperatives and prosumers offer their flexibility capabilities to the SESP platform competing for the corresponding revenues from DSO.

The flexibility market is executed in hours ahead time frames and its time schedule is shown in the Fig. 5.2. At the end of the day-before the operation, the DSO determines the flexibility need for the entire operation day. Based on the DSO request, the SESP can schedule flexible resources optimally considering the entire operation day. In the EMPOWER Project, the LFM is executed at 11 p.m. and the period unit is quarter hour.

In this market, the flexibility providers sign contracts with the SESP specifying which resources offer flexibility, the price of using the offered flexibility and different constraints such as the day time when the flexibility can be used among other information if needed. The flexibility contract price is settled by the flexibility provider and it cannot be higher than the maximum price defined by the SESP. Low price flexible assets will be activated more often than high price ones if they are available. Additionally, flexibility providers are responsible for the change in their flexibility prices to adjust their comfort and profitability balance.

In order to avoid market dominance and over-costs, the flexibility revenues are paid-as-contract. As flexibility contracts can be updated periodically, daily and weekly modifications could be found. Due to the lack of experience from prosumers creating bids, the LFM is organized in pay-as-contract, a similar way like the so called pay-as-bid. The pay-as-clear approach would increase the cost of flexibility for the DSO because all providers would receive the clearing price, and for all society at the end.

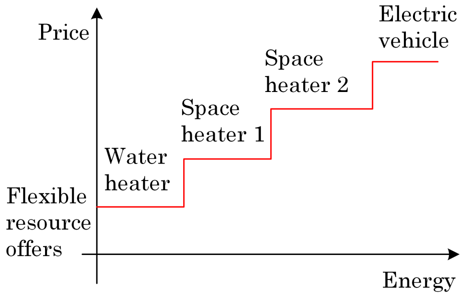


Fig. 5.3: Consumer's flexibility offers example

Flexibility contracts specify the activation cost per flexible load. Therefore, consumers can assign lower prices to less valued loads and they can be more flexible if the reward is higher. Fig. 5.3 exemplifies a consumer flexibility offer based on its contract with four FD sorted from the cheapest offer to the most expensive one, which are an electric water heater and an electric vehicle respectively.

Therefore, according to the DSO requirements to manage power quality issues, the SESP decides which resources are necessary to meet the request and sends the control signals to them. After that, the participants with activated resources are then rewarded based on their flexibility contract. Following the previous flexibility definition, the activated flexibility of each resource is measured with the following steps:

1. The consumption or generation forecast of every flexible asset is done by the SESP and it needs the approval of the DSO to be used as the baseline scenario.

2. Once the SESP sends a command to a flexible resource in order to modify its generation/consumption, the amount of the activated flexibility is counted as the absolute value of the difference between the predicted power consumption/generation and the measured power in the device metering point.

3. The activation of the flexibility ends when the SESP sends an *END* command permitting the resource to operate freely again.

Finally, it must be taken into account that the LFM presented in this work is limited to provide flexibility to DSO.

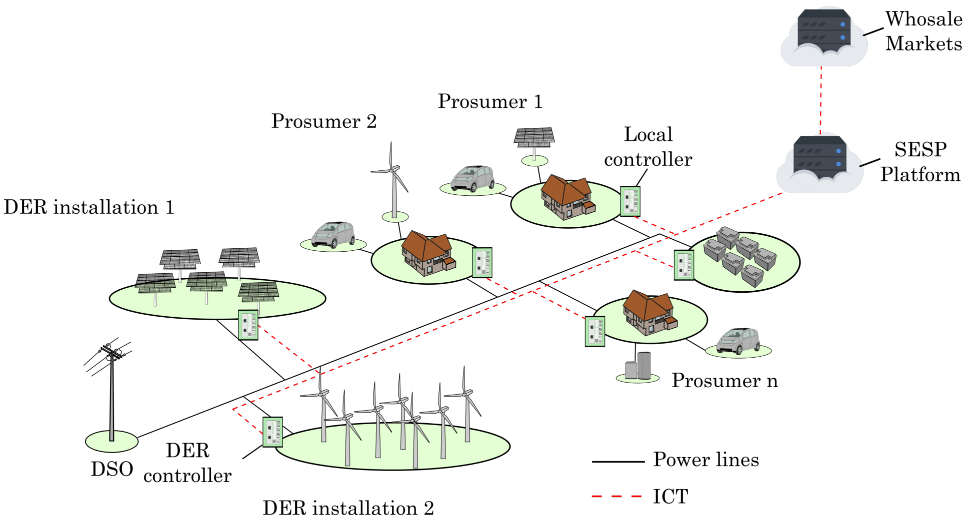


Fig. 5.4: System description

5.3.2 System under analysis

The electric system analysed covers LV and MV distribution grid and includes prosumers installations and DER facilities, as depicted in Fig. 5.4. The main actors involved are prosumers, DER's owners, the DSO and the SESP. Many prosumers can be grouped forming a community, which can be understood as another actor. Prosumers, DERs and LECs offering flexibility to the system and, in return, can be rewarded based on flexibility contracts and SESP decisions. In order to participate in the local market they have to install a local controller (LC) in every participant house in order to receive and apply the SESP control signals.

LC are small computers with communication capabilities for households to monitor and control production, flexible consumption and storage if they are available. Every LC communicates with the SESP Platform to report the energy resource status. For example, the water heater smart plug receives control signals from the LC and disconnects it.

5.3.3 LFM architecture

SGAM methodology [210] proposes a three-dimensional representation of smart grids, separating smart grid zones, domains and interoperability layers. Based on this conceptualisation, the local market interoperability com-

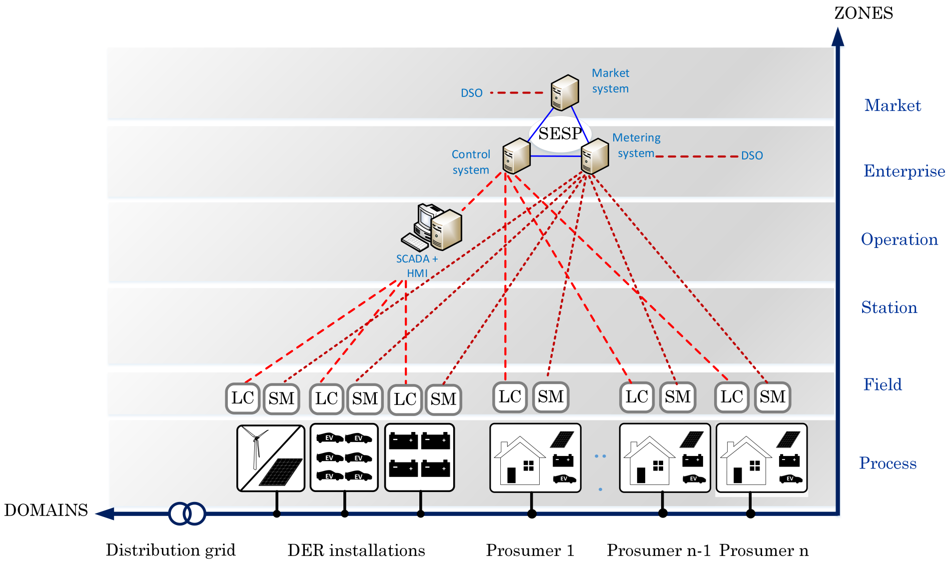


Fig. 5.5: System architecture based on SGAM

ponent layer is depicted in Fig. 5.5 to identify components of each zone and domain. The zones layer splits the smart grid into five activities: process, station, operation, enterprise and market activities. In contrast, domain layer distinguishes between distribution, DER and customer premises.

The domains affected cover from prosumers and DER installations up to the distribution grid. The zones identified as Market and Enterprise comprise three subsystems that make SESP operation possible. They are the market, control and metering systems. The market is responsible for the management of transactions needed to implement the LFM. It covers energy scheduling, flexibility, settlement, billing and accounting applications. The control subsystem is in charge of the management of the orders determined in the market. The metering subsystem manages the data resulting from smart meters and LC on the field zone. They allow to connect the SESP with the Process zone, where the electricity transactions take place. The SESP information exchanges with these field elements can be direct with prosumers. In contrast, communications with DER premises go through a supervisory control and data acquisition (SCADA) system in the operation zone. The communication, information and function interoperability layers reflecting specificities like the communication protocols used are explained in [212].

The utilization of local controllers on every storage, household and generation unit could compromise the system scalability. However, the recent developments of Big Data techniques will improve the LFM operation in large scale systems. Additionally, the utilization of direct control signals from the SESP platform could compromise the cyber-pysical security [217, 218] but the recent developments of cyber-security techniques will be included in further LFM developments [219]. Finally, the economic feasibility of the entire system depends on the potential benefits of the LFM operation. Alternative approaches are under consideration like sharing a LC per group of households but economies of scale would help to reduce LC costs. Furthermore, this is an open research question that will be answered in further works based on the pilot experience.

5.4 Local flexibility market problem formulation

The local flexibility market problem presented in this section is an extension of the one explained by Ottesen in [220] for operating building energy systems with flexible resources and minimizing the electricity cost. The novelty of the present approach is to include the functionality to activate flexibility under DSO requests operated in a local flexibility market framework with a SESP as BRP and local market operator simultaneously. Additionally, local market participants are active traders deciding on their flexibility price. Previous approaches mentioned assumed to have information about the current status of the grid but this is not possible in the near future. Therefore, the presented model is closer to the current regulatory framework. Additionally, the presented optimization problem will be implemented in the EMPOWER H2020 pilots. As in [220], in the current study it is assumed that local controllers receive direct control signals from the SESP and the problem is formulated as an mixed-integer linear programming (MILP).

The formulated problem assumes that a baseline is an agreed parameter between the SESP and the DSO. According to the New York Independent System Operator report [221], *"A baseline is the estimated amount of energy use expected by a facility if a load reduction had not occurred in response to the NYISO instruction or schedule "*. The same concept is applied for the present study, the baseline is the scenario in the absence of the SESP agent.

The optimization problem description is divided in different sub-sections: Objective function, flexibility sources models, and DSO request constraints. This approach includes the following flexibility sources: flexible generators, batteries and flexible loads.

5.4.1 Objective function

The objective function shown in Eq. (5.1) reflects the minimization of the SESP's operation cost of meeting a request from the DSO during the following periods. Each flexibility cost (P) comes from the SESP-community member contract and it is predefined before the operation phase. All sets, parameters and variables are explained as they appear and are listed in the Nomenclature.

The majority of cost parameters can be different every period t to consider cost fluctuations. In contrast, prices for flexible loads are constant during the operation day to facilitate the customer participation to the LFM. The time resolution t is a flexible parameter in the problem. In the EMPOWER system and the case study, it is defined as 15 minutes as this is the common resolution of current balancing markets.

The objective function can be decomposed in different flexibility costs:

- $P^{Gr}_{g,t} \cdot \chi^{Gr}_{g,t}$: cost of reducing generation output of the unit $g \in \mathcal{G}^r$ during period t
- $P^{Gd}_{g,t} \cdot \chi^{Gd}_{g,t}$: cost of disconnecting the generator $g \in \mathcal{G}^d$ during period t
- $P^{bat,ch}_{b,t} \cdot \sigma^{ch}_{b,t}$, $P^{bat,dis}_{b,t} \cdot \sigma^{dis}_{b,t}$: cost of charging or discharging the battery unit $b \in \mathcal{B}^{bat}$ during period t, respectively
- $P^{CD}_{k} \cdot (\delta^{start}_{k,t} + \delta^{run}_{k,t})$: cost of switching off the curtailable disconnectable load $k \in \mathcal{K}^{CD}$ during period t
- $P^{SP}_{k} \cdot (\rho^{SP}_{k,c} - V^{start}_{k,c})$: cost of shifting $\rho^{SP}_{k,c} - V^{start}_{k,c}$ periods the shiftable load $k \in \mathcal{K}^{SP}$ during shifting period c

Notice that the cost for using flexibility from curtailable and shiftable loads is not dependent of the energy activated. This approach avoids disputes after the operation day, to determine the economic compensation for the activated flexibility.

The variables included in the objective function are the flexibility to be activated of each resource at each period. They can be used to calculate the corresponding control signals after executing the LFM operation problem. For instance, the reducible photovoltaic generators must receive a setpoint signal based on the difference between the current production and the flexibility activated.

$$
\begin{aligned}
min f_{obj}^{LFM} = \sum_{t\in\mathcal{T}} \Bigg(\sum_{g\in\mathcal{G}^r} P_{g,t}^{Gr}\chi_{g,t}^{Gr} + \sum_{g\in\mathcal{G}^d} P_{g,t}^{Gd}\chi_{g,t}^{Gd} + \\
\sum_{b\in\mathcal{B}^{bat}} (P_{b,t}^{bat,ch}\sigma_{b,t}^{ch} + P_{b,t}^{bat,dis}\sigma_{b,t}^{dis}) + \sum_{k\in\mathcal{K}^{CD}} P_k^{CD}\cdot(\delta_{k,t}^{start} + \delta_{k,t}^{run})\Bigg) + \\
\sum_{k\in\mathcal{K}^{SP}} \sum_{c\in\mathcal{C}(k)} P_k^{SP}\cdot(\rho_{k,c}^{SP} - V_{k,c}^{start})
\end{aligned}
\tag{5.1}
$$

This objective function is subject to the following constraints:

5.4.2 Flexible generator model

Flexible generation installations with remote control capability can provide downward regulation during periods of energy surplus. There are two types of curtailable generators: reducible ($g \in G^r$) and disconnectable ($g \in G^d$). Reducible generators can receive control signals of energy production adjusting their power output during a specific period of time. In contrast, disconnectable generators are those that can only be switched on and off and they cannot receive setpoints.

The decision variables for reducible and disconnectable production are $\chi_{g,t}^{Gr}$ and $\chi_{g,t}^{Gd}$ respectively and they represent the amount of active energy curtailed.

Eq. (5.2) limits the energy flexibility supplied by generation g during period t up to its forecasted production $W_{g,t}^{G}$ and Eq. (5.2) relates activated flexibility and expected energy production ($\psi_{g,t}^{G}$). Additionally, the disconnectable generation constraint of Eq. (5.4) includes a binary variable ($\delta_{g,t}^{G}$) to define if the generator g is disconnected or not during period t. Eq. (5.5) relates curtailed production and expected production ($\psi_{g,t}^{G}$).

$$0 \leqslant \chi_{g,t}^{Gr} \leqslant W_{g,t}^{G} \qquad \forall g\in\mathcal{G}^r, \forall t\in\mathcal{T} \tag{5.2}$$

$$\chi_{g,t}^{Gr} = W_{g,t}^{G} - \psi_{g,t}^{G} \qquad \forall g\in\mathcal{G}^r, \forall t\in\mathcal{T} \tag{5.3}$$

$$0 \leqslant \chi_{g,t}^{Gd} = \delta_{g,t}^{G}\cdot W_{g,t}^{G} \qquad \forall g\in\mathcal{G}^d, \forall t\in\mathcal{T} \tag{5.4}$$

$$\chi_{g,t}^{Gd} = W_{g,t}^{G} - \psi_{g,t}^{G} \qquad \forall g\in\mathcal{G}^d, \forall t\in\mathcal{T} \tag{5.5}$$

Where $\chi_{g,t}^{Gr}$ and $\chi_{g,t}^{Gd}$ represent the flexibility activated and their setpoints are the difference between the forecasted production and the flexibility requested.

The cost of curtailing a generator is a fee established in the agreed flexibility contract. Particularly, it is defined as the price of reducing or disconnecting energy generation, period by period, and is represented by $P_{g,t}^{Gr}$ and $P_{g,t}^{Gd}$ respectively.

5.4.3 Battery model

Electricity storage units can provide up and down regulation discharging or charging energy respectively. This model divides the energy charging and discharging decision variables in $\sigma_{b,t}^{ch}$ and $\sigma_{b,t}^{dis}$ correspondingly. These variables define the energy setpoint of each battery unit b during each period t. SOC Eq. 5.6 considers the round-trip efficiency each time that battery unit b delivers ($A_b^{bat,dis}$) or stores electricity ($A_b^{bat,ch}$).

$$\sigma_{b,t}^{soc} = \sigma_{b,t-1}^{soc} + \sigma_{b,t}^{ch} A_b^{bat,ch} - \frac{\sigma_{b,t}^{dis}}{A_b^{bat,dis}} \qquad \forall b \in \mathcal{B}^{bat}, \forall t \in \mathcal{T} \tag{5.6}$$

Battery constraints 5.7 and 5.8 limit the maximum energy charged or discharged by batteries per period according to their specified in energy capacity (Q_b^{ch}, Q_b^{dis}). Moreover, Eq. (5.9) ensures that the maximum storage capacity (O_b^{max}) is not exceeded.

Finally, the initial battery state-of-charge must be introduced in the model (SOC_0).

$$\sigma_{b,t}^{ch} \leqslant Q_b^{ch} \delta_{b,t}^{bat} \qquad \forall b \in \mathcal{B}^{bat}, \forall t \in \mathcal{T} \tag{5.7}$$

$$\sigma_{b,t}^{dis} \leqslant Q_b^{dis} (1 - \delta_{b,t}^{bat}) \qquad \forall b \in \mathcal{B}^{bat}, \forall t \in \mathcal{T} \tag{5.8}$$

$$\sigma_{b,t}^{soc} \leqslant O_b^{max} \qquad \forall b \in \mathcal{B}^{bat}, \forall t \in \mathcal{T} \tag{5.9}$$

In this formulation, the day-ahead market price is used as a reference for optimizing the acquisition in the intraday market where the energy is meant to be finally bought. Additionally, batteries with dedicated smart meters are spread in the distribution grid to attend local grid constraints and they are owned by the SESP. Therefore, the cost for charging batteries ($P_{b,t}^{bat,ch}$) is the summation of the DA market price and the grid tariff cost.

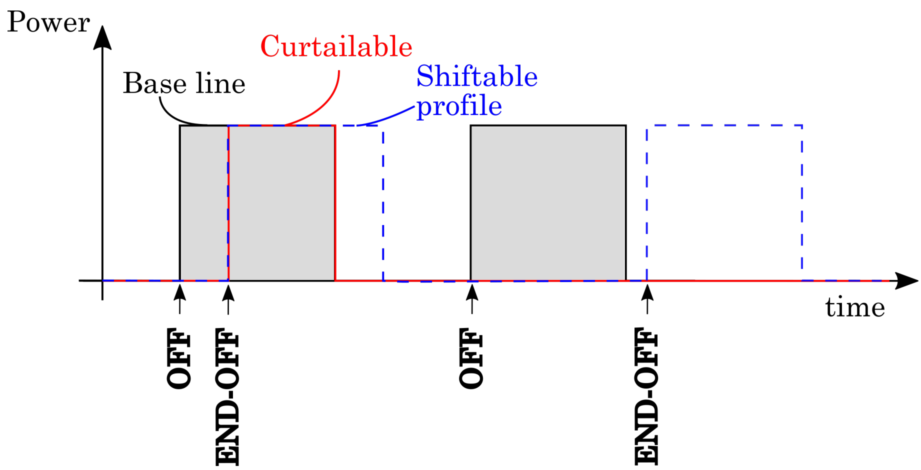


Fig. 5.6: Comparison of SP and CD flexible loads behaviour under the same command signals

Later on, the cost of discharging batteries ($P_{b,t}^{bat,dis}$) is set according to their the lifespan reduction value for the whole charging and discharging process and it is considered linear in order to simplify. In further developments, the ownership of batteries and the real degradation cost will be studied in depth.

5.4.4 Flexible loads model

Following the CENELEC classification [222], flexible loads can be divided in buffered and non-buffered loads. Buffered loads typically have thermal inertia and the consumption can be moved backward or forward. In contrast, non-buffered loads cannot store electricity increasing the consumption profile. The LFM operation problem presented in this chapter considers non-buffered flexible loads ($\mathcal{K}$) and they can be subdivided in two categories: curtailable disconnectable (CD), when the consumption is interrupted and non-recovered, and shiftable profile (SP), which can be postponed without changing the consumption profile.

Fig. 5.6 shows this distinction and compares the result of the same signals on both types. As soon as a disconnection order is received, both CD and SP loads disconnect. However, the difference occurs when the order ends. In this case, CD loads follow the baseline profile while SP loads applies the curtailed profiles. Additionally, if a SP load receives a switch on signal, it will consume the same amount of energy and power as the baseline. In contrast, the CD load consumes as the baseline.

Curtailable disconnectable load model

CD loads ($\mathcal{K}^{CD}$) are those flexible loads that do not consume the curtailed energy once they are reconnected. CD loads can be for example programmable space heaters with a scheduled consumption and for a short disconnection period. If the reconnection signal arrives out of the time program, the control signal will not switch the load on.

They are remotely controlled with binary signals *OFF* ($\delta_{k,t}^{start}$) and *END-OFF* ($\delta_{k,t}^{end}$). When an *OFF* order ($\delta_{k,t}^{start} = 1$) is sent to the curtailable load k, independently of the baseline status, the load is switched off. When the load receives an *END-OFF* order ($\delta_{k,t}^{end} = 1$), the load goes back to the baseline consumption profile. Additionally, the time between the OFF and END-OFF signals is calculated using the binary variable $\delta_{k,t}^{run}$.

Regarding the *END-OFF* control signal, all signals in this model are actions at the beginning of the period. Then, the *END-OFF* signal means to reconnect the load at the beginning of the period if the baseline forecasted to consume. For example, if the *OFF* signal is 1 during period $t = 2$ ($\delta_{k,2}^{start} = 1$) and the *END-OFF* signal is 1 during period $t = 8$ ($\delta_{k,8}^{end} = 1$), then $\delta_{k,t}^{run}$ is 1 between $t \in [3, 7]$. In order to ensure the appropriate curtailment decision, the model includes the following constraints.

Eqs. (5.10),(5.11) avoid simultaneous actions during the same period t of the load k; Eq. (5.10) prevents simultaneous curtailment and disconnection, and Eq. (5.11) ensures that load is not disconnected and reconnected.

$$\delta_{k,t}^{start} + \delta_{k,t}^{run} \leqslant 1 \qquad \forall k \in \mathcal{K}^{CD}, \forall t \in \mathcal{T} \tag{5.10}$$

$$\delta_{k,t}^{start} + \delta_{k,t}^{end} \leqslant 1 \qquad \forall k \in \mathcal{K}^{CD}, \forall t \in \mathcal{T} \tag{5.11}$$

Continuity constraint Eq. (5.12) ensures that once the load is disconnected ($\delta_{k,t-1}^{start} = 1$) or running up ($\delta_{k,t-1}^{run} = 1$), it can only remain disconnected ($\delta_{k,t}^{run} = 1$) or be reconnected ($\delta_{k,t}^{end} = 1$).

$$\delta_{k,t-1}^{start} + \delta_{k,t-1}^{run} = \delta_{k,t}^{run} + \delta_{k,t}^{end} \qquad \forall k \in \mathcal{K}^{CD}, \forall t \in \mathcal{T} \tag{5.12}$$

Flexibility contracts allow defining the maximum number of disconnection orders (N_k^{max}) per day that a flexible load can receive and constraint shown in Eq. (5.13) includes this functionality.

$$\sum_{t=1}^{\mathcal{T}} \delta_{k,t}^{start} \leqslant N_k^{max} \qquad \forall k \in \mathcal{K}^{CD} \tag{5.13}$$

Additionally, constraint 5.14 includes the capability to assure the minimum resting time (D_k^{min}) between load disconnections.

$$\delta_{k,t}^{end} + \sum_{i=t}^{t+D_k^{min}-1} \delta_{k,i}^{start} \leqslant 1 \qquad \forall k \in \mathcal{K}^{CD}, \forall t \in \mathcal{T} \tag{5.14}$$

Finally, flexibility contracts can include the possibility to define the maximum disconnection duration (D_k^{max}). The corresponding constraint is shown in Eq. 5.15.

$$\sum_{i=t}^{t+D_k^{max}} \delta_{k,i}^{end} \geqslant \delta_{k,t}^{start} \qquad \forall k \in \mathcal{K}^{CD}, \forall t \in \mathcal{T} \tag{5.15}$$

The cost of disconnecting load k is the number of periods disconnected times its disconnection fee (P_k^{CD}).

Shiftable profile load model

SP loads ($\mathcal{K}^{SP}$) are those that postpone the consumption keeping the same profile. Additionally, they consume as soon as possible. Therefore, the routine must start sending the *END* signal if the load has to be shifted forward. It is assumed that it is not possible to split the energy profile. Those loads can be for example dish washers, washing machines, dryers, electric water heaters, heat pumps, and electric vehicle chargers because the profile will be exactly the same whenever they receive an *END-OFF* signal.

Due to the need to schedule flexible resources the day before, it is assumed that there is no information available apart from the contracts and data from previous experiences. Then, this model relies on the SESP forecasting system capable to foresight the consumption by requesting a minimum information from the end-user. Decisions on real time operations are left for further developments.

SP model consists in defining a framework to operate shiftable loads. Therefore, it is used to decide the new energy profile for each appliance k within its shiftable periods allowed by the user. Different shiftable periods for the same appliance are indexed with c and they allow only one shift. SP model is used to define when to activate upward and downward regulation by sending the *END-OFF* signal ($\rho_{k,c}^{SP}$). SESP determines the new load consumption profile ($\omega_{k,t}^{SP}$) of each period t accordingly.

Flexibility contract defines the shiftable period c for each appliance k with the parameters $T_{k,c}^{start}$ and $T_{k,c}^{end}$ which determine the time span in which is possible to schedule consumption. Within this shiftable period c, the

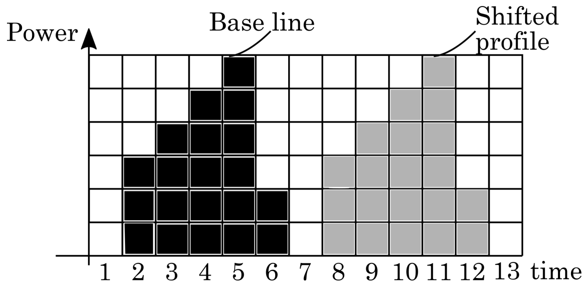


Fig. 5.7: Illustration of a shiftable profile load

forecasted consumption is denoted with $V_{k,c}^{start}$ and $V_{k,c}^{end}$ representing the beginning and ending of the energy profile in the base case.

Additionally, $\gamma_{k,t}^{SP}$ is the binary variable which indicates the *END-OFF* signal. For example, $\gamma_{k,t^*}^{SP} = 1$ if $\rho_{k,c}^{SP} = t^*$ being t^* the period to send the *END-OFF* signal. Fig. 5.7 shows an example case with shiftable period $T_{k,c}^{start} = 2$ and $T_{k,c}^{end} = 13$, and with base profile ($W_{k,t}^{SP}$) in black which begins at $V_{k,c}^{start} = 2$ and ends at $V_{k,c}^{end} = 7$. The corresponding decision variables for shiftable load k during shifting period c are $\gamma_{k,t}^{SP} = 1$ for $t = 8$, $\rho_{k,c}^{SP} = 8$ and the corresponding $\omega_{k,t}^{SP}$ is the shifted profile in grey.

This model is limited to shift forward the entire profile because it is assumed that these loads consume as soon as they can. Therefore, the base case is already the earliest period when they can consume. Eq. (5.16) ensures that the shiftable load is scheduled within the shiftable period ($T_{k,c}^{start}, T_{k,c}^{end}$), even if the load is not postponed ($\rho_{k,c}^{SP} = V_{k,c}^{start}$).

$$\sum_{d=T_{k,c}^{start}}^{T_{k,c}^{end}-(V_{k,c}^{end}-V_{k,c}^{start})} \gamma_{k,d}^{SP} = 1 \qquad \forall k \in \mathcal{K}^{SP}, \forall c \in \mathcal{C}(k) \tag{5.16}$$

Eq. (5.17) ensures that the new load profile ($\omega_{k,t}^{SP}$) consumes the same power as the baseline load ($W_{k,t}^{SP}$).

$$\omega_{k,t}^{SP} = \sum_{n=0}^{T_{k,c}^{end}-T_{k,c}^{start}} \gamma_{k,t-n}^{SP} \cdot W_{k,(T_{k,c}^{start}+n)}^{SP}$$
$$\forall t \in [T_{k,c}^{start}, T_{k,c}^{end}], \forall k \in \mathcal{K}^{SP}, \forall c \in \mathcal{C}(k) \tag{5.17}$$

Once the new profile is established, Eq. (5.18) defines the starting period ($\rho_{k,c}^{SP}$) to calculate the corresponding flexibility cost of load k in shifting period c in the objective function. The cost for shifting the load k is defined by the consumption delay $(\rho^{SP}_{k,c} - V^{start}_{k,c})$ times the cost per time unit (P^{SP}_{k}) settled in its flexibility contract.

$$\rho^{SP}_{k,c} = \sum_{t=T^{start}_{k,c}}^{T^{end}_{k,c}-(V^{end}_{k,c}-V^{start}_{k,c})} \gamma^{SP}_{k,t} \cdot t \qquad \forall k \in \mathcal{K}^{SP}, \forall c \in \mathcal{C}(k) \tag{5.18}$$

5.4.5 DSO request constraints

Finally, DSO constraints represent the request for fulfilling upward and downward regulation. These constraints are defined as the minimum required amount of active energy variation with respect to the forecasted baseline scenario and are denoted as FR_t. Positives and negative values of FR_t mean upward and downward regulation respectively.

Eqs. (5.19) and (5.20) are constraints that ensure that flexible resources comply with the DSO upward and downward regulation request respectively. All flexibility resources are included in both equations because they can be in favour or against the request.

During up-regulation periods ($t \in \mathcal{T}^{+}$) defined as positive DSO flexibility requests ($FR_t > 0$), controllable resources are batteries delivering active energy ($\sigma^{dis}_{b,t}$), disconnectable loads ($W^{CD}_{k,t} \cdot (\delta^{start}_{k,t} + \delta^{run}_{k,t})$), and shiftable loads ($W^{SP}_{k,t} - \omega^{SP}_{k,t}$). Additionally, down-regulation resources like reducible and disconnectable generators ($\chi^{Gr}_{g,t}, \chi^{Gd}_{g,t}$) and batteries storing energy ($\sigma^{ch}_{b,t}$) are included in the up-regulation constraint to include the possibility of discharging batteries for further needs or disconnecting generators for other reasons.

$$\begin{aligned} &\sum_{b\in\mathcal{B}^{bat}} \sigma^{dis}_{b,t} - \sum_{b\in\mathcal{B}^{bat}} \sigma^{ch}_{b,t} + \sum_{k\in\mathcal{K}^{CD}} W^{CD}_{k,t}(\delta^{start}_{k,t} + \delta^{run}_{k,t}) + \\ &\quad \sum_{k\in\mathcal{K}^{SP}} (W^{SP}_{k,t} - \omega^{SP}_{k,t}) - \sum_{g\in\mathcal{G}^{r}} \chi^{Gr}_{g,t} - \sum_{g\in\mathcal{G}^{d}} \chi^{Gd}_{g,t} \geqslant FR_t \quad \forall t \in \mathcal{T}^{+} \end{aligned} \tag{5.19}$$

For each downward regulation period ($t \in \mathcal{T}^{-}$), defined as negative request ($FR_t < 0$), the upward and downward flexibility resources have negative and positive sign respectively in Eq. (5.20).

$$\sum_{g \in \mathcal{G}^r} \chi_{g,t}^{Gr} + \sum_{g \in \mathcal{G}^d} \chi_{g,t}^{Gd} + \sum_{b \in \mathcal{B}^{bat}} \sigma_{b,t}^{ch} + \sum_{k \in \mathcal{K}^{SP}} (\omega_{k,t}^{SP} - W_{k,t}^{SP}) - \\ \sum_{b \in \mathcal{B}^{bat}} \sigma_{b,t}^{dis} - \sum_{k \in \mathcal{K}^{CD}} W_{k,t}^{CD} (\delta_{k,t}^{start} + \delta_{k,t}^{run}) \geqslant -FR_t \quad \forall t \in \mathcal{T}^- \quad (5.20)$$

Notice that reconnection of SP loads in Eq. (5.20) has the opposite sign than in Eq. (5.19) because the new SP consumption was not included in the baseline previously. Therefore, the SP load is considered as downward source when it is shifted to down regulation periods. In contrast, CD loads are not supplying downward regulation because they cannot consume out of the baseline.

5.5 Case study

In order to test the proposed problem, this section introduces a case study that includes all implemented functionalities in the problem formulation. Additionally, this section exposes the results obtained during the simulation process in order to define the control signals.

The optimization problem is validated using the high-level Julia programming language and JuMP. JuMP is an open source algebraic modelling language for linear, quadratic, and non-linear constrained optimization problems embedded in Julia [223, 224]. The solver used was the Coin-Branch & Cut (CBC) in a computer with i7-6600 CPU 2.60 GHz and 16.0 GB RAM memory, and the problem took 8.084 seconds to find the case study optimal solution considering 0.2% of maximum error.

5.5.1 Scenario description

The case study illustrates with figures a small scale LFM composed by four households with DER listed with their characteristics in Table 5.1. Loads are typically space and water heaters that can be disconnected within the flexibility contract constraints. Local generators are photovoltaic (PV) panels installed in the rooftops of households. Two of them can be remotely controlled setting their setpoints and others only can be remotely disconnected. Batteries can be fully controlled remotely.

Load and generation profiles are from winter and summer data respectively to show up all capacities of the formulated problem during a single day. That contains different consumption and generation behaviour. The

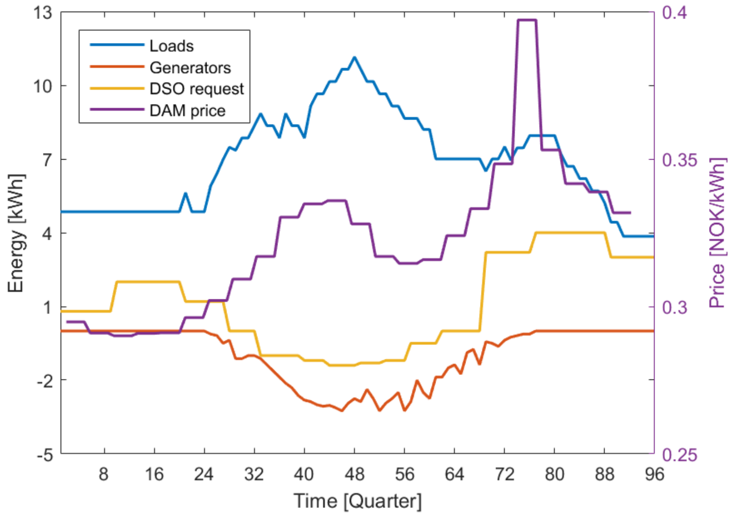


Fig. 5.8: Energy charging prices during the case study day

case is a weekday and resources for weekend are not available during this time horizon.

In this case study, flexibility prices for each load are constant during the operation day and sorted in ascending order for the sake of clarity. According to the Section 5.4.1, the cost for activating flexible loads is not dependent of the activated energy and it is quantified in NOK/period. In contrast to flexible loads, flexible generators are quantified per energy activated as NOK/kWh because the flexibility activated is time dependent and related, for example, to solar radiation. Additionally, flexibility prices for generators are also constant during the day and higher than load prices.

Battery charging prices are from the DA market. In the case study, the prices are from the Elspot market from NordPool of 30/10/2016 in the Oslo area NO1, and it is the same price for all batteries which varies from [290.05, 397.11] NOK/MWh and they are represented in Fig. 5.8. During 2016, the average exchange rate for EUR and NOK has been 9.2906 NOK/EUR according to the European Central Bank [225] In contrast, prices for discharging are constant because they only include the degradation of battery according to end-user criteria and they are included in the Table 5.1.

Additionally, Fig. 5.8 shows the aggregated flexible loads forecasted profile $(W_{k,t}^{CD} + W_{k,t}^{SP})$ with a maximum demand of 11.15 kWh during period 48. Generation forecasting $(W_{g,t}^{Gr} + W_{g,t}^{Gd})$ of all units has a peak during period 52

Table 5.1: Case study flexible resources portfolio and characteristics

House	Resource	ID	Power [W]	Flexibility periods	Control type	Price
1	Load-CD	1	2000	All day	on/off	0.1
1	Load-CD	2	2200	6:00-18:00	on/off	0.3
1	Load-CD	3	3200	10:00-15:00	on/off	0.5
1	Load-CD	4	1000	08:00-20:00	on/off	0.7
1	Load-CD	5	1500	Weekend	on/off	0.9
1	Load-CD	6	3100	05:00-22:00	on/off	1.1
1	Load-CD	7	2300	Weekend	on/off	1.3
1	Load-SP	1	2000	Weekend	shiftable	0.5
1	Load-SP	2	2000	Weekend	shiftable	0.7
1	Load-SP	3	2000	Weekend	shiftable	0.9
1	PV	1	3100	All day	reducible	1.5
1	PV	2	3100	All day	reducible	1.7
2	Load-CD	8	3000	All day	on/off	2.1
2	Load-CD	9	2100	00:00-07:00	on/off	2.3
2	Load-CD	10	1200	All day	on/off	2.5
2	Load-CD	11	1800	All day	on/off	2.7
2	PV	1	3100	All day	disconnectable	2.9
3	Load-CD	12	3000	All day	on/off	3.1
3	Load-CD	13	1200	All day	on/off	3.3
3	Load-CD	14	2000	09:00-17:00	on/off	3.5
3	Load-CD	15	2000	09:00-17:00	on/off	3.7
3	Load-CD	16	1600	07:00-15:00	on/off	3.9
3	Load-CD	17	2500	Weekend	on/off	4.1
3	Load-CD	18	3700	Weekend	on/off	4.3
3	Load-SP	4	2000	All day	shiftable	1.1
3	Load-SP	5	2000	All day	shiftable	1.3
3	PV	2	3100	All day	disconnectable	4.5
4	Load-CD	19	2000	All day	on/off	4.9
4	Load-CD	20	1200	08:00-00:00	on/off	5.1
4	Load-CD	21	1800	08:00-14:30	on/off	5.3
4	Load-CD	22	3100	All day	on/off	5.5
4	Load-CD	23	2300	06:30-22:30	on/off	5.7
4	PV	3	3100	All day	disconnectable	5.9
SESP	Battery	1	3000	All day	full	1.9
SESP	Battery	2	3000	All day	full	4.7

of 3.25 kWh. The FR_t is the DSO request for the operation day. In the case study, the available flexibility is larger than the DSO need for all periods. Therefore, SESP has to execute the LFM to allocate the cheapest flexible resources considering the problem constraints. If the SESP has not enough resources, it cannot attend the DSO request completely.

The time periods used in this case study are quarter hour and the time horizon is one day. The SESP algorithm is executed once per day before the operation day begins. Previously, the DSO has sent its flexibility needs. Furthermore, this case study has a deterministic approach to clearly explain the operation procedure. In further developments, it can manage parameters with uncertainty such as $W_{g,t}^{Gr}, W_{g,t}^{Gr}, W_{k,t}^{CD}, W_{k,t}^{SP}, V_{k,c}^{start}, V_{k,c}^{end}$.

This SESP algorithm does not apply corrective actions based on field data but the local flexibility market design presented in [226] includes such capability.

Fig. 5.9 shows the total flexibility request by the DSO (FR_t) and which flexible resource is providing up or down regulation.

Flexibility is quantified in energy (kWh) and it is based on the forecasted values. During the up-regulation periods, the DSO request is compensated by disconnecting loads and discharging batteries and shifting loads. In contrast, the down-regulation request is compensated reconnecting shiftable loads, charging batteries, and disconnecting or reducing photovoltaic generators. Additionally, between up- and down-regulation periods regulations are not needed. Nevertheless, the shiftable loads are disconnected in order to be connected during the down-regulation period.

Fig. 5.10 shows the state-of-charge (SOC) evolving from a 50% status and 3 kWh per battery to 0% to support the up-regulation request. After that, charging up to 100% and 6 kWh per battery during down-regulation storing energy from PV panels and discharging such energy during the night. This case study begins the simulation day with 50% of SOC and includes a constraint to end the simulation horizon with the same amount of energy from the beginning to compensating the storage units effect on the objective function introducing free energy.

Fig. 5.11 exposes the disconnection (*OFF*) and reconnection (*END-OFF*) binary signals sent to flexible loads in blue and black respectively. Additionally, the read line represents the period when the CD load is not consuming and the green line is the baseline ($W_{k,t}^{CD}$).

Flexibility contract parameters are equal for all of them and minimum resting time D_k^{min} is 8 periods, maximum disconnection time D_k^{max} is 60 periods and the number of disconnections per day N_k^{max} is 2.

In terms of analysing the activation signals, some loads are not useful

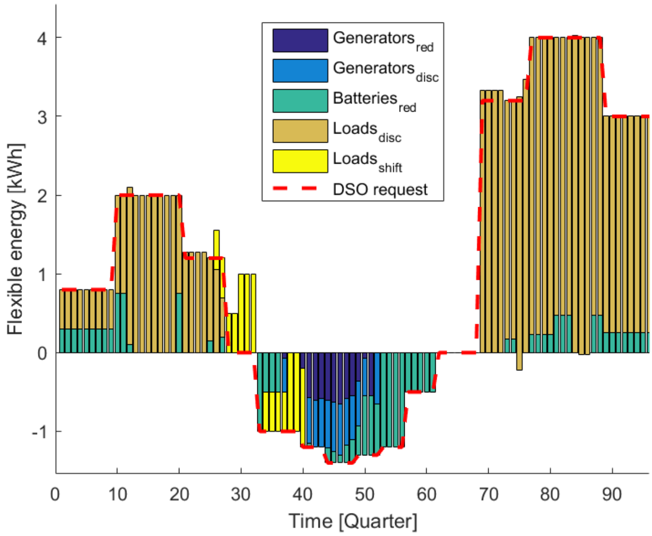


Fig. 5.9: Flexibility control signals aggregated by source type

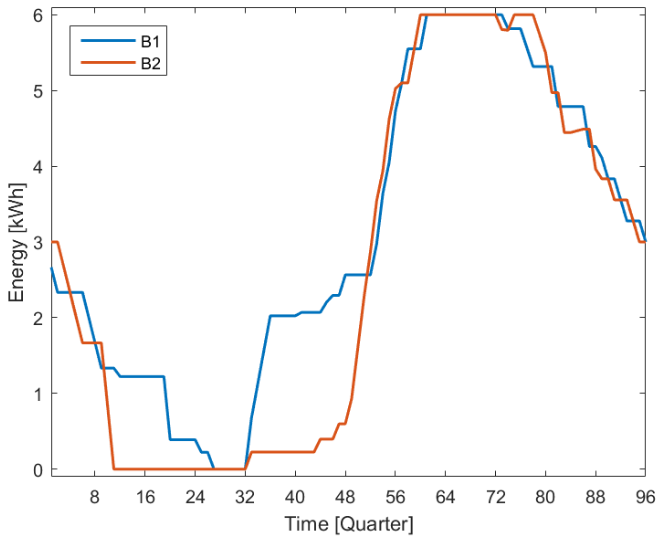


Fig. 5.10: Batteries state-of-charge evolution

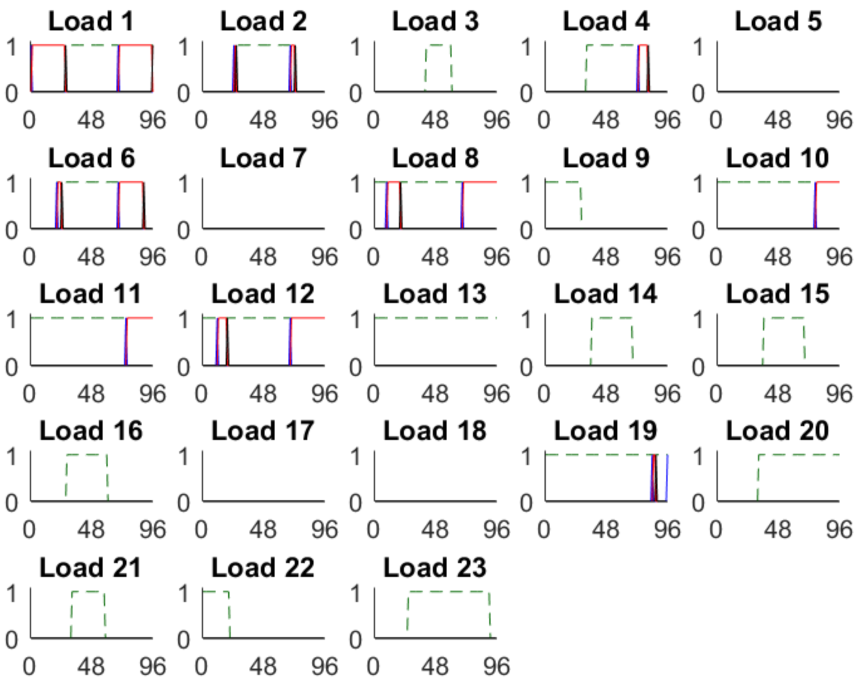


Fig. 5.11: Control signals sent to flexible loads

because they consume only during down-regulation periods like Loads-CD ID 3, 14, 15, 16 and 21 based on the reference ID appeared in Table 5.1.

Additionally, during the second downward regulation period, loads 13, 19 and 20 could provide the flexibility service at lower cost than load 22 but their power is not enough.

5.6 Experimental validation

The purpose of the experimental validation in this study is to verify that the laboratory emulators can carry out SESP Platform tests. In order to do that, the laboratory devices and functionalities must be verified to ensure the proper laboratory performance.

An emulation platform allows to transform software computed variables to real physical magnitudes such as voltages, currents or powers as defined in [227]. This way, real equipment can be connected to the emulator to check its proper behaviour. So, the platform is adequate to test the system presented above while, at the same time, the communication architecture can be validated.

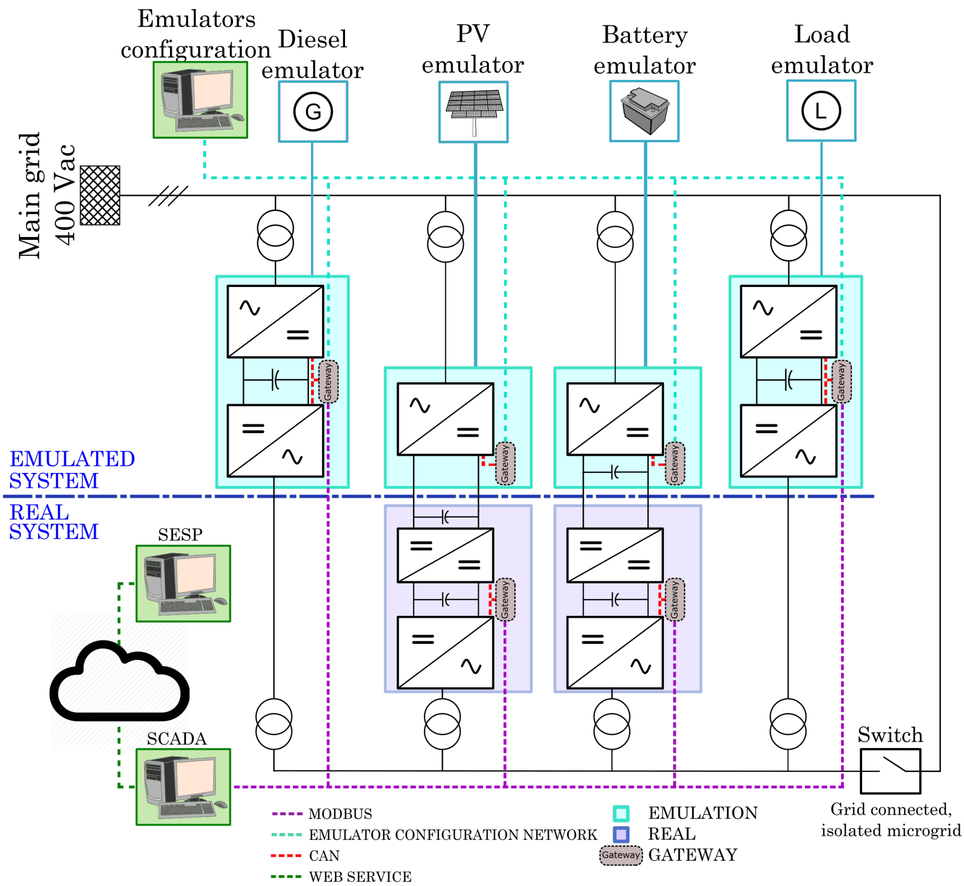
5.6.1 Test platform description

The test platform scheme is shown in Fig. 5.12a. It consists of two subsystems. The first one is composed by the emulated systems such as diesel generators, photovoltaic generators, batteries and loads. These emulators mimic the behaviour of the corresponding real device and their configuration is performed through a central emulators configuration PC, which is interconnected with the emulators through an internal communication network. The second subsystem is composed by real devices like photovoltaic and battery inverters. Moreover, they can be connected or disconnected from the external grid to emulate an isolated or grid connected system. This paper only considers the grid connected operation and the switch is closed. Additionally, the real subsystem includes the power transformers, SESP cloud, laboratory SCADA and their communication network with the test platform.

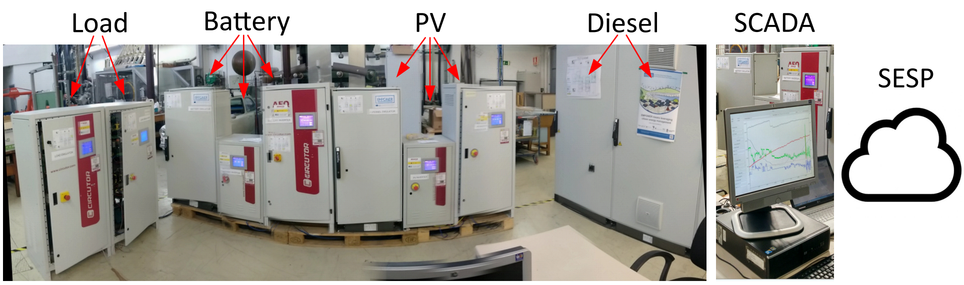
In the case study, laboratory emulators behave as EMPOWER field devices and the laboratory SCADA reports metered values to the SESP Platform as local controllers do in the real field. The load emulator output is the aggregated consumption of several loads. These loads can be connected or disconnected according to the predefined contracts and the SESP orders. In the same way, the PV emulator represents several PV systems that can be controlled by the SESP individually. The case study has two batteries and the corresponding emulator applies directly the sum of the SESP battery setpoints. There are no diesel generators. Additionally, control signals are set by the laboratory SESP computer emulating SESP control signals and platform.

5.6.2 Results

The first test performed is the baseline emulation. Using the emulator configuration computer, the baseline scenario has been introduced into the emulators. This scenario corresponds to the system without SESP commands. Despite not receiving any order in this test, the emulators includes the flexibility contracts for each load, generator and battery and the functionality to act accordingly to the order received. Fig. 5.13 compares the simulated case



a) CITCEA-UPC test platform scheme



b) Microgrid photo

Fig. 5.12: CITCEA-UPC test platform

study and the emulated one. It can be observed a good accuracy between the results and how the test platform can reproduce the scenario properly. From this result, it can be concluded that the emulators behave properly in the absence of SESP orders.

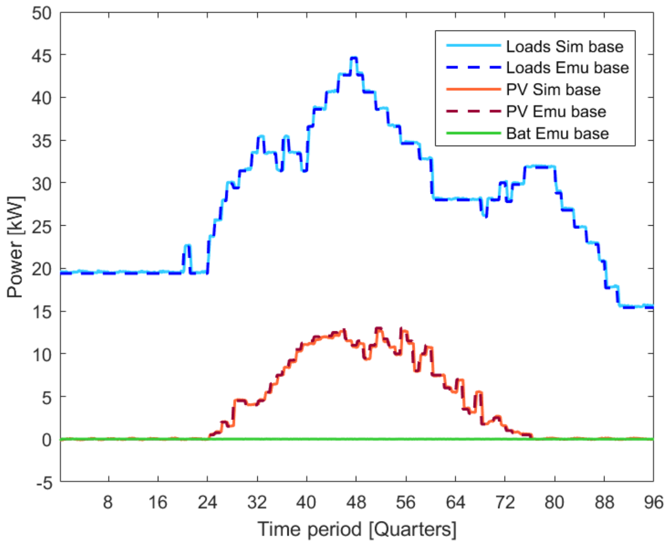


Fig. 5.13: Comparison between simulated and emulated results: baseline case (SESP is disabled)

Once the emulators have been tested, the next step is to check the real platform in charge to execute the optimal market operation and to send the different orders in real time to the different devices. This platform corresponds to the SESP and SCADA systems. The SESP has been implemented in a personal computer which executes the optimization problem and obtains all planned orders for the whole day. Then, these orders are sent to the SCADA system. This system executes a real-time routine to send the orders at the required instant. The orders are sent by Ethernet under modbus protocol to the different devices (loads, PV generators and batteries). Fig. 5.14 shows a comparison of the simulated and the emulated results, including the real SESP and SCADA systems. In contrast to the results shown in the previous section, which are presented in terms of energy, here it is shown the active power. Nevertheless, as periods represent quarters, the difference relies on a multiplication factor of 4. As it can be observed, the simulated and emulated results agree. The emulated baseline scenario

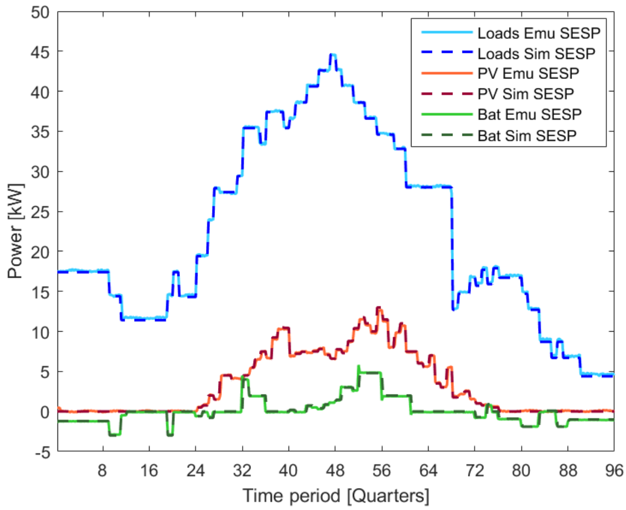


Fig. 5.14: Comparison between simulated and emulated results with the SESP. Emulated results includes the real SESP platform implemented

and the emulated scenario with the SESP platform agrees with the simulated results. So, it can be concluded that the activated flexibility meet the DSO request as shown in the simulated case in the previous section. Hence, it can be concluded that the real implementation of the SESP platform is successful.

5.7 Conclusions

The local flexibility market explained in the previous two chapters includes the required algorithm to optimally manage flexibility devices. The algorithm consists of a formulation of an optimization problem and its implementation in Julia/JuMP. The optimization problem is formulated to include multiple DER devices such as disconnectable and shiftable loads, flexible reducible and disconnectable generators as well as batteries. Its purpose is to offer to DSOs the possibility to increase or decrease the generation and load of a local area. A study case has been simulated showing the proper behaviour of the software. Then, this simulation case study has been implemented in a laboratory platform verifying that the developed local flexibility market and the SESP Platform can be tested in the laboratory.

Chapter 6

Centralised and Distributed Optimization for Aggregated Flexibility Services Provision

6.1 Introduction

In the context of smart grids and flexibility services in place, balance responsible parties (BRPs) and distribution system operators (DSOs) can benefit by activating flexibility in distribution grids as explained in the introduction Chapter 1.

In this scenario, remotely controlled distributed batteries at prosumer premises could help to provide flexibility services for dealing with the issues mentioned previously, like INVADE H2020 project proposes [167]. An energy cloud platform can remotely manage batteries and it can be operated by an aggregator with a portfolio formed by a group of prosumer sites. These sites can belong to different BRPs and DSO, and they can be grouped according to their grid and BRP zones. For instance, all sites with contracts of flexibility provision for DSO service within the same grid zone can be operated to respond to a DSO flexibility request (FR). Therefore, DSOs can increase their grid capacity to host more renewable generation or reduce network congestions during peak production or consumption periods respectively. Similarly, during the periods of high prices, BRPs could maintain their day-ahead generation and consumption portfolio by activating flexibility instead of paying penalties for their deviations or paying high intraday market costs to keep their energy portfolio [182]. The present chapter deals with the short-term operation of distributed batteries behind-the-meter in order to provide flexibility services to BRPs or DSOs at the minimum cost.

6.1.1 Home energy management systems

Previous work in topics of decision-making at site level and home energy management systems (HEMS) include optimization algorithms to find the best possible scheduling of flexibility devices (FDs). Therefore, HEMS algorithms consider that sites are independent of each other, metered separately and focuses on individual site's benefit. A detailed analysis of HEMS and FD is presented in [174, 228], which present different types of optimization problem formulations to achieve similar objective functions. Profitability and operation possibilities of distributed generation, home batteries and electric vehicles depend on the electricity tariff structure for the point of connection. For instance, [229] presents different electricity markets and electricity tariff structures for HEMS. [230] provides an economic analysis of storage for self-consumption in Germany and concludes that the cases with high demand and larger PV installations are the only profitable cases. However, aggregated flexibility services can provide additional value for storage owners and the present chapter provides two optimization algorithms that combines both site and their aggregated level solution.

6.1.2 Aggregated flexibility services

Moreover, aggregated flexibility can be used not only for providing technical services to cope with distribution grid congestion issues [161] or to increase the grid hosting capacity [184], but also can help to improve the efficiency of electricity markets [163]. For instance, [231] presents a collection work that represents current trends in energy management systems from the aggregators point of view. In addition, [232] proposes a centralised method for aggregators to schedule flexibility in different electricity markets. Furthermore, [233] discusses the potential value that aggregators may provide under different regulatory frameworks and how the inadequacy in regulation can harm other power system objectives.

The most recent works include battery aggregated operation in distribution grids [175, 211, 234–239]. [234] presents an analysis of operating central storage units directly connected to medium-voltage grids to provide power system services. [235] compares the technical service provision to self-consumption maximization service using a centralised battery at distribution level. However, [234, 235] do not consider distributed batteries at prosumer level which can change their operation with an economic incentive mechanism. Furthermore, [236] formulates a HEMS capable of providing flexibility to DSOs and [237] presents a bi-level agent-based optimization algorithm including the DSO operation cost. Unfortunately, this algorithm cannot be implemented in some countries. For instance the European Union (EU) electricity market unbundling does not allow to merge DSO and end-users objectives as grid information cannot be shared with aggregators. Thus, current studies for the European Union applications assume DSO quantifies the flexibility needed to solve the grid problem in accordance to their operating costs as a separate problem and the aggregator assists the DSO by grid zones as suggested in [211] and [175]. [238] presents a flexibility provision HEMS and it is solved with an heuristic particle swarm optimization algorithm. Though, augmented Lagrangian methods facilitate to find global optimal solutions in a reasonable computational time in a distributed manner. Finally, [239] presents a market based flexibility exchange framework for multiple aggregators competing to solve the same congestion problem. It provides basis to formulate algorithms that are capable to deal with multiple aggregators and the work presented in this chapter answers the question regarding re-scheduling FDs where an aggregator needs to compromise by activating a certain flexibility volume. The case of multiple aggregators competing for the same service is out of the scope of this chapter and thesis.

Another way of handling large-scale flexibility portfolios is using aggregation and disaggregation techniques like [240, 241]. [240] presents a scalable aggregation decision-making algorithm for scheduling electric vehicles. [241] presents a scalable approach for flexible energy systems based on zonotopic sets. Instead of using aggregation and disaggregation steps for decision-making, this work has the advantage of using simple formulation of site-level cost functions and constraints while managing sensitive information independently.

6.1.3 Alternating direction method of multipliers

The alternating direction method of multipliers (ADMM) is a decomposition algorithm for distributed convex optimization, but it can be also considered as an heuristic algorithm for solving non-convex problems [242]. Nowadays, ADMM is widely applied in distributed computing environments. ADMM can be used to solve problems involving large amount of data and variables in the field of smart grids. For example, a fully distributed optimal power flow problem is presented in [243], and [244] suggests an ADMM approach for a generation investment problem in electricity markets. In the field of ancillary services, [245] show a decentralised multi-block ADMM for primary frequency control.

Cloud computing services and big data research can also benefit from

ADMM algorithms as they allow to distribute computational power to solve different sub-problems that can be assigned to different processing units [242]. [246] presents the mathematical formulation of network energy management, robust state estimation and security constrained optimal power flow problems in a distributed manner via ADMM. [247] formulates the parallel multi-block ADMM for generic problems like exchange problem, $\ell 1$-minimization and distributed large-scale $\ell 1$-minimization, and tested them on a cloud computing platform.

For applications regarding energy management in smart grids, [248] reviews the work of different authors on community-based and peer-to-peer (P2P) market mechanisms. [249] solves a novel cost allocation in P2P electricity markets using the consensus ADMM algorithm. [250] formulates a distributed operation of energy collectives using an ADMM algorithm by varying penalty parameter adapted to each case study. [251] presents a distributed optimization for community microgrids where each site has its own HEMS. However, the applied ADMM method is very case-sensitive to the augmented Lagrangian penalty parameter for meeting the energy balance constraint. Therefore, this chapter presents a novel two-steps accelerated method which uses the Proximal Jacobian regularization to find optimization solutions faster without large variations in the objective function.

6.1.4 Summary of contributions

Under the before mentioned change of paradigm presented in the previous references about energy/flexibility exchanges at distribution level, the present chapter aims to contribute in the area of large-scale aggregator portfolio optimal scheduling. The main contributions of this chapter are threefold:

- Formulation of a centralised optimization problem for aggregated flexibility service provision from prosumers with batteries to third parties like DSOs and BRPs considering battery ageing factors. The framework of this problem includes an aggregator in charge of scheduling batteries for prosumer minimum cost operation under two situations: regular operation and constrained operation when BRP/DSO send a flexibility request to aggregator.

- Distributed version of the previous aggregation problem including the detailed battery ageing model using a novel accelerated ADMM algorithm to find suitable solutions in less than 10 minutes. This problem could be suitable for centralized aggregator as a decision maker or distributed decision frameworks like P2P. In both frameworks, batteries need to receive new control signals every 15 minutes to adapt to new conditions such as solar radiation or new flexibility requests.

- Sensitivity analysis of the centralised and distributed algorithms in relation to the aggregator portfolio size and the number of variables, ADMM algorithm acceleration parameters, and execution time.

The case study presented is the evidence for ease of implementation of the distributed algorithm.

6.2 System Description

Aggregators can respond to flexibility requests from BRPs for day-ahead and intraday portfolio optimization or from DSOs to reduce network congestions [182]. A FR can be defined as the difference between the baseline and the desired load profile. It can be measured in energy per programming time unit (PTU). PTUs can vary depending on the applicant and the application case. For instance, BRPs dealing with electricity markets would be interested in hourly PTUs. However, DSOs could be interested in higher time granularity with quarterly PTUs or even 5 minutes time resolution. This chapter goes for hourly PTUs for simplicity but the formulation is valid for different time steps. A FR can be for up-regulation which corresponds to an increase in generation or a decrease in consumption. Similarly, the FR for down-regulation can be defined as a decrease in generation or an increase in consumption. The baseline load profile at transmission level is defined based on market settlements, which cannot be applied at distribution grid level. Moreover, DSOs, BRPs and aggregators have different portfolios and their baselines cannot be analogous. In the present framework, DSO and BRP use aggregator's load baseline as reference for their flexibility settlements.

This chapter assumes the local flexibility market (LFM) framework presented in [252] (Chapter 4) where an aggregator is responsible for re-scheduling FDs to meet an external FR without violating the end-user agreements. Fig. 6.1 shows the framework and all involved agents. The aggregator is in charge of managing the energy cloud platform which remotely controls distributed devices, such as batteries, in prosumer premises. Each prosumer has a contract with a retailer for energy prices and it might include a grid tariff. Retailers can offer electricity contracts indexed to wholesale markets, but also flat price or peak-valley prices. Therefore, end-user prices can be different from each other. Retailer, BRP and aggregator are linked through flexibility contracts which specify the conditions for flexibility trading as explained in [176]. As mentioned above, BRP and DSO are interested in activating flexibility and they send FRs to aggregator. In this scenario, aggregator is in charge of seeking the cheapest combination of flexibility activations to reduce operational cost such as battery degradation. Thus, prosumers provide flexibility to BRP/DSO (orange arrows), who pay the aggregator for providing these services. A portion of the benefits can go to prosumers included in their retailer electricity bill. All deviations from BRP's market position represent a money flow which is out of the scope of this work as the BRP is responsible of taking them into account before submitting FRs.

Nevertheless, aggregator agent could be surpassed and every prosumer could decide their own contribution to the FR individually without any third party. In such case, BRPs and DSOs could interact directly with prosumers and the distributed optimal flexibility provision algorithm presented in this work could be applied. Additionally, this possibility would allow end-users to protect their personal information such as consumption patterns and habits. This possibility opens many aspects to be discussed in detail but this is not the objective of the present work and future publications could discuss it in more detail.

Additionally, aggregator applies a traffic light system as suggested in [175, 252, 253] to solve potential conflicts between simultaneous or even contradictory FR. Decisions are made centrally using two-way communications, where aggregators send direct control signals and receive metered consumption and status from each FD. In [159] it is stated that the architecture used has potential scalability limitations. However, in this chapter it is shown that distributed optimization can overcome scalability issues.

6.3 Stationary battery model

This section provides the stationary battery model used in the present chapter. The elemental battery state-of-charge (SOC) evolution constraint of prosumer site i is shown in (6.1a). Battery SOC has upper (O_i^{max}) and lower boundaries (O_i^{min}), and charging and discharging power limits are (Q_i^{ch}) and (Q_i^{dis}).

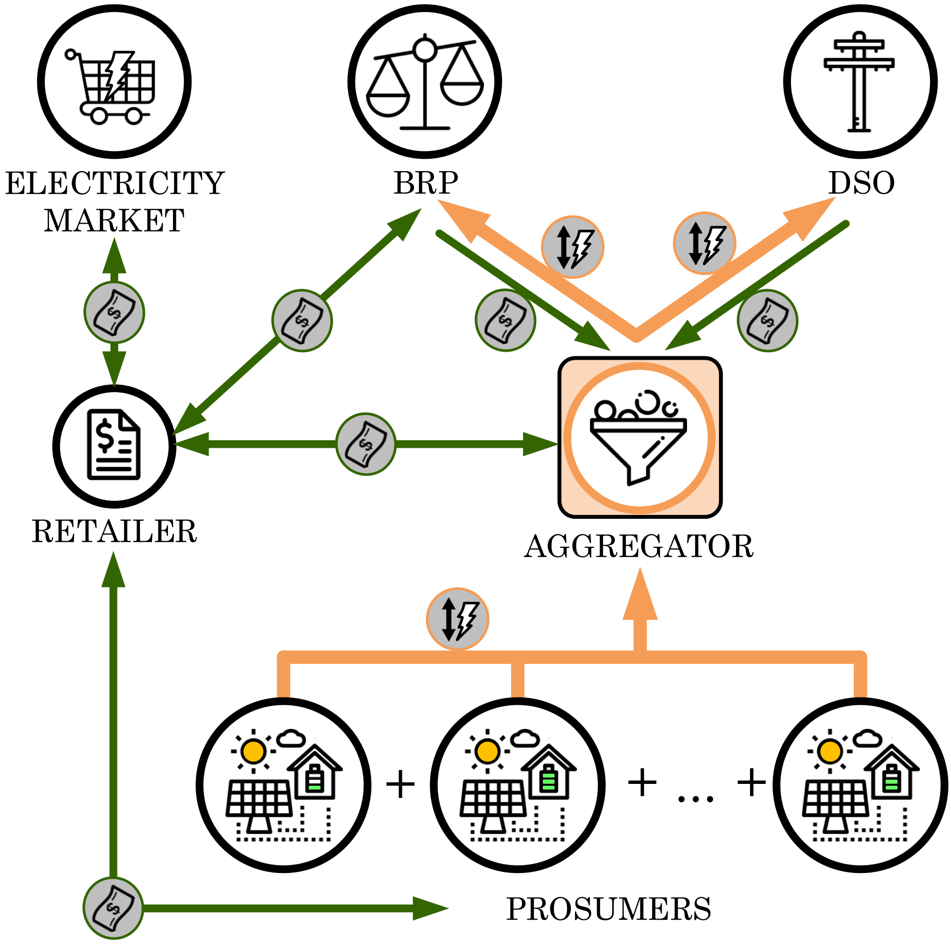


Fig. 6.1: Local flexibility market framework.

$$
\begin{aligned}
\sigma_{i,t}^{SOC} =& \sigma_{i,t-1}^{soc} + \sigma_{i,t}^{ch} A_i^{bat,ch} a^{inv,ch} \\
& - \frac{\sigma_{i,t}^{dis}}{A_i^{dis} a^{inv,dis}} && \forall i,t && \text{(6.1a)} \\
& O_i^{min} \le \sigma_{i,t}^{SOC} \le O_i^{max} && \forall i,t && \text{(6.1b)} \\
& \sigma_{i,t}^{ch} \le Q_i^{ch} \delta_{i,t}^{bat} && \forall i,t && \text{(6.1c)} \\
& \sigma_{i,t}^{dis} \le Q_i^{dis} (1 - \delta_{i,t}^{bat}) && \forall i,t && \text{(6.1d)}
\end{aligned}
$$

Because batteries are expensive and suffer from higher rate of degradation under heavy stress [254], an advanced battery model has been developed in order to make more accurate decisions. The developed battery model is formulated by including battery degradation cost in such a way to reflect real costs of operation as closely as possible to reality while maintaining the computational burden at an acceptable level. The battery model has 4 main attributes in addition to the simple model which are cycle and calendar degradations, power limitations when approaching fully charged and fully discharged states to avoid reaching the voltage limits, and piecewise linearized inverter efficiency. The following section describes these attributes in detail.

Cycle degradation

The most common stationary batteries at end-user level today are lithium ion batteries, typically li-ion nickel-manganese-cobalt (LI-NMC) batteries. The degradation factors of such batteries are predominantly depending on charge-discharge cycle depth during operation. Therefore, the lifetime of these batteries depends on the depth and number of cycles. In addition, shallow cycles have significantly lower degradation cost than deep ones. A detailed cycle degradation model is presented in [255]. The cycle degradation model factorizes the cycle depth and accounts degradation as a cost of discharging the battery with a certain depth. In order to keep track of the depth-of-discharge, the battery model adds virtual segments indexed by j as presented in [255]. (6.2a) tracks the segmented SOC evolution given segmented variables, whereas (6.2b) restrains the maximum energy per segment. (6.2c) and (6.2d) sums the power in all segments j to equal the original variables. Finally, (6.2e) calculates the degradation cost as function of discharge power.

Calendar ageing

The calendar ageing is modelled as a function of SOC dependent cost per time period, as shown in (6.3). The core idea is that calendar based degradation cost increases with higher SOC and it incentives the battery to stay at a low SOC when not utilized. The tuning factors S_i^0 and S_i^{SOC} implicate how much the calendar ageing depends on SOC as described in [256].

Constant-voltage charging/Constant-current discharging

The constant-voltage charging and constant-current discharging regions of a battery does not apply to the full SOC area of a battery. (6.4a) and (6.4b) reduces the allowed charging and discharging power when approaching the maximum and minimum energy levels respectively.

$$\sigma_{i,t,j}^{seg,SOC} = \sigma_{i,t,j}^{seg,ch} A^{bat,ch} a^{inv,ch}(\sigma_{i,t,j}^{seg,ch}) - \frac{\sigma_{i,t,j}^{seg,dis}}{A^{bat,dis} a^{inv,dis}(\sigma_{i,t,j}^{seg,dis})} + \sigma_{i,t-1,j}^{seg,SOC} \qquad \forall i,t \tag{6.2a}$$

$$\sigma_{i,t,j}^{seg,SOC} \leq O_{i,j}^{seg,max} \qquad \forall i,j,t \tag{6.2b}$$

$$\sigma_{i,t}^{ch} = \sum_{j\in\mathcal{J}} \sigma_{i,t,j}^{seg,ch} \qquad \forall i,t \tag{6.2c}$$

$$\sigma_{i,t}^{dis} = \sum_{j\in\mathcal{J}} \sigma_{i,t,j}^{seg,dis} \qquad \forall i,t \tag{6.2d}$$

$$\beta_{i,t}^{cyc} = \sum_{j\in\mathcal{J}} C_{i,j}\sigma_{i,t,j}^{seg,dis} \qquad \forall i,t \tag{6.2e}$$

$$\beta_{i,t}^{cal} = \frac{C_i^{bat}}{S_i^{LT}} \cdot \left(S_i^0 + \frac{1}{2}S_i^{SOC} \cdot (\sigma_{i,t}^{SOC} + \sigma_{i,t-1}^{SOC})\right) \forall i,t \tag{6.3}$$

$$\sigma_{i,t}^{ch} \leq \frac{O_i^{max} - \sigma_{i,t-1}^{SOC}}{(1 + W_i^{bat})} \qquad \forall i,t \tag{6.4a}$$

$$\sigma_{i,t}^{dis} \leq \frac{\sigma_{i,t-1}^{SOC} - O_i^{min}}{(1 + W_i^{bat})} \qquad \forall i,t \tag{6.4b}$$

Piecewise linearized inverter efficiency

The total storage system efficiency is a combination of two factors, the inverter efficiency ($a^{inv,ch}$) and the battery efficiency ($A^{bat,ch}$). A piecewise linearized approach is chosen in order to capture the power dependency of inverter efficiency. At low input power inverter efficiency is very low, on the other hand the efficiency reaches 98% at high input power. The piecewise linearization is modelled using a special order sets of type 2 (SOS2) approach to approximate the non-linear dependency on input power. This approach adds four additional binary variables per time step (two for charging, two for discharging) to the problem, and is one of the preferred methods first developed in [257].

6.4 Site Level Optimization Problem

The site level optimization problem defined in (6.5) schedules all FDs by considering battery and PV constraints, forecasted inputs and costs for the site, but not the FR. Nomenclature is listed at the beginning of the thesis in the Nomenclature Section. This problem is formulated as an mixed-integer linear programming (MILP) as it follows. Linear objective function (6.5a) represents the cost minimization for prosumer site i including flexibility costs for either using the battery or curtailing the PV if needed. Purchasing ($P_{i,t}^{buy}$) and selling prices ($P_{i,t}^{sell}$) typically come from retailer contracts which are known in advance. Otherwise, prices can be indexed to day-ahead markets. The present framework assumes to be executed some hours in advance of the operation day, when the day-ahead prices are already published. (6.5b) is the electricity balance of site i, which depends on the forecasted inflexible load ($W_{i,t}^{l}$) and PV generation ($\psi_{i,t}$). Additionally, (6.5c) and (6.5d) limit site import and export capacity and (6.5e) ensures site i does not import and export electricity simultaneously at period t. Thus, each prosumer site problem has 72 binary variables including the battery model. Battery charging ($\sigma_{i,t}^{ch}$) and discharging ($\sigma_{i,t}^{dis}$) decision variables from Eq. (6.5b) are limited by common Eq. (6.1), cycle ageing Eq. (6.2), calendar ageing Eq. (6.3), and voltage Eq. (6.4). Moreover, the battery system efficiency depends on the inverter power-efficiency relation and a constant battery efficiency. Constraint (6.5f) considers the cost of activating flexibility from battery of each site i as the addition of cycling ageing ($\beta_{i,t}^{cyc}$) and calendar ageing costs ($\beta_{i,t}^{cal}$) from Eq. (6.3) and Eq. (6.2e) respectively. Battery flexibility cost depends on charging and discharging decisions [255]. The aggregated result of all prosumer site optimization problems is the load baseline in aggregated flexibility services.

$$\min_{\chi,\zeta} \sum_{t\in\mathcal{T}} \left(P_{i,t}^{buy}\chi_{i,t}^{buy} - P_{i,t}^{sell}\chi_{i,t}^{sell} + \zeta_{i,t}^{flex} \right) \qquad \forall i \tag{6.5a}$$

$$\text{s.t.}\chi_{i,t}^{buy} + \sigma_{i,t}^{dis} + \psi_{i,t}^{G} = \chi_{i,t}^{sell} + \sigma_{i,t}^{ch} + W_{i,t}^{l} \qquad \forall i,t \tag{6.5b}$$

$$\chi_{i,t}^{buy} \leq \delta_{i,t}^{buy} X_{i}^{imp} \qquad \forall i,t \tag{6.5c}$$

$$\chi_{i,t}^{sell} \leq \delta_{i,t}^{sell} X_{i}^{exp} \qquad \forall i,t \tag{6.5d}$$

$$\delta_{i,t}^{buy} + \delta_{i,t}^{sell} \leq 1 \qquad \forall i,t \tag{6.5e}$$

$$\zeta_{i,t}^{flex} = P_{i,t}^{Gr}(W_{i,t}^{Gr} - \psi_{i,t}^{G}) + \beta_{i,t}^{cyc} + \beta_{i,t}^{cal} \qquad \forall i,t \tag{6.5f}$$

6.5 Centralised Flexibility Provision

The centralised flexibility service provision algorithm formulated in this section is composed of two consecutive problems:

- Aggregated level flexibility offer (ALFO) formulation finds the available flexibility without violating local constraints according to the FR.
- Aggregated level flexibility management (ALFM) problem finds the cheapest scheduling of FDs once the aggregator received a FR acceptance from a BRP and/or DSO.

6.5.1 Centralised flexibility provision algorithm

The centralised Algorithm 1 for aggregated flexibility scheduling first optimizes the battery of each prosumer to reduce energy cost individually following the problem (6.5) based on the forecasted values of electricity consumption and PV production. The obtained result is the energy baseline considering the optimal battery scheduling. This information is sent to the DSO and BRP. The DSO baseline energy notice is referred to the prosumers of each grid zone and BRP needs to know the consumption of its customers. Based on this information, DSO and BRP can send FRs if needed. Then, the aggregator executes the ALFO problem (6.6) to calculate the flexibility offer for the BRP/DSO based on the FR. As it could be higher than the portfolio capability, it is necessary to optimize FDs for offering equal or less flexibility than the FR. Each DSO and BRP can decline, accept the offer fully or only parts of it. In case the offer is completely accepted, the aggregator can use flexibility scheduling from the ALFO optimization step to generate control signals. In case the flexibility offer is partially accepted, the aggregator has to execute the ALFM problem (6.8) in order to re-schedule FDs to meet the accepted FR. In contrast to the previous ALFO problem, aggregator already knows FR is reachable and ALFM optimization needs equal or more flexibility than the accepted FR as slightly more flexibility is not a real problem if it is cheaper than less flexibility. This is necessary in case of having binary decision variables as it can be difficult to exactly match the requested flexibility amount of a FR. The algorithm 1 prevents infeasible instances due to this two-steps structure and two optimization problems.

This process schedules all FDs for an optimization planning horizon and it can be repeated periodically considering new forecasted inputs and FRs. It is to be noted that the baseline demand could be updated each time new forecasted values are obtained. However, it can be convenient to keep a constant baseline within a day to avoid confusions between aggregator, BRP and DSO about the reference scenario. [119] presents example cases of aggregated flexibility services using this architecture.

ALFO and ALFM objective functions and aggregation constraints are (6.6) and (6.8) respectively:

6.5.2 Aggregated level flexibility offer (ALFO) problem formulation

Objective function (6.6a) considers the electricity and flexibility costs of each site i over the planning horizon. This problem is formulated as an mixed-integer nonlinear programming (MINLP) as flexibility costs include quadratic penalty for the flexibility that is not served. The penalty is defined as the difference between the total load scheduled in each site optimization problem ($\chi_{i,t}^{tot}$) as per constraint (6.7a), and the expected load after applying a FR as per constraint (6.7b). In case of a lack of flexibility where the aggregator cannot meet the FR completely, the quadratic penalty ensures that the flexibility provided will follow the shape of the FR. Otherwise, a linear penalty in the objective function would reduce the computational burden but not necessarily generate flexibility provision for all constrained time periods. From practical point of view, it means to consider all flexibility time periods with the same priority according to the flexibility power requested and the aim is to provide flexibility during all requested periods. The quadratic penalty ensures that the flexibility provided will follow the shape of the FR. Otherwise, in case of flexibility scarcity, linear difference

Algorithm 1: Centralized optimal flexibility provision

Input: $W^{l}_{i,t}, \psi_{i,t}$

Optimize each site flexibility according to Eq. (6.5) for minimum cost operation

Output: $\chi^{buy}_{i,t}, \chi^{sell}_{i,t}, \sigma^{ch}_{i,t}, \sigma^{dis}_{i,t}$

Send baseline energy notice ($W^{base}_{t} = \sum_i \chi^{buy}_{i,t} - \chi^{sell}_{i,t}$) to BRP/DSO

if $FR_t \neq 0$ **then**

  Prioritize FR_t of each period

  Optimize each site flexibility to minimize their costs and meeting the FR according to ALFO problem (6.6)

  Output: $\chi^{buy}_{i,t}, \chi^{sell}_{i,t}, \sigma^{ch}_{i,t}, \sigma^{dis}_{i,t}$ and flexibility offer to BRP/DSO

  if *Accepted* $FR_t \neq 0$ **then**

    Optimize each site flexibility including the accepted FR according to ALFM problem (6.8)

    Output: $\chi^{buy}_{i,t}, \chi^{sell}_{i,t}, \sigma^{ch}_{i,t}, \sigma^{dis}_{i,t}$ from Eq. (6.8) including accepted FR_t

    Send control signals ($\sigma^{ch}_{i,t}, \sigma^{dis}_{i,t}$) from Eq. (6.8) to batteries.

  else

    Send control signals ($\sigma^{ch}_{i,t}, \sigma^{dis}_{i,t}$) from Eq. (6.5) to batteries.

  end

else

  Send control signals ($\sigma^{ch}_{i,t}, \sigma^{dis}_{i,t}$) from Eq. (6.5) to batteries.

end

would not necessarily generate flexibility provision for all constrained time periods. As previously explained, constraints (6.6b) and (6.6c) ensure that the activated amount of flexibility is less or equal to the up and down FR respectively. Additionally, constraints (6.6d) and (6.6e) are necessary in cases of grid congestions to ensure that the rebound effect is not causing new load peaks before or after the activation of the FR.

$$\begin{aligned}
\min_{\chi_i,\zeta_i} \ & \sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}} \Bigg(P^{buy}_{i,t}\chi^{buy}_{i,t} - P^{sell}_{i,t}\chi^{sell}_{i,t} + \zeta^{flex}_i + \\
& P^{penal}\sum_{t\in\mathcal{T}^{\pm}}\Big(W^{flex}_t - \sum_{i\in\mathcal{I}}\chi^{tot}_{i,t}\Big)^2\Bigg) && && (6.6a)\\
\text{s.t.} \ & \sum_{i\in\mathcal{I}}\chi^{tot}_{i,t} \geq W^{flex}_t && \forall t\in\mathcal{T}^{+} && (6.6b)\\
& \sum_{i\in\mathcal{I}}\chi^{tot}_{i,t} \leq W^{flex}_t && \forall t\in\mathcal{T}^{-} && (6.6c)\\
& \sum_{i\in\mathcal{I}}\chi^{buy}_{i,t} \leq \max(W^{flex}_t) && \forall t && (6.6d)\\
& \sum_{i\in\mathcal{I}}\chi^{sell}_{i,t} \leq \max(W^{flex}_t) && \forall t && (6.6e)
\end{aligned}$$

$$\chi^{tot}_{i,t} = \chi^{buy}_{i,t} - \chi^{sell}_{i,t} \tag{6.7a}$$

$$W^{flex}_t = W^{base}_t - FR_t \tag{6.7b}$$

6.5.3 Aggregated level flexibility management (ALFM) problem formulation

Once the aggregator estimates the available flexibility, it is communicated as flexibility offers to the BRP or DSO. If they accept the offer either partially or entirely, the aggregator can execute the ALFM optimization problem to fulfil it. The objective function (6.8a) is the same as objective function (6.6a) but removing the quadratic penalty for not meeting the FR as the ALFO problem ensures there is sufficient flexibility. In this MILP optimization problem, constraints (6.8b) and (6.8c) ensure enough flexibility and the site cost is penalizing the excessive battery usage. We can include constraints (6.6d) and (6.6e) if it is necessary to avoid new undesired load peaks like in Section 6.5.2.

$$
\min_{\chi_i,\zeta_i} \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} \left(P_{i,t}^{buy} \chi_{i,t}^{buy} - P_{i,t}^{sell} \chi_{i,t}^{sell} + \zeta_i^{flex} \right) \tag{6.8a}
$$

$$
\text{s.t.} \sum_{i\in\mathcal{I}} \chi_{i,t}^{tot} \le W_t^{flex} \qquad \forall t \in \mathcal{T}^+ \tag{6.8b}
$$

$$
\sum_{i\in\mathcal{I}} \chi_{i,t}^{tot} \ge W_t^{flex} \qquad \forall t \in \mathcal{T}^- \tag{6.8c}
$$

The main advantage of this formulation is its simplicity. However, problems (6.6) and (6.8) may have scalability limitations as mentioned before. Therefore, this chapter explores methods to decompose the problem to improve its computational performance with large-scale implementations.

6.6 Distributed Flexibility Provision

The distributed flexibility provision algorithm aims to solve the same problem previously presented in Section 6.5 but using the alternating direction method of multipliers (ADMM) in order not only to improve computational performance in terms of memory usage and execution time, but also to keep end-user private data separately. As stated before, this formulation could be extended for peer-to-peer flexibility exchange frameworks as the algorithm could be executed in distributed computation frameworks. The proposed distributed algorithm is based on the optimal exchange problem presented in [242] but applied in local flexibility markets where each prosumer settles their contribution to the FR in parallel. Therefore, high performance computers or energy cloud platforms can solve distributed algorithms with less scalability limitations using multi-processor architectures. Additionally, the distributed formulation can deal with FRs that surpasses the available flexibility. Thus, both ALFO and ALFM are substituted by a single distributed optimization algorithm.

6.6.1 Augmented Lagrangian

The augmented Lagrangian relaxation ($\mathcal{L}_\rho$) is presented in (6.9) and it is equivalent to the previous problems Eqs. (6.6) and (6.8) relaxing constraints (6.6b), (6.6c), (6.8b), (6.8c). It is to be noted that previous constraints are formulated as inequalities. However, they can be rewritten as equalities for simplicity as small errors above or below FR threshold are not significant from engineering point of view. Thus, Eq. (6.9) assumes constraint (6.6b) as equality because the ADMM is designed for equality constraints and final error is small enough for the case study. According to [242], the regular ADMM algorithm consists of an iterative process to minimize $\mathcal{L}_\rho$ and to update the dual variable ($\lambda_t^{(k)}$) for each constrained period t by giving a fixed penalty parameter ($\rho > 0$). In ADMM implementations, it is necessary to identify generic values for penalty parameters (ρ) capable of providing satisfying solutions in reasonable computation time for multiple cases.

$$\begin{aligned} \mathcal{L}_\rho = f(x_i) + \sum_{t\in\mathcal{T}^\pm} \lambda_t^{(k)}\Big(\chi_{i,t}^{tot} - \frac{W_t^{flex}}{N}\Big) + \\ \frac{\rho}{2}\sum_{t\in\mathcal{T}^\pm}\Big\|\chi_{i,t}^{tot} + \sum_{\substack{j\in\mathcal{I}\\ j\neq i}}\chi_{j,t}^{tot,(k)} - (W_t^{flex}))\Big\|^2 \end{aligned} \tag{6.9}$$

In the present work, each site i can decide individually their contribution to the FR according to its cost function (6.10a) using (x_i) as decision variable vector (6.10b), the dual variable ($\lambda_t^{(k)}$) and the result of other sites ($j \in \mathcal{I}, j \neq i$) in the previous step ($k$). It is noticeable x_i contains continuous variables $\chi_{i,t}^{tot}$ and $\psi_{i,t}^{flex}$ from problem (6.5). Therefore, ADMM only contains continuous variables. Additionally, every step branch-and-bound solves the site problem including binary variables and constraints (6.5). Therefore, Eq. (6.9) can be solved with MILP solvers such as Gurobi once $\lambda_t^{(k)}$ is updated.

$$f(x_i) = \sum_{t\in\mathcal{T}}\Big(P_{i,t}^{buy}\chi_{i,t}^{buy} - P_{i,t}^{sell}\chi_{i,t}^{sell} + \zeta_{i,t}^{flex}\Big) \tag{6.10a}$$

$$x_i = [\chi_i^{tot}, \zeta_i^{flex}] \tag{6.10b}$$

Finally, it is important to highlight Problems (6.5), (6.6), (6.8) and (6.9) are MILP, so non-convex. Therefore, ADMM nor other decomposition techniques ensure to find the global optimum solution. However, Section 5.5 shows the present work is able to converge and find a sub-optimal but feasible solution in a reasonable computation time.

6.6.2 ADMM algorithm modifications

As explained in [246], the general form of ADMM is presented for two blocks of functions and variables. However, the present problem has as many blocks as prosumers in the portfolio. This is important to ensure privacy of end-users information. [246] and [258] present two modifications to the original ADMM. First, they suggested to update the primal variables concurrently as the sequential variable update would slow down obtaining the solution. Otherwise, every prosumer should wait for the variable update of its neighbour before calculating the optimal solution. This allows for a larger problem dimension since it can be solved in a distributed computing system concurrently. Also, it reduces the computational cost as the parallelization gains overcome the overhead derived from it. Second, they introduce the Proximal Jacobian (PJ) regularization term $\left(\frac{1}{2}\|(x_i - x_i^{(k)})\|_{P_i}^2\right)$, which preserves parallel updating. The norm of this term is defined as $\|x_i\|_{P_i}^2 = x_i^T P_i x_i$ with $P_i = Id$. It guarantees strong convexity of the problem and enhances stability. The damping parameter γ is set to 1.5 as suggested in [246].

6.6.3 Penalty parameter and dual variables updating

Algorithm 2 illustrates the dual update accelerated iteration process divided in two steps:

Step 1 - Fast updating

The early iterations (k) are accelerated by varying the penalty parameter $\rho^{(k)}$ according to (6.11) as per the approach adapted by [242]. τ^{incr} and τ^{decr} are increasing and decreasing factors in order to speed up the algorithm. $\rho^{(k)}$ is used to update dual variables $\lambda_t^{(k+1)}$ according to (6.12a), (6.12b) is the primal residual, and (6.12c) is the dual residual. $r_t^{(k)}$ is positive when the set of prosumer sites I cannot provide enough up-regulation to meet the FR at iteration k and dual variable $\lambda_t^{(k)}$. Otherwise, $r_t^{(k)}$ is negative.

$$\rho^{(k+1)} := \begin{cases} \tau^{incr}\rho^{(k)} & \text{if } \|r^{(k)}\|_2 > \mu\|s^{(k)}\|_2 \\ \rho^{(k)}/\tau^{decr} & \text{if } \|s^{(k)}\|_2 > \mu\|r^{(k)}\|_2 \\ \rho^{(k)} & \text{otherwise,} \end{cases} \tag{6.11}$$

$$\lambda_t^{(k+1)} := \lambda_t^{(k)} + \gamma\rho^{(k)} r_t^{(k)} \qquad \forall t \in \mathcal{T}^{\pm} \tag{6.12a}$$

$$r_t^{(k)} = \sum_{i \in \mathcal{I}} \left(\chi_{p,t}^{tot,(k)} - W_t^{flex}\right) \qquad \forall t \in \mathcal{T}^{\pm} \tag{6.12b}$$

$$s_t^{(k)} = r_t^{(k)} - r_t^{(k-1)} \qquad \forall t \in \mathcal{T}^{\pm} \tag{6.12c}$$

Step 2- Soft updating

The dual update changes to (6.13) at iteration k^* once the primal error is equal or less than threshold value like 5% of the FR. Then, it starts collecting accumulated primal error over iterations from k^* to k and includes integration and dual residual regulation parameters K^i and K^d inspired in classic control theory [259]. They allow to better regulate the dual variables update and damp oscillations in the error and objective function along the iterative solution process. However, at this moment it is unclear how to tune the parameters to accelerate the convergence. It is to be noted that penalty parameter $\rho^{(0)}$ is the initial value.

$$\begin{aligned} \lambda_t^{(k+1)} := \lambda_t^{(k)} + \gamma\rho^{(0)} r_t^{(k)} + \\ K^i \sum_{i=k^*}^{k} r_t^{(i)} + K^d s_t^{(k)} \qquad\qquad \forall t \in \mathcal{T}^{\pm} \end{aligned} \tag{6.13}$$

The algorithm stops when the norm of the primal and dual residuals are both smaller than some given thresholds (ϵ^{pri} and ϵ^{dual} respectively). Additionally, a maximum number of iterations k^{max} and computational time (CT^{max}) are specified as well. Depending on the requirements of the case, it might be interesting to compute as many iterations as possible in a pre-specified time, or on the contrary run for as long as needed the algorithm until we reach a precision requirement. Both scenarios are tested in Section 6.8 experiments.

6.7 Case study

The case study considered for analysis consists of 100 domestic houses which have photovoltaic panels installed and their historic measurement data are available through the Dataport [260]. The household consumption data and PV generation data considered for the case study are for the date June the 28th of 2018 because the consumption and PV generation were significantly high. The electricity price is from the Spanish day-ahead market price for the same day in combination with the Spanish two-periods grid tariff which has valley hours from 11 pm until 13 pm on the next day (14 hours) and the rest of the hours are considered as peak hours for summer period. Metering and forecasted values have hourly resolution and the optimization horizon is one day. The optimization process is assumed to be executed at 11:45 pm

Algorithm 2: Two-steps Fast-PJ-ADMM for optimal flexibility provision.

Initialize: $x_i^{(0)}, \lambda_t^{(0)}, \rho^{(0)} > 0$
Input: $K^i, K^d, \epsilon^{pri}, \epsilon^{dual}, \tau^{incr}, \tau^{decr}, CT^{max}, k^{max}, W^{flex}$
while $\epsilon^{pri} > \|r_t^k\|_2$ *and* $\epsilon^{dual} > \|s_t^k\|_2$ **do**
    for *i=1,2,...,I* **do**
        (x_i is updated **concurrently**)
        $x_i^{(k+1)} := \underset{x_i}{\operatorname{argmin}} \mathcal{L}_\rho(x_i, x_{j\,j\neq i}^k, \lambda_t^k, \rho^{(k+1)}) + \frac{1}{2}\|(x_i - x_i^{(k)})\|_{P_i}^2$
        s.t. Site i constraints: (6.5b)(6.5c)(6.5d)(6.5e)
    end
    Update dual and penalty variables
    if $\|r_t^{(k)}\|_2 > 0.05\|FR_t\|_2$ **then**
        Fast update: $\rho^{(k+1)}$ according to (6.11)
        Update $\lambda_t^{(k+1)} := \lambda_t^k + \gamma\rho^{(k+1)} r_t^{(k+1)}$, $\forall t \in \mathcal{T}^{\pm}$
    else
        Soft update: $\lambda_t^{(k+1)}$ according to (6.13)
    end
    Update $\|r_t^{(k)}\|_2$, $\|s_t^{(k)}\|_2$, $k = k + 1$
end

each day and takes decisions based on the load and PV power production forecast for each site. For simplicity, the study considers only one FR which is for one period (1 hour).

The simulation set-up will be complete by adding a battery to each household, which is the flexibility source and the battery model is explained in the Section 6.3. Battery parameters for the case study are the investment cost which is EUR 3,000 for the first site and it is increased in steps of 1% for the successive sites. Moreover, batteries' maximum charging and discharging power are 3.8 kW and capacity is 10 kWh for all batteries. Battery converter parameters and efficiency are taken from technical data sheet of SMA-SBS3.7-10 converter by assuming the average operational voltage is $V_{DC} = 550$ V [261]. The diversity in the battery technology and their ageing in the considered population of 100 batteries are also represented by their efficiency. The battery efficiency for the first site is considered as 98% and the battery efficiency in the successive households are reduced in steps of 0.1%. The values used for constant voltage charging parameter and calendar ageing related parameters are as follows $W_i^{bat} = 0.2$, $S_i^{LT} = 10$ years, $S_i^0 = 0.3$ and $S_i^{SOC} = 1.7$ according to [254,256], and they are the same for all battery units. The cycle ageing model considers the battery as 10 segments.

The FR in this case study is formulated to reduce the evening peak at 8 pm according to the local DSO needs. Though the household consumption shows a peak at 10 pm, the network congestion can happen at hours other than hours at which the households portfolio shows a peak. Therefore, the present case study does not cut the portfolio peak as it is not the purpose of the present flexibility service provision.

6.8 Results

6.8.1 Site level optimization

In site level optimization, every individual prosumer is optimized to achieve low energy cost independent from others. Fig. 6.2 shows the aggregated results of problem (6.5). Results show that batteries are partially charged during the afternoon to store the PV power production surplus and they are discharged during the evening. This phenomenon is due to calendar ageing penalty, batteries tend to charge at the latest possible low priced period to reduce the time between charge and discharge. In addition, the cycling and calendar ageing factors prevent to charge and discharge batteries for arbitrage as the economic margin does not surpass the battery degradation costs. It is noticeable that some PV systems are oversized. As there is not

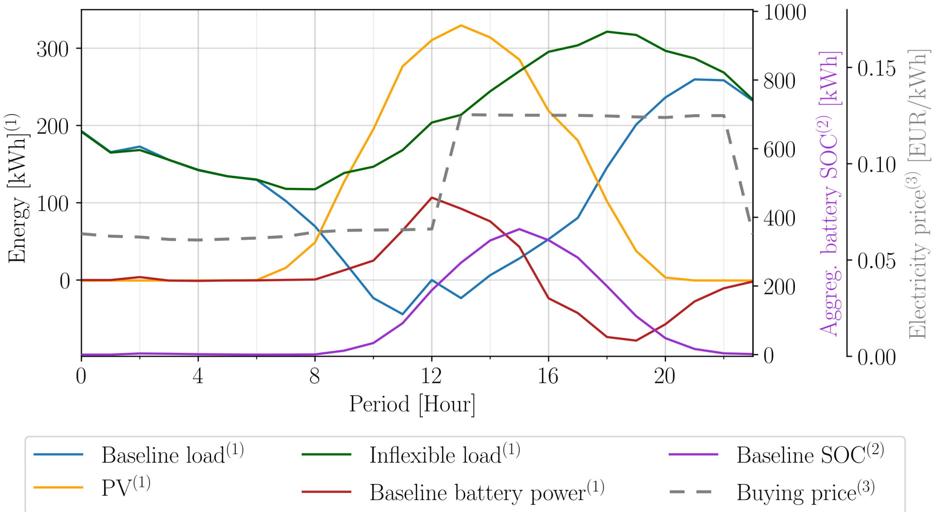


Fig. 6.2: Aggregated results of the site level optimization problem (6.5)

enough load during sunny hours or battery capacity, the baseline load shows some periods with net aggregated export of energy.

The aggregation of each site's net load after optimization of the case study forms the baseline load and it is shown in Fig. 6.3

6.8.2 Centralised flexibility provision

This section shows the results of centralised ALFO and ALFM algorithms for the described case study. The available flexibility is calculated by the ALFO problem (6.6). The FR is for 400 kWh at 8 pm and the households portfolio provides 308.86 kWh as the maximum available flexibility. Aggregator cannot provide more flexibility as some battery discharges are already scheduled by the site optimization problem. Fig. 6.3 shows the increase in battery charging during the hours before FR to charge all batteries sufficiently for latter discharge at 8 pm during FR.

Afterwards, the accepted FR is 50 kWh (lower than the available maximum flexibility). Therefore, the ALFM step (6.8) is executed to re-schedule batteries to meet the accepted FR. Fig. 6.4 shows the new feasible solution for the accepted FR at minimum cost for all sites. The complexity of the case study is the significant number of possibilities to attend the accepted FR as the it represents 17% of the portfolio available flexibility. From computational point of view, the accepted FR constitutes a complicated case

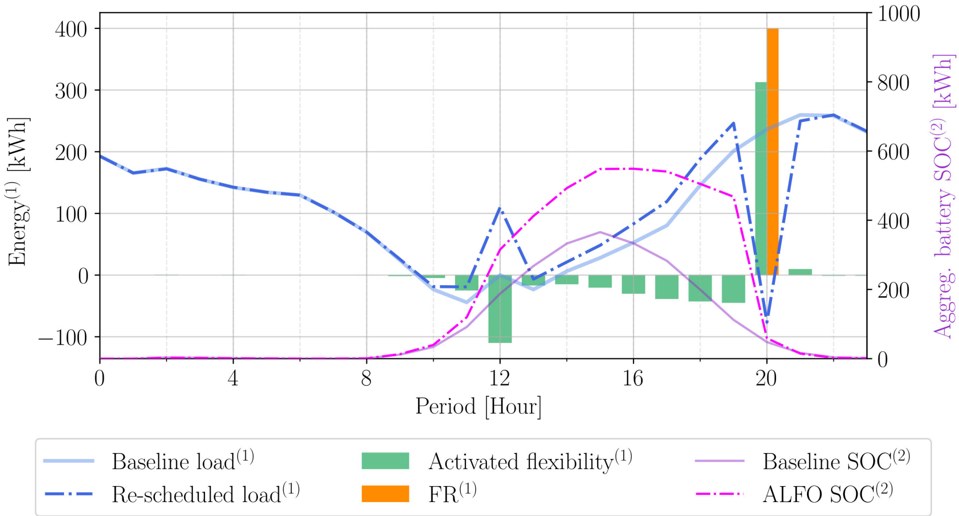


Fig. 6.3: ALFO problem results of re-scheduling of 100 sites and batteries under a FR of 400 kWh.

as many combinations of batteries could satisfy constraint (6.8b) at similar cost.

6.8.3 Distributed flexibility provision

The proposed distributed ADMM Algorithm 2 is tested with the same case study compared with centralised algorithm. Fig. 6.5 shows the primal and dual errors, dual variable $\lambda_t^{(k)}$ and the total prosumer cost converge for 11 iterations. The rate of change of primal error in successive iterations is high till the iteration $k = 5$. After that, the error variation is low. This phenomenon is due the fast dual variable updating according to (6.12a) when error is lower than 5% of FR. Thereafter, the soft updating is activated and it changes error rate smoothly by avoiding large variations. The initial value of $\lambda_t^{(0)}$ at zero provides a solution which corresponds to the site optimization result. When Algorithm 2 updates $\lambda_t^{(k)}$, the portfolio tends to increase flexibility provision and the primal error decreases. The solution is found in less than 5 minutes and the memory usage is very low (around 200 MB) as each iteration is a separated optimization problem per site and the memory contents are flushed after each iteration.

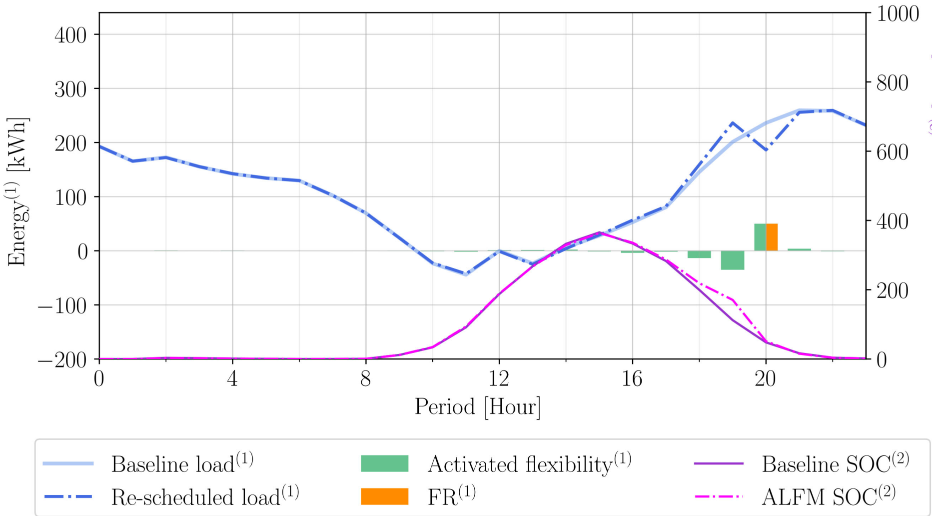


Fig. 6.4: ALFM problem results under a FR of 50 kWh of 100 sites.

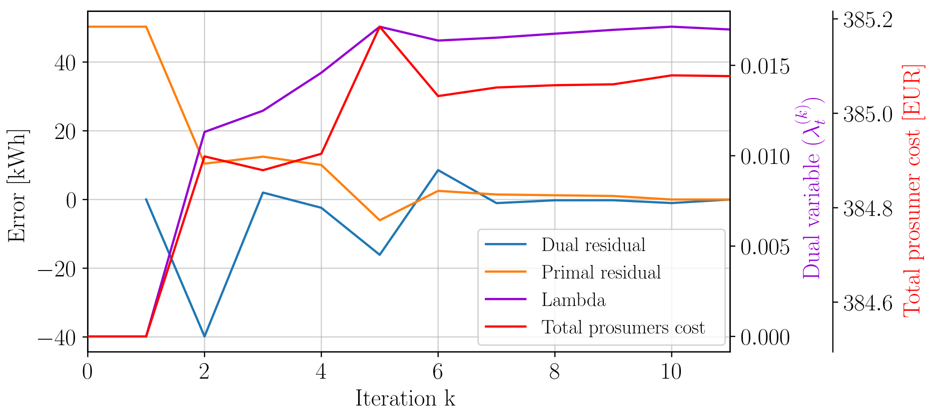


Fig. 6.5: Comparison of errors, total prosumers costs and dual variable per iteration of Algorithm 2 with $K^i = 2 \cdot 10^{-4}$ and $K^d = 5 \cdot 10^{-7}$.

6.8.4 Scalability analysis

Regarding scalability limitations, the centralised algorithms using the Gurobi solver with the branch-and-bound and the dual simplex algorithms, they consume the maximum available RAM memory of 16 GB for the 100 sites case study and takes approximately 1 hour to solve the ALFO problem and around 20 minutes for the ALFM problem on high performance computer with AMD Ryzen Threadripper 16 Core Processor running at 3.5 GHz. The ALFO problem takes more time due to the quadratic flexibility penalty term in the objective function. Fig. 6.6 shows that the Fast-PJ-ADMM Algorithm 2 which finds solutions at similar duration in comparison with ALFM and ALFO problems in the case with 50 sites but centralised algorithms take between 5 and 12 folds more time for the 100 sites case. Therefore, there is a scalability limit to solve large-scale flexibility problems with complicating constraints (6.8b) and (6.8c), and detailed battery models using centralised algorithms.

From a theoretical perspective the situation is the following. As the complexity of the model increases by including more sites, the centralised algorithms begin to suffer because of the exponential increase of paths within the binary variable decision tree. Additionally, these algorithms are not parallelisable due to intrinsic limitations. The ADMM parallelisation solves these two issues. First, it limits the size of each decision tree by restricting the binary variables to those corresponding to that particular site. Additionally, it enables to solve each site independently by applying the original centralised algorithm now to a problem several orders of magnitude smaller. We claim that this solution is scalable since individual site problems remain of constant size independently of the number of sites in the general problem.

6.8.5 Distributed algorithm acceleration comparison

This section discusses around four versions of the ADMM algorithms previously presented in the literature namely Regular (orignal algorithm [242]), Fast (acceleration via penalty parameter [242]), PJ (parallelized, regularized version [258]), and Fast-PJ (combination of acceleration, parallelization, and regularization), and the novel version Two-steps Fast-PJ Algorithm 2 by comparing the way penalty parameter ($\lambda_t^{(k)}$) is updated for the optimal flexibility exchange problem in each algorithm. Therefore, it is possible to see the impact of acceleration, parallelization, regularization and the two-step algorithm modifications. All accelerated algorithms begin with the same penalty parameter value ($\rho^{(0)} = 10^{-4}$) and they continue with the soft up-

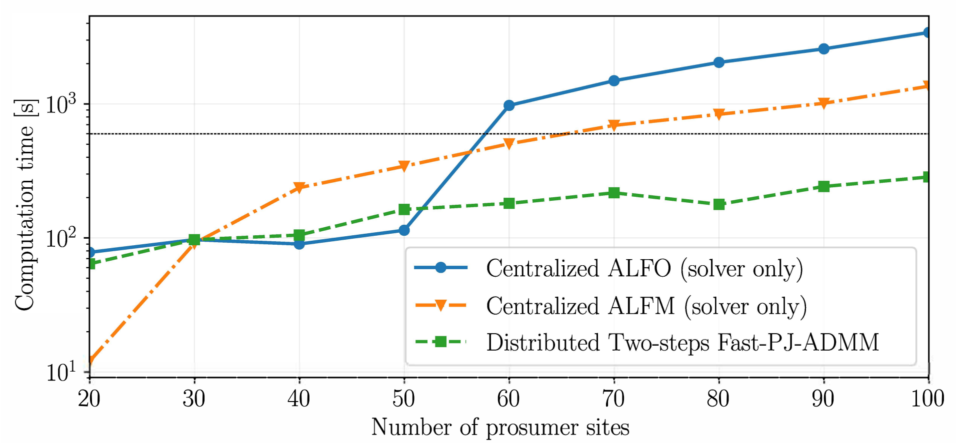


Fig. 6.6: Computational cost comparison of ALFO, ALFM and Fast-PJ-ADMM Algorithm 2. Horizontal dashed line highlights 10 minutes computation time threshold.

date when $\|r_t^{(k)}\|_2$ and $\|s_t^{(k)}\|_2 \leq 0.05$ kWh.

Fig. 6.7 shows a comparison of absolute primal error values change per iteration of different distributed optimization algorithms. It is to be noted that the absolute error value hide cases when primal errors varies between positive and negative values as shown in Fig. 6.5. Although they are reaching the same optimal cost, the regular ADMM with $\rho = 10^{-5}$ takes 20 iterations to find a solution with primal error $r_t^{(k)} = 20$ kWh, and 200 iterations for 1% error. In case of increasing the penalty parameter to $\rho = 10^{-4}$, the regular ADMM performance differs from the previous case near sub-optimal solutions from *k=4*. This phenomenon is due to the drastic change in dual update. The regular ADMM and all the following algorithms proved to provide better solutions if they use an initial value for dual variable as $\lambda_t^{(0)} = 0$. Thus, the performance of the algorithm differs from no flexibility provision to the optimal battery schedule to provide full FR.

The Fast-ADMM changes the penalty parameter according to (6.11) using the following acceleration parameters: $\tau^{incr} = 1.5$, $\tau^{decr} = 2$ and $\mu = 2$. In all accelerated algorithms, dual variable λ_t changes at a higher rate between successive iterations until iteration *k=5* where they reach a primal error equal or lower than 5% of FR ($\|r_t^{(k)}\|_2 = 2.5$ kWh). Thereafter, their performance differs from each other around the optimal solution. The inclusion of the PJ regularization term in the Algorithm 2 according to [246] allows to stabilize the objective function and it finds an optimal solution with 2% er-

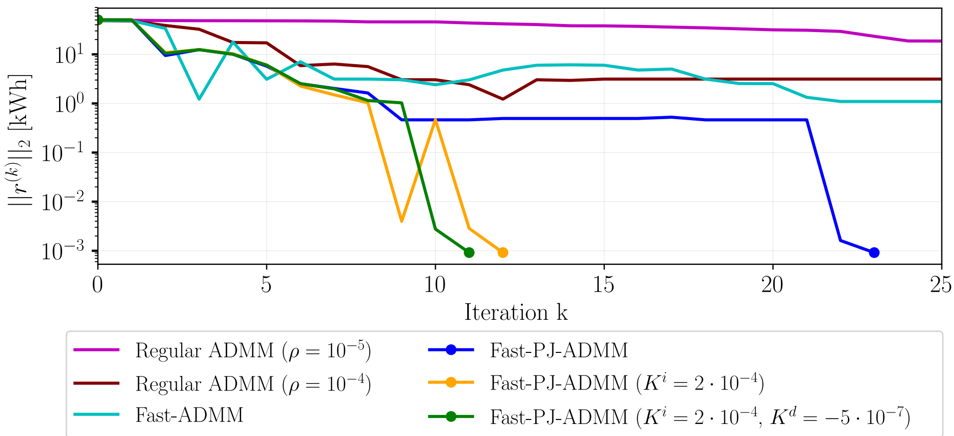


Fig. 6.7: Primal error comparison of different acceleration algorithms under a FR at 8 pm of 50 kWh in a portfolio of 100 sites including the soft updating in all algorithms when $r^{(k)} = 2.5$ kWh. Markers indicate when algorithms meet $\epsilon^{pri} = \epsilon^{dual} = 10^{-3}\%$.

ror in 9 iterations. Additionally, it finds an optimal solution ($\epsilon^{pri} < 10^{-3}\%$) in 24 iterations if parameters are $\rho^{(0)} = 10^{-4}$ and $K^d = K^i = 0$ during the soft update. In contrast to the previous algorithms, Fast-PJ-ADMM Algorithm 2 with $K^i = 2 \cdot 10^{-4}$ and $K^d = -5 \cdot 10^{-7}$ finds the optimal solution in 11 iterations. The effect of K^i is to faster approach to the objective function expected value and K^d smooths variations.

Fig. 6.8 shows the total prosumer cost variation over the resolution time of centralised and multiple distributed algorithms. This cost corresponds to the primal objective without the dual objective in order to compare the ADMM results with the ALFM branch-and-bound and dual simplex algorithm. Moreover, the ADMM results tend to increase from the starting point as the initial dual variable (λ_t) is initiated with null value. All methods find very similar solutions but they approach to the objective value differently. The centralised ALFM algorithm takes 2,000 seconds before reaching a feasible solution. In contrast, most of distributed algorithms find a suitable solution in less than 200 seconds. Notice the Regular ADMM takes 3,000 seconds to reach the optimal value and the Fast ADMM varies around the optimal solution. The PJ regularization term reduces variations and the K^i and K^d parameters allow to accelerate the path to the optimal objective cost without creating variations in the objective function. The reader can observe that the starting point of ADMM algorithms is close to the primal final

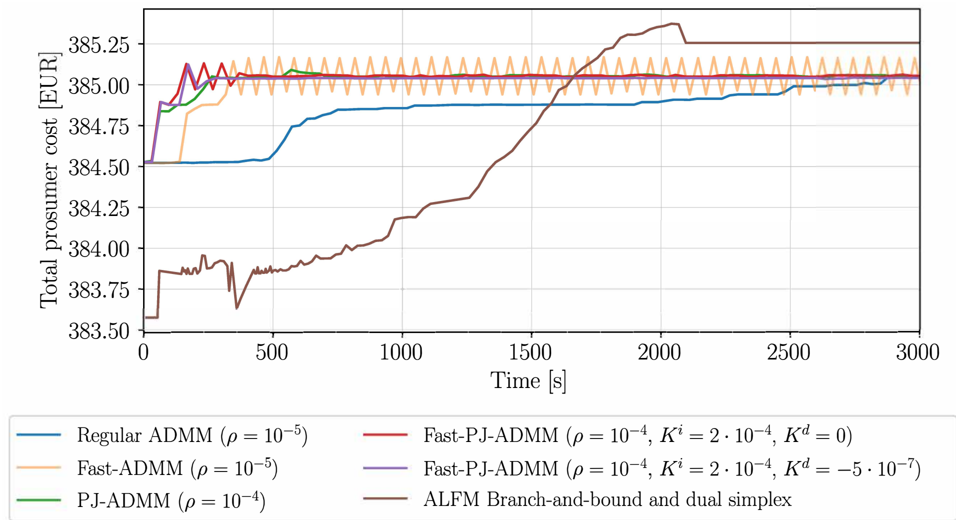


Fig. 6.8: Prosumer total cost over computation time of centralised and distributed algorithms with FR=50 kWh and $\epsilon^{pri} = \epsilon^{dual} = 10^{-5}\%$.

objective. However, Fig. 6.7 shows this is not a valid solution. Additionally, it is relevant to mention that the initial point, when $\lambda_t^{(k=0)}$, is equivalent to the site optimization problem (6.5) which is previously calculated and the addition of the FR in the problem is not significant in terms of the primal objective. However, the dual objective changes significantly as Fig. 6.9 shows. In the case of the regular ADMM it takes more than 2,000 seconds to convergence. Regarding modified ADMM algorithms, Fast and PJ-ADMM algorithms accelerate their convergence and Fast-PJ-ADMM algorithms get stable in less than 500 seconds.

6.8.6 Sensitivity analysis

FR=50 kWh

Fig. 6.10 shows the results of the regular ADMM with FR=50 kWh. It takes more than 10 times more iterations compared to the 11 iterations needed previously in Fig. 6.7. The objective function result when the algorithm meets the stopping criteria is EUR 385.05.

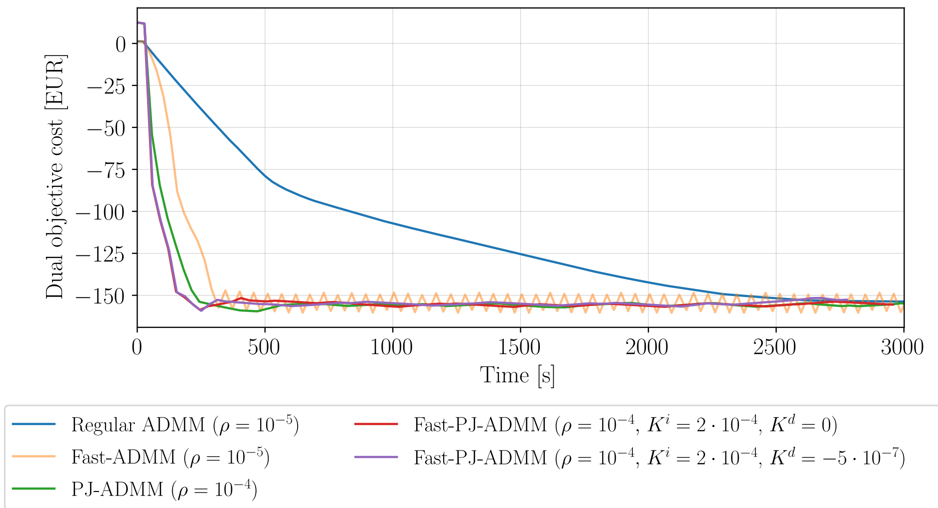


Fig. 6.9: Dual objective cost over computation time of distributed algorithms with FR=50 kWh and $\epsilon^{pri} = \epsilon^{dual} = 10^{-5}\%$.

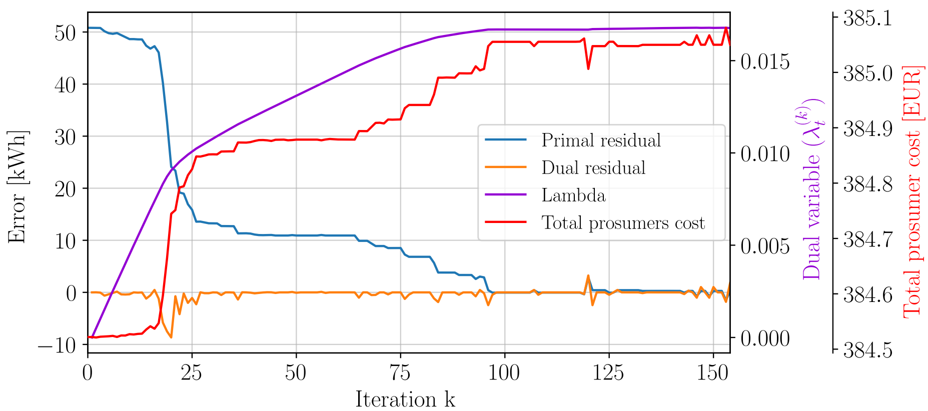


Fig. 6.10: Results of the regular ADMM Algorithm with $\rho = 5 \cdot 10^{-5}$ and FR=50 kWh

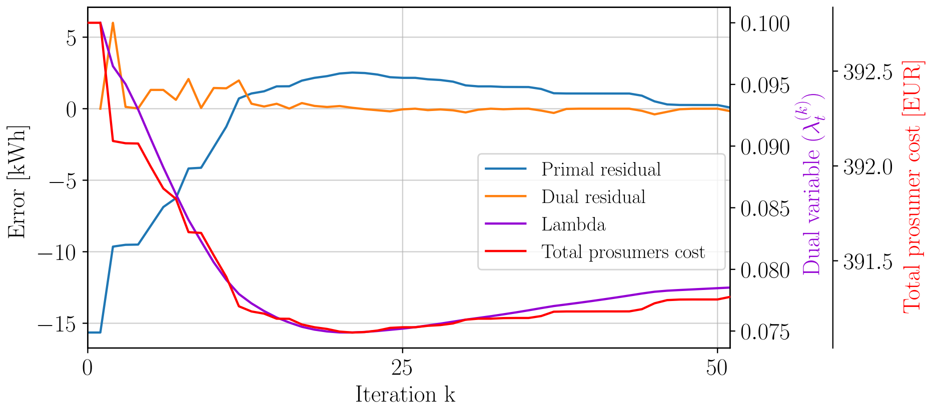


Fig. 6.11: Results of the Algorithm 2 of $\lambda_t^{(0)} = 0.1$ and FR $= 200$ kWh

FR=200 kWh

Fig. 6.11 shows primal and dual errors changing each iteration with Algorithm 2 with initial $\lambda_t^{(0)}$ =0.1. It takes 24 minutes to reach a solution with 0.1% error over the FR but in 5 minutes at iteration 13, errors are below 1%. It is noticeable the primal residual variation. In case of high initial value of $\lambda_t^{(0)}$, the portfolio provides more flexibility than needed and reducing lambda it approaches to the minimum objective function value.

Fig. 6.12 shows the Algorithm 2 results if the initial $\lambda_t^{(0)}$ is zero as no flexibility provision and the stopping criteria is thousand times smaller than in previous cases. It can reach very good results in a few iterations but it cannot find solutions below 0.01% error over the FR. That is probably due to the non-linearities from the battery model. Therefore, the algorithm as it is here can be not suitable for very error sensitive cases with several binary variables.

6.9 Conclusions

The present work provides a novel formulation to optimize the operation of distributed storage units behind-the-meter to provide flexibility services to a balance responsible party or distribution system operator. In this context, an aggregator manages a group of prosumers with storage units who are willing to participate in the local flexibility market. In addition, this chapter includes the decomposed optimization problem formulation for large-scale

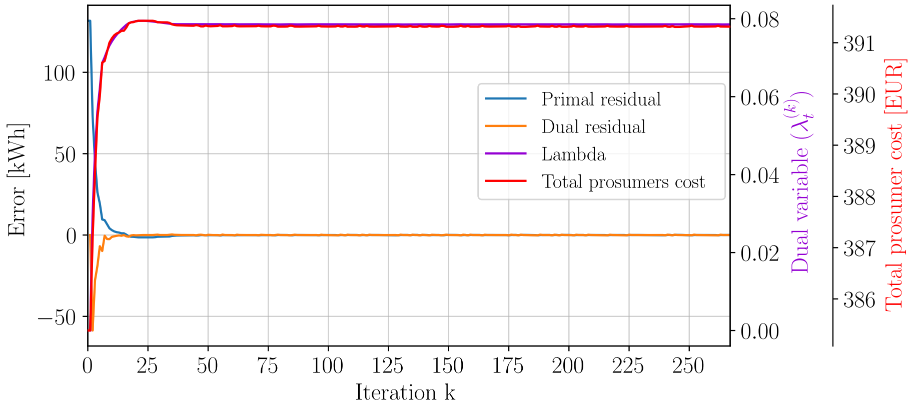


Fig. 6.12: Results of the Algorithm 2 of $\lambda_t^{(0)} = 0$ and FR = 200 kWh

portfolios using a modified accelerated PJ-ADMM algorithm divided in two steps: fast and soft dual variable updating. The fast and soft updating accelerate the iterative process reducing variations in the dual variable and objective functions. The soft update might be relevant for case studies with binary variables as dual errors can be zero although the dual variable changes. Case study results show that this formulation is best suited for large scale implementations as it can find aggregated optimal solutions faster by considering local constraints and prices with the appropriate parameters tuning. The results also highlight that the centralised and distributed methods find very similar solutions but the distributed one can overcome the scalability limitations. For instance, the case study shows a break-even point at 50 prosumer sites when the distributed algorithm is less computationally demanding than the centralised.

Chapter 7

Conclusions

This thesis gathers several studies related to local markets and each chapter provides specific and detailed conclusions. Moreover, the present chapter exposes the main thesis conclusions, includes a summary of contributions and lists some further work needed to solve open issues.

7.1 General conclusions

After all work presented in the current document, the main conclusion is about the presented technical algorithms to manage flexibility from distributed resources. It is important to mention this thesis relies on the assumption there is a communication platform to send control signals to flexibility devices. Recent developments in fields such as internet-of-things, communication protocols and standards, and big data technology allow us to be confident very soon there will be effective and cheap ways to interconnect machines. On top of that, recent developments in optimization solvers and artificial intelligence are crucial tools to solve large-scale problems based on historic values.

The initial research question of the thesis was about the possibility of electric vehicles charging demand threatening local grids and electricity markets in the future. The conducted studies presented in Chapter 2 aim to prove how technical solutions could alleviate potential risks in distribution grids. Moreover, the present work concludes aggregation agents could help network operators to avoid grid congestions in a beneficial way for all involved actors. Additionally, electricity market prices could become more volatile due to electric vehicles consumption peaks and market marginal price effect. However, electricity cost could be reduced implementing energy management systems (EMSs) provided by aggregators responding to price variations. Thanks to the recent regulatory developments from the EU Commission, there will be business models in the near future when EVs are more numerous and electricity price volatility increases.

Furthermore, new regulatory developments are expected to promote more coordination between TSOs, DSOs and aggregators. National regulatory agencies have to define economic incentives for DSOs to solve grid constraints without increasing its capacity and TSO ancillary service markets must be open for distribution-level demand response. The current regulation is not sufficient to prevent potential grid outages as there are not price signals during unexpected grid congestions, grid tariffs are based on day time, not on events, and there is no regulatory framework to economically compensate demand response for dealing with local network congestions.

After proving there could be situations with grid capacity limitations due to high consumption periods where aggregators could provide solutions, the consequent research question would be which is the way aggregators can activate flexibility for different purposes and circumstances. Moreover, how aggregators decide which flexibility to activate depending on time of day, value of activation and the volume of requested flexibility. In such question, it is necessary to consider the presence of variable and distributed generators as wind turbines and photovoltaic panels as they can alleviate or enlarge the issue. The holistic local market design presented in Chapter 3 named day-ahead micro-market (DAMM), could represent a solution to integrate more renewable generation, provide price signals to demand response and better usage of storage units. However, the deployment of such local markets would require significant regulatory changes in the European Union as local market operators should take some of current distribution grid operator roles. Additionally, it requires a significant development of automatic trading agents and artificial intelligence algorithms for house-level bidding tasks. As a result, the author realised regulatory obstacles to implement DAMMs where very difficult to break in the short term considering the current trend in the EU unbundling utility companies. Therefore, the research after that period was focused on what was possible considering the EU unbundling regulatory framework. However, other countries with vertically integrated utilities could implement DAMMs for managing distributed energy resources. The main advantage of the DAMM is the new role of grid operators dispatching flexibility in a way the obtained solution satisfies both end-users needs and grid operation constraints while activating the cheapest distributed flexibility.

Once the DAMM local market design is dismissed for its application in the EU, Chapter 4 deals with the possibility of organizing a local market for flexibility provision from a population of customers managed by an aggregator within the current or near future EU regulation. Nevertheless, it was necessary to assume regulators will remunerate local grid operators for activating flexibility instead of network expansions. This assumption is not yet true and nowadays it is under consideration by regulatory bodies but results obtained in Chapter 2 allow us to be optimistic in the mid-term horizon when real problems would occur. Moreover, the logic candidates to manage such kind of local markets are aggregators due to their spirit of controlling distributed resources. However, retailers or balance responsible parties could manage local markets as well. The main conclusion of Chapter 4 is the way to organize flexibility activations through a small-scale market. Still there are some pending aspects which could be case dependent like the way profits are shared between an aggregator and its energy community, what messages are necessary between aggregator, BRP, DSO and energy community members, what is the minimum number of participants to create an efficient and fair local market, and the way to prevent abuse of a dominant market positions by big energy consumers in the local market.

Once Chapter 4 has set a general framework of LFM previously, it is important to show how they could operate. The aim of Chapter 5 is to present the minimum viable LFM algorithm for flexibility trading for its implementation in EMPOWER and INVADE H2020 project. Such LFM should help DSOs to avoid grid congestions sending flexibility requests to an aggregator. This work underlines the LFM possibilities to avoid grid outages. This work also highlights the necessity of defining a specific remuneration mechanism for every type of flexibility device. Nevertheless, this chapter assumes no information of each community member electricity contract. Mainly for this reason, the LFM can only apply demand response under DSO flexibility requests which restricts the business model severely and reduces aggregator potential profitability. Thus, the author concludes it is necessary to have more information from end-users such as smart meter records and electricity tariff to make LFM more valuable in technical and economic terms.

Chapter 6 includes electricity bill information and site-level electricity consumption in the LFM problem. Consequently, LFM can become more beneficial for energy communities as they can offer flexibility services for prosumer optimal scheduling and aggregated level optimization. For example, in case a DSO detects a local grid constraint, it can request flexibility to alleviate the grid congestion. Similarly, a BRP could reduce its cost of market position instead of bidding in the intraday market or paying deviation penalties. The author concludes the multi-objective approach is technically possible when DSOs and BRPs are able to send flexibility requests to the LFM.

It is noticeable the scalability limitation of the centralised algorithm while requires private information such as energy consumption and contract data with other parties. Then, last research question of the present thesis is related to develop a distributed LFM operation algorithm which can prevent privacy-related issues and scale-up to thousands of energy community members without simplifications. In order to provide a solution, the author presented a decomposition algorithm based on the alternating direction method of multipliers (ADMM) algorithm which can reduce the computational burden and time in order to make aggregated flexibility markets free to scale up. Additionally, this algorithm could be executed from multiple computation devices for reaching aggregated solutions without sharing private information. The author determines the principles of such algorithm and provides a basis for further development. Nevertheless, there are still pending questions such as the system architecture, cost of communications and computation time in real cases.

To sum up, the operation of demand response with distributed energy resources is technically possible, the market-based structure ensures a clear mechanism to integrate different community members' willingness to participate and further regulatory changes are needed to fully deploy their potential.

7.2 Contributions

The main contributions are listed below:

- Chapter 2:
  - Development of an agent-based algorithm to estimate future EV charging demand based on social and mobility data from local surveys and test this methodology in a case study of Barcelona with a IEEE adapted reference medium-voltage grid.
  - Analyse the potential impact on prices due to the new demand from EV charges based on national level mobility data in the Spanish day-ahead market using data of 2012 in cases of uncontrolled EV charging.
  - Provision of a flexibility management system for scheduling electric vehicles in buildings for cases of limited information access and receiving capacity limitations from the local grid operator.
- Chapter 3:
  - Development of a local market (DAMM) for variable renewable energy production better integration considering grid constraints

in the algorithm. This design offers the possibility of using centralised energy storage units to increase the local social welfare.

- Chapter 4:
  - Description of a local flexibility market for aggregators managing a portfolio of flexibility devices in a market-based manner. This thesis contributes with the roles, flexibility contracts and market interactions between, BRP, DSO and aggregator.
- Chapter 5:
  - Formulation of a flexibility market optimization problem for meeting DSO flexibility requests using a portfolio of flexibility devices managed by an aggregator. This algorithm is tested by simulation and emulation.
- Chapter 6:
  - Extension of the flexibility market problem with the formulation and simulation of a centralised algorithm which includes the electricity cost and constraints of each site and flexibility device.
  - Decomposition of the centralised optimization problem in case of facing computation limitations.

7.3 Future work

Local markets are a new topic with multiple approaches and ways to solve local grid congestions. Even though local markets are still under development an a few pilots are deployed for early testing, there are significant gaps in the literature and some open questions for more research. Probably the most important question is the local market profitability and minimum market size but both depend on regulation.

Additionally, this thesis discusses all pending questions in detail in each chapter. Moreover it provides resume of topics for future work regarding each chapter:

- Chapter 2:
  - Provide a site level energy management system including stochastic variables and new forecast inputs of each new decision period.
  - Analyse data of electric vehicle charging patterns from real cases.

- Chapter 3:
  - Extend the flow-based local market design for managing different flexibility devices applied to citizen energy communities operating their own distribution grid bidding intraday and balancing markets.
  - Consider the influence and interactions of the distribution locational marginal pricing in local markets.
  - Assess the influence of wholesale and local price variations on flexibility decisions and centralised energy storage performance.
- Chapter 4:
  - Analyse the economic viability of the local market design under a regulatory framework which specifies the remuneration of flexibility services for congestion management.
  - Develop the traffic light concept applied to local markets for dealing with conflicts between DSO and BRP flexibility requests.
  - Develop a business model and relation between aggregator and energy communities.
  - Develop market rules for increasing mutual trust in order to strength DSO-Aggregator and BRP-Aggregator relations.
- Chapter 5:
  - Develop new optimization flexibility models without binary variables to reduce computational burden and time.
- Chapter 6:
  - Include new energy resource models in the centralised flexibility provision algorithm like electric water heaters, space heaters or electric vehicles.
  - Improve the centralised algorithm code to reduce computational time and compare other solvers like CPLEX or CBC.
  - Test the distributed flexibility provision algorithm with other case studies and flexibility requests
  - Design a methodology to define the ADMM parameters of this formulation.
  - Test the distributed algorithm in peer-to-peer electricity markets for optimal exchange of energy and/or flexibility

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Appendix A

Publications

This chapter presents the publications related to the specific topics of this thesis the author has contributed to. This list includes 4 journal papers (3 published and 1 submitted), 9 conference papers, and 5 book chapters included in the thesis. Additionally, 6 journal papers, 1 journal paper submission, 10 conference papers, 4 conference presentations, 10 supervised bachelor and master thesis, and 13 technical reports were developed during the thesis period but not included in the thesis in collaboration with colleagues.

Included in the thesis

Published journal papers

J1 P. Olivella-Rosell, R. Villafafila-Robles, A. Sumper, J. Bergas-Jané, "Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks," *Energies*, vol. 8, no. 5, pp. 4160-4187, May 2015. doi: 10.3390/en8054160

J2 P. Olivella-Rosell, P. Lloret-Gallego, Í. Munné-Collado, R. Villafafila-Robles, A. Sumper, S. Ottesen, J. Rajasekharan, B. Bremdal, "Local flexibility market design for aggregators providing multiple flexibility services at distribution network Level," *Energies*, vol. 11, no. 4, p. 822, Apr. 2018. doi: 10.3390/en11040822

J3 P. Olivella-Rosell, E. Bullich-Massagué, M. Aragüés-Peñalba, A. Sumper, S. Ottesen, J. Vidal-Clos, R. Villafafila-Robles, "Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources," *Applied Energy*, vol. 210, no. 15, pp. 881-895, Jan. 2018. doi: 10.1016/j.apenergy.2017.08.136

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S-J1 P. Olivella-Rosell, F. Rul·lan, P. Lloret-Gallego, E. Prieto-Araujo, R. Ferrer-San-José, S. Barja-Martinez, S. Bjarghov, V. Lakshmanan, A. Hentunen, J. Forsström, S. Ø. Ottesen, R. Villafafila-Robles, A. Sumper, "Centralised and distributed optimization for aggregated flexibility services provision," *Submitted to IEEE Transactions on Smart Grid.* Available in arXiv:1907.08125

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C1 R. Villafafila-Robles, F. Girbau-Llistuella, P. Olivella-Rosell, A. Sudrià-Andreu, J. Bergas-Jané, "Assessment of impact of charging infrastructure for electric vehicles on distribution networks," *15th European Conference on Power Electronics and Applications (EPE)*, Lille, France, Sep. 2013. doi: 10.1109/EPE.2013.6634671

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C3 P. Olivella-Rosell, G. Viñals-Canal, A. Sumper, R. Villafafila-Robles, B. A. Bremdal, I. Ilieva, S. Ø. Ottesen, "Day-ahead micro-market design for distributed energy resources," *IEEE International Energy Conference (ENERGYCON)*, Leuven, Belgium, Apr. 2016. doi: 10.1109/ENERGYCON.2016.7513961

C4 I. Ilieva, B. Bremdal, S. Ø. Ottesen, J. Rajasekharan, P. Olivella-Rosell, "Design characteristics of a smart grid dominated local market," *CIRED Workshop*, Helsinki, Finland, June 2016. doi: 10.1049/cp.2016.0785

C5 P. Olivella-Rosell, J. Rajasekharan, B. A. Bremdal, "Design and operational characteristics of local energy and flexibility markets in the distribution grid," *SET Plan Central Europe Energy Conference*, Bratislava, Slovakia, Dec. 2016.

C6 B. A. Bremdal, P. Olivella-Rosell, J. Rajasekharan, "Creating a local energy market," *CIRED Conference*, Glasgow, Scotland, United Kingdom, June 2017. doi: 10.1049/oap-cired.2017.0730

C7 B. A. Bremdal, P. Olivella-Rosell, J. Rajasekharan, "EMPOWER: A network market approach for local energy trade," *IEEE PowerTech*, Manchester, United Kingdom, June 2017.
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C8 P. Olivella-Rosell, P. Lloret-Gallego, R. Villafafila-Robles, S. Ø. Ottesen, R. Gallart-Fernandez, A. Sumper, "The INVADE Project: Towards the flexibility operator concept and its application to the Spanish pilot," *CIRED Workshop*, Ljubljana, Slovenia, June 2018. doi: 10.5281/zenodo.3258018

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BC2 P. Olivella-Rosell, J. Rajasekharan, B. A. Bremdal, R. Villafafila-Robles, A. Sumper "Design and operational characteristics of local energy and flexibility markets in the distribution grid," in Nicoló Rossetto (ed) Design the electricity market(s) of the future. Proceedings from the Eurelectric-Florence School of Regulation conference, European University Institute, pp. 6-10, 2017 doi: 10.2870/420547

BC3 Í. Munné-Collado, P. Olivella-Rosell, A. Sumper, "Power Market Fundamentals," in A. Sumper (ed) Micro and Local Power Markets, John Wiley & Sons, pp. 1-35, 2019. doi: 10.1002/9781119434573.ch1

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BC5 P. Olivella-Rosell, S. S. Torbaghan, M. Gibescu, "Coupled Local Power Markets," in A. Sumper (ed) Micro and Local Power Markets, John Wiley & Sons, pp. 165-191, 2019. doi: 10.1002/9781119434573.ch4

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J4 N. Leemput, F. Geth, J. Van Roy, P. Olivella-Rosell, J. Driesen, A. Sumper, "MV and LV Residential Grid Impact of Combined Slow and Fast Charging of Electric Vehicles," *Energies*, vol. 8, no. 3, pp. 1760-1783, Mar. 2015. doi: 10.3390/en8031760

J5 E. Prieto-Araujo, P. Olivella-Rosell, M. Cheah-Mañe, R. Villafafila-Robles, O. Gomis-Bellmunt, "Renewable energy emulation concepts for microgrids," *Renewable and Sustainable Energy Reviews*, vol. 50, pp. 325-345, Oct. 2015. doi: 10.1016/j.rser.2015.04.101

J6 P. Lloret-Gallego, M. Aragüés-Peñalba, L. Van Schepdael, E. Bullich-Massagué, P. Olivella-Rosell, A. Sumper, "Methodology for the evaluation of resilience of ICT Systems for smart distribution grids," *Energies*, vol. 10, no. 9, p. 1287, Aug. 2017. doi: 10.3390/en10091287

J7 E. Bullich-Massagué, F. Díaz-González, M. Aragüés-Peñalba, F. Girbau-Llistuella, P. Olivella-Rosell, A. Sumper, "Microgrid clustering architectures," *Applied Energy*, vol. 212, no. 15, pp. 340-361, Feb. 2018. doi: 10.1016/j.apenergy.2017.12.048

J8 S. Fuentes-Ruiz, R. Villafafila-Robles, P. Olivella-Rosell, J. Rull-Duran, "International tendencies on energy security," *ENERLAC*, *Accepted.*

J9 Í. Munné-Collado, F. M. Aprà, P. Olivella-Rosell, R. Villafafila-Robles, A. Sumper, "The potential role of flexibility during peak hours on greenhouse gas emissions: a life cycle assessment of five targeted national electricity grid mixes," *Energies*, vol. 12, no. 23, Nov. 2019. doi: 10.3390/en12234443

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S-J2 S. Fuentes-Ruiz, R. Villafafila-Robles, P. Olivella-Rosell, J. Rull-Duran, S. Galceran-Arellano, "Transition to a greener power sector: Four different scopes on energy security," Submitted to *Renewable energy focus*

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C10 B. Felisart-Serlavos, R. Villafafila-Robles, P. Olivella-Rosell, R. Ramírez-Pisco, A. Sudrià-Andreu, "Energy market regulations for electric vehicle encourage. Study of current frames," *XIII Conferencia hispano-lusa de ingeniería eléctrica (XIII CHLIE)*, València, Spain, Jul. 2013.

C11 M. Yagües, P. Olivella-Rosell, R. Villafafila-Robles, A. Sumper, "Ageing of electric vehicle battery considering mobility needs for urban areas," *International Conference on Renewable Energies and Power Quality (ICREPQ'14)*, Córdoba, Spain, Apr. 2014.

C12 D. Valero-Bover, P. Olivella-Rosell, R. Villafafila-Robles, S. Cestau-Cubero, "Performance analysis of an electric vehicle fleet for commercial purposes," *IEEE International Electric Vehicle Conference (IEVC)*, Florence, Italy, Dec. 2014. doi: 10.1109/IEVC.2014.7056161

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C16 S. Barja-Martinez, P. Olivella-Rosell, P. Lloret-Gallego, R. Villafafila-Robles, A. Sumper, "A scheduling optimization model of electric water heaters for electricity cost minimization with limited information," *Modern Power Systems (MPS)*, Cluj-Napoca, Romania, May 2019.

C17 S. Barja-Martinez, P. Olivella-Rosell, P. Lloret-Gallego, R. Villafafila-Robles, "Centralized flexibility services for distribution system operators through distributed flexible resources," *Congreso Iberoamericano de Ciudades Inteligentes (ICSC-CITIES)*, Soria, Spain, Oct. 2019.

C18 I. Munné-Collado, P. Lloret-Gallego, P. Olivella-Rosell, R. Villafafila-Robles, S. Ø. Ottesen, R. Gallart-Fernandez, V. Palma-Costa, A. Sumper, "System architecture for managing congestions in distributions grids using flexibility,"

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P-C1 Presentation of "Microxarxes i biomassa," in *Congrés d'energia de Catalunya*, Tarragona, Spain, Apr. 2014.

P-C2 Presentation of "Electricity micro markets with centralised electricity storage," in *International Community Electricity Storage Workshop*, Berlin, Germany, Feb. 2016.

P-C3 Presentation of "Design and operational characteristics of local energy and flexibility markets in the distribution grid," in *Design the electricity market(s) of the future. Eurelectric & Florence School of Regulation*, Brussels, Belgium, Apr. 2017

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T2 R. Pacheco-Bubí, "Desenvolupament d'una eina de càlcul de flux de càrregues trifàsic per a sistemes desequilibrats," Bachelor's thesis, Universitat Politècnica de Catalunya, June 2015.

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T9 L. Haupt, "Centralised battery flexibility assessment for imbalance management in Spain considering lithium-ion degradation mechanism," MS thesis, Universitat Politècnica de Catalunya, Sep. 2018.

T10 N. Escobosa-Pineda, "Stochastic programming for home energy management system optimization," MS thesis, Universitat Politècnica de Catalunya, Sep. 2018.

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TR3 M. Aragüés-Peñalba, P. Lloret-Gallego, P. Olivella-Rosell, S. E. Tønnesen, C. Cordobés, "EMPOWER Deliverable 3.1 Control cloud technical architecture," Nov. 2015.

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