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Electric vehicle integration into distribution systems : Considerations of user behavior and frameworks for flexibility implementation

Felipe Gonzalez Venegas

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Electric vehicle integration into distribution systems. Considerations of user behavior and frameworks for flexibility implementation.

Thèse de doctorat de l'université Paris-Saclay

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**Thèse présentée et soutenue à Paris-Saclay,
le 9/07/2021, par**

Felipe GONZALEZ VENEGAS

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.

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Lists of Acronyms

EV	Electric vehicle
DER	Distributed energy resource
PV	Photovoltaic system
DSO	Distribution system operator
TSO	Transmission system operator
BRP	Balancing responsible party
BESS	Battery energy storage system
CO ₂	Carbon dioxide
NO _x	Nitrogen oxides
GHG	Greenhouse gas
ToU	Time of Use (electricity tariff)
BEV	Battery electric vehicle
PHEV	Plug-in hybrid electric vehicle
REX	Range-extender vehicle
SoC	State of charge
EVSE	Electric vehicle supply equipment (charging station)
V2G/H/B/X	Vehicle-to-grid/home/building/everything
V1G	Smart charging
FCR	Frequency containment response
ABM	Agent-based model
CEER	Council of European energy regulators
INSEE	French National Institute of Statistics and Economic Studies
GIS	Geographical information system
UKPN	UK Power Networks

LIST OF ACRONYMS

Nomenclature

Sets

EV Set of EVs

S_e Set of charging sessions for EV e

Parameters of EV agent-based model (Ch. 3)

d_i Daily distance driven for day i [km]

η Driving efficiency [kWh/km]

ν Charging efficiency

ν_d Discharging efficiency

b Battery size [kWh]

ρ Range anxiety factor

α Plug-in preference factor

SoC_i State of Charge at beginning of charging session for day i

ξ_i Required SoC for next day ($i + 1$) trips

E_s Charged energy in session s

Pch Charging power [kW]

\mathbf{x} Charging profile of an EV (vector)

n_{evs} Number of EVs

$AS_e(t)$ Accessible storage of EV e at time t

AS_f Average accessible storage of an EV fleet

ts_{avg} Average duration of a charging session

Parameters of EV integration into distribution grids (Ch. 4)

δ_{ev} EV diffusion

wr Access to work-place charging

$TotNev_{h/w,i}$ Total number of vehicles of residents/workers in infra-communal cell i

$Nev_{h/w,i}$ Number of simulated electric vehicles of residents/workers in infra-communal cell i

Parameters of long-term tenders (Ch. 5)

sd	Flexibility service duration
n_{act}	Number of flexibility activations per year
bs	Minimum bid size
aw	Availability window
Γ	Flexibility value [€ per firm kW]
Θ	Penalty [% of payment]
λ	Penalty threshold [% of committed flexibility]
CF_f	Committed flexibility of fleet f [kW]
$DF_{f,a}$	Delivered flexibility of fleet f at activation a
$ActPayment_{f,a}$	Activation payment of fleet f for activation a

Other variables

nd_e	Number of days of EV e spent in the Electric Nation trial
R	Resistance of conductor c [Ω/km]
X	Reactance of conductor c [Ω/km]
C	Capacitance of conductor c [nF/km]
V_{nom}	Nominal voltage [V]
ΔV	Voltage drop [V]
ΔV_{max}	Maximum allowed voltage drop in a feeder [V]
I	Current [A]
P	Active power [MW]
$Lmax_f$	Maximum length of feeder f [km]
κ	Security factor for rated current of conductors
$PVres/mid_{i/r}$	Installed capacity of small-scale/medium-scale PV systems in infra-communal cell i or region r
δ_{PVres}	Diffusion of small-scale (residential) rooftop PV
δ_{PVmid}	Diffusion of medium-scale rooftop PV
$S_{res/mid}$	Average size of PV installations (small/medium-scale)
Nsd/lb_i	Number of single-dwelling residences/large buildings in cell i

Publications

International journals

- [1] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. (2021) Active integration of electric vehicles into distribution grids: barriers and frameworks for flexibility services. *Renewable & Sustainable Energy Reviews*, doi:10.1016/j.rser.2021.111060
- [2] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. (2021) Plug-in behavior of electric vehicles users: insights from a large-scale trial and impacts for grid integration studies. *Under review at eTransportation*.
- [3] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. (2021) Participation of electric vehicle fleets in local flexibility tenders: Analyzing barriers to entry and workable solutions. *To be submitted*. Published as a working paper in: [EUI-FSR Working papers](#)

International conferences with proceedings

- [4] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. Electric Vehicles as Flexibility Providers for Distribution Systems. A Techno-Economic review. In: *25th International Conference on Electricity Distribution (CIRED 2019)*, July 2019, Madrid, Spain. doi:10.34890/554
- [5] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. Can DERs fully participate in emerging local flexibility tenders?. In: *16th International Conference on the European Energy Market, EEM*, September 2019, Ljubljana, Slovenia. doi:10.1109/EEM.2019.8916343
- [6] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. Impact of Non-Systematic Electric Vehicle Charging Behaviour on a Distribution Substation. A Techno-Economic review. In: *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, Bucharest, Romania, September 2019. doi:10.1109/ISGTEurope.2019.8905710
- [7] **Gonzalez Venegas, F.**, Petit, M., Perez, Y. Quantifying the participation of EV fleets in local flexibility tenders. In: *CIRED Berlin Workshop on How to Implement Flexibility in the Distribution System?*. Online, September 2020.

- [8] **Gonzalez Venegas, F.**, Meunier, S., Protopapadaki, C., Perez, Y., Salaens, D., Petit, M. Impact of distributed energy resources and electric vehicle smart charging on low voltage grid stability. In: *26th International Conference on Electricity Distribution (CIRED 2021)*. Online, September 2021.

Other conferences and invited talks

- [9] Ensuring flexibility delivery: the role of penalties on long-term distribution flexibility tenders. *1st IAEE online conference*, July 2021.
- [10] EV fleet participation in distribution flexibility tenders, an international comparison, *Chaire European Electricity Markets seminar on “Financing Long-Term Investment in Hybrid Electricity Markets”*. Online seminar, February 16th, 2021.
- [11] EV fleet participation in distribution flexibility tenders, an international comparison, *French Association of Energy Economists Webinar on “New flexibility actors for the power systems”*. Online webinar, November 10th, 2020.
- [12] Participation of EV fleets in distribution flexibility tenders, *IEA - Hybrid & Electric Vehicle Technology Collaboration Programme, Task 39 & Task 43 Joint Workshop on “Electric Vehicle: Grid and Market Integration”*, Online Webinar, June 10th, 2020.
- [13] Electric Vehicle load modeling at a distribution substation, *CIRED Electric Vehicle Modeling Working Group*, Brussels, February 18th, 2020

Chapter 1

Introduction: towards future smart grids

1 Towards a low-carbon future

Global warming will have serious effects on ecosystems and people, including loss of biodiversity, sea level rise and extreme meteorological events. The causes of global warming are well known: the emission of green-house gases (GHG) by human activities, mostly due to CO₂ emission from burning fossil fuels [1], as shown in Figure 1.1.

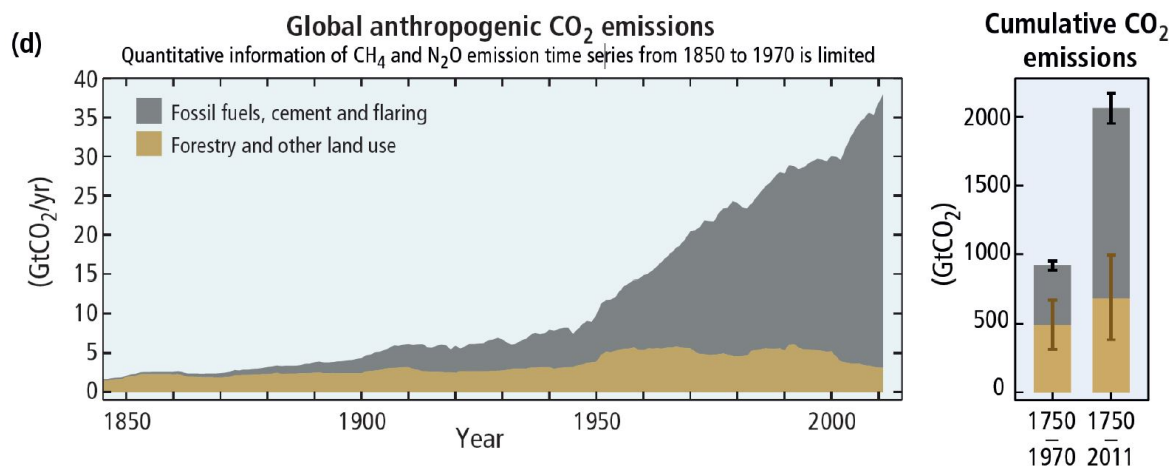


Figure 1.1: Global anthropogenic green-house gas emissions since 1850. [1]

During the 21st Conference of Parties on Climate Change, which was held in Paris in December 2015, 196 parties agreed on a common goal to “*hold the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C*” [2]. However, the risks posed by climate change can be reduced if the increase in temperature above pre-industrial levels is limited to 1.5°C (current temperature rise is around 1°C above pre-industrial levels) [3]. To achieve this, human society would need to transition to net-zero GHG emission by 2050 [4], cutting drastically GHG emissions and the burning of fossil fuels. In particular, the

European Union adopted the objective of net-zero emission by 2050, strongly taken the stance towards limiting the impacts of climate change.

The transition towards net-zero emissions would pass by two major axis: electrification of fossil-fuel dependent processes, such as transport by internal combustion vehicles, and decarbonization of electricity generation, through the integration of low-carbon generation sources such as renewable energy (mainly solar photovoltaic and wind generation).

1.1 The emergence of electric vehicles

GHG emission are dominated by energy, transport and industry sectors, as shown in Figure 1.2. The transport sector accounts for 14% of emissions worldwide, and it reaches 28% in the US [5] and 27% in the Europe Union [6]. Road transport, which includes vehicles, buses and trucks, accounts for 70% these emissions, and it is strongly dependent on fossil fuel (gasoline and diesel) [1]. To reduce the GHG emissions transport will need to be electrified. Battery electric vehicles (EVs), which have an electric drivetrain instead of a combustion engine and a battery pack for energy storage, appear as the main technology capable of allowing the transition towards a low-carbon transport sector.

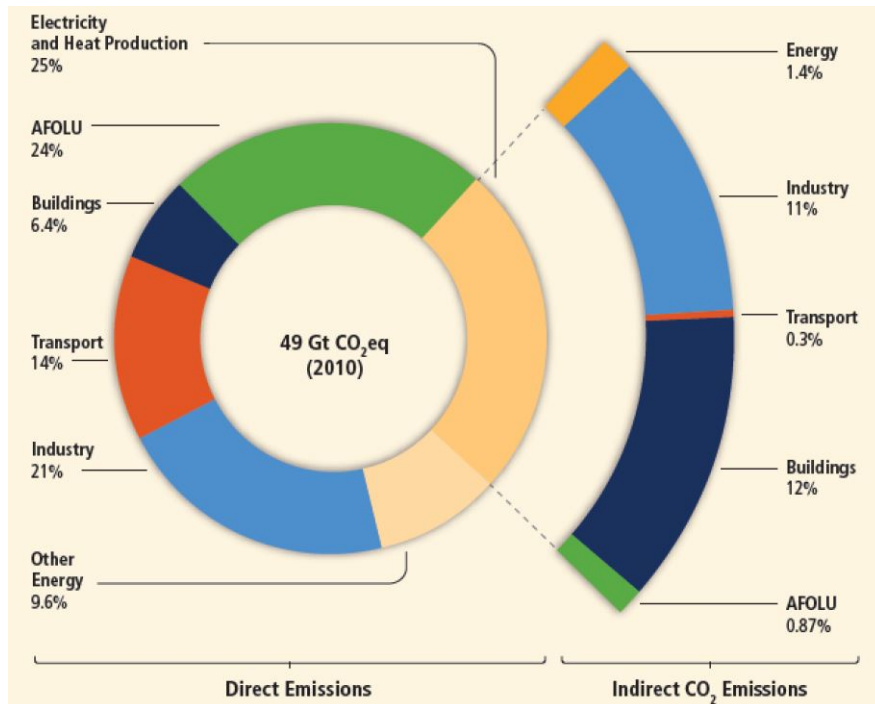


Figure 1.2: Global green-house gas emissions by economic sector, from [1]. AFOLU stands for Agricultural Forestry and Other Land Use.

The transitioning of combustion engine vehicles to BEVs, if coupled with low-carbon electricity generation, can achieve significant reduction in GHG emissions, as shown in Figure 1.3 in the case of wind generation. EVs can also contribute to reduce noise levels in cities and local atmospheric pollution, which include NO_x, particulate matter and sulfur

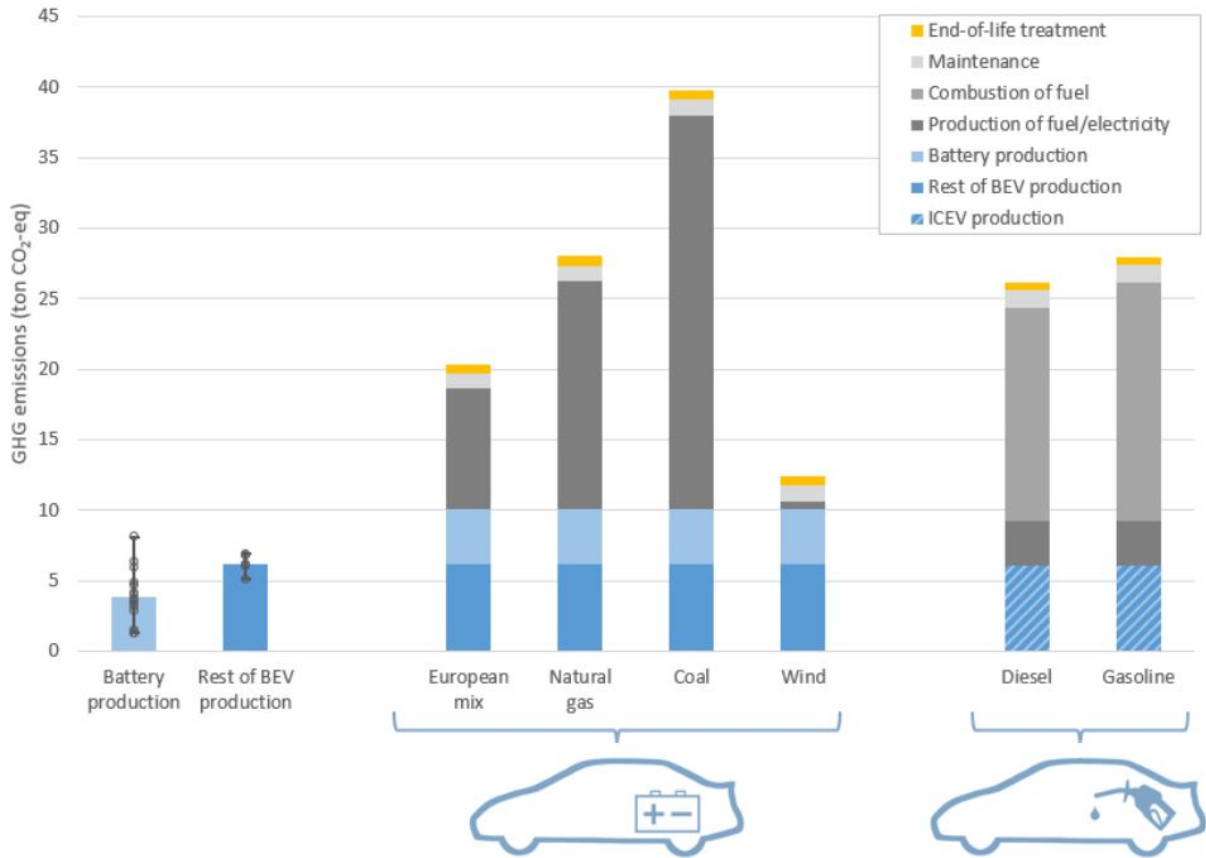


Figure 1.3: Life-cycle GHG emissions for a 24 kWh battery electric vehicle. From [8].

dioxides, that pose serious health risks [7]¹.

The benefits of battery electric vehicles have pushed cities and governments worldwide to adopt pro-EV measures, with several countries announcing bans on sales of new petrol/diesel vehicles in the next 10 to 20 years, such as the Netherlands by 2030 and France and the UK by 2040. These factors have spurred the EV market’s rapid growth, with over 2.1 million EVs sold in 2019 [9] to more than 3.2 million in 2020 [10]. This trend is expected to continue, with projections pointing to over 200 million EVs in the streets by 2030 according to IEA’s best-case scenario. Automotive manufacturers are transitioning to this new paradigm by developing new EV models. For example, Stellantis plans to propose an electrified version of 98% of its models by 2025² and 100% by 2030³ [11].

2 Smart grids and the need for flexibility

The transition towards a low-carbon future puts in the center the electricity system. In particular, the electricity distribution systems, which comprise the medium and low voltage grids (MV and LV) where most end-customers are connected, are facing a change

¹The production and end-of-life phase of electric vehicles, in particular of the battery pack, still present significant environmental impacts which need to be overcome.

²Including Plug-in hybrids and battery electric vehicles

³All of them as BEVs

of paradigm for their operation and planning.

The integration of distributed renewable energy resources (RES), such as PV panels and wind turbines, create bidirectional flows in the distribution grid, and the massive integration of EVs and the electrification of the heating sector (integration of heat pumps) adds additional demand which can create increase peak load. The integration of these new resources can create problems in the grid, which can be categorized in load and voltage issues. The additional demand (such as the load coming from EV charging) can increase active power losses and create congestion in distribution grid assets. Overloading of transformers or lines can cause equipment degradation and failure. Voltage issues affect the quality of service delivered to end-users, which should be maintained in a suitable range (EN50160 standard in Europe [12]). Additional demand can create voltage drops and phase-unbalances beyond these grid requirements. To solve this, distribution system operators (DSOs) would need to invest in infrastructure upgrades (i.e., new or larger transformers or lines) to accommodate the new generation and demand.

However, the development in communication and control technologies is enabling the transformation from passive distribution grids to active, controllable **Smart Grids**. In a smart grid, distribution system operators (DSOs) monitor and control network assets, and end-users or distributed generators can monitor and adapt their consumption/production patterns, reacting to the electricity system conditions. With the integration of distributed energy resources, such as PV panels, end-customers can become active agents, the *prosumers*, producing and consuming electricity in a *smart* fashion. This way, end-customers can provide **flexibility** to the grid, allowing for improved system operation and reducing the need for new infrastructure investments.

In this context, flexibility is defined as *"the modification of generation injection and/or consumption patterns, in reaction to an external signal (price signal or activation) in order to provide a service within the energy system"* [13].

Electric vehicles appear as a promising technology to provide flexibility. Indeed, EVs are idle over 80% of the time [14] and their average daily consumption can be charged in under 3 hours with a standard 3.7 kVA home charger [15]. This leaves ample margin for controlling the charging process, what is called **smart charging**. With smart charging, the charging process can be shifted in time and/or modulated in power, allowing, for example to charge the vehicle during low price hours. The EV can also be used as a energy storage system using a bidirectional charger, allowing to provide power back to the home (vehicle-to-home, **V2H**), building (vehicle-to-building, **V2B**) or the grid (vehicle-to-grid, **V2G**). With V2G, EVs can, for example, inject power during peak demand periods, allowing to reduce the stress on the grid. This is shown in Figure 1.4.

When assessing the flexibility of EV charging, we can distinguish three main dimensions that will determine the *amount* of flexibility it can provide to the system [16]: **time, power, and energy**. The flexibility of a charging session depends on the *idle time*, which is the time spent connected but not charging, and quantifies the time during which flexibility can be provided without affecting the user's driving needs. The power component will be determined by the charger level (standard charger powers are 3.7, 7.4 and 11 kVA) and the capacity of bidirectional flows. Finally, the energy that can be provided (absorbed or injected) to the grid (in kWh), will be closely related to the storage capacity of the battery.

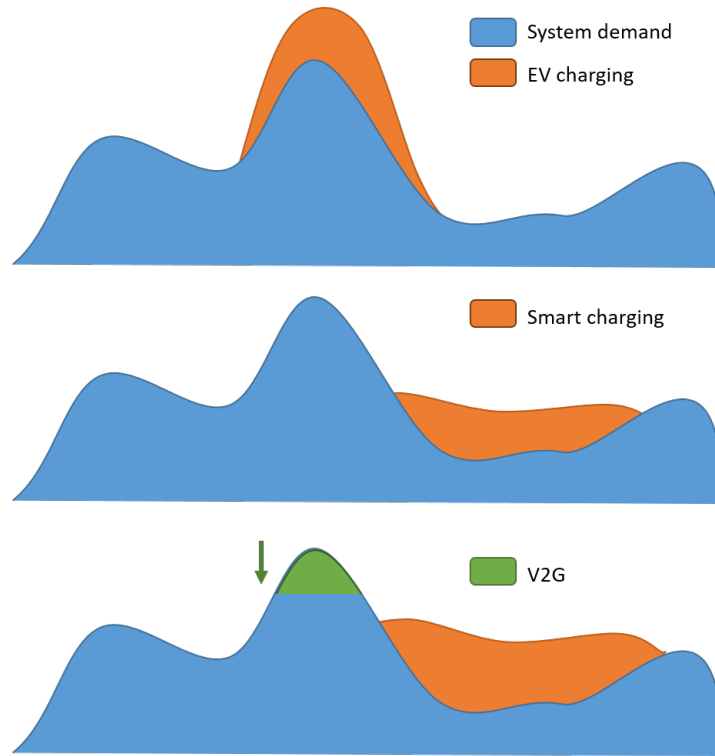


Figure 1.4: Example of uncontrolled EV charging (top), smart charging (middle), and vehicle-to-grid flexibility (bottom) to reduce peak load in a system.

3 Thesis objectives

In objective of this thesis is to evaluate the potential of EV fleets to provide flexibility to distribution systems. A multi-disciplinary approach is required for such a study. First, the **technical** requirements for the provision of flexibility need to be determined. Then, we need to understand the **economics** of the use of flexibility, what is its value and what frameworks can enable its delivery. A **regulatory** analysis of the frameworks is needed to ensure the ability of EV fleets participation. Finally, the **user behavior** aspects need to be considered, as how EVs are used and charged will determine the ability of EV fleets to provide flexibility.

The questions this thesis addresses are the following: what are the use cases for flexibility in the distribution grid? For these cases: what frameworks enable the provision of flexibility? In these frameworks: what technical, economic barriers and regulatory barriers appear for the participation of EV fleets? And finally, **how will EV-user driving and charging behavior affect their integration into distribution grids and their participation in flexibility mechanisms?**

To address these questions this thesis is structured as follows:

1. **Chapter 2** presents a review of the scientific literature to identify the remaining barriers for proactive EV integration into distribution grids. It proposes an holistic view of the subject, addressing technical, economic, regulatory and user-related aspects. Research gaps are identified which help positioning this thesis within the scientific literature.

2. **Chapter 3** analyzes the plug-in behavior of EV users (how often they charge their EV). Insights from real-world behavior are obtained from a large-scale EV trial in the UK, and a model to simulate EV charging that considered non-systematic plug-in behavior (i.e., users not plugging-in every day) was developed. We use the model to assess how non-systematic plug-in behavior affects EV charging grid impacts and the ability of EV fleets to provide flexibility.
3. **Chapter 4** investigates impact of the spatial distribution of EVs and the consideration of local mobility patterns in EV grid integration. First, we analyze the impact of EV charging when considering local mobility patterns (urban vs. rural/peri-urban) at the primary substation level with case studies based on French distribution grids. Then we assess the joint integration of EVs and PV systems in a mixed urban-rural MV grid from south-west France. We study different spatial distribution patterns of EV charging and PV systems to identify potential complementarities between these two technologies.
4. **Chapter 5** analyzes five recent implementations of market-based flexibility mechanisms at the distribution level in Europe. We perform a qualitative analysis of market rules to identify barriers to entry for EV aggregators. In a second step, we study in detail the case of long-term flexibility tenders. We carry out a quantitative analysis to assess the participation of EV fleets into these mechanisms which considers market rules, technical capabilities of EV fleets and different user-behavior patterns.
5. **Chapter 6** presents the conclusions of this thesis. Recommendations for EV manufacturers, distribution system operators and regulators are formulated.

Chapter 2

Active integration of EVs into distribution systems

As discussed in the previous chapter, EV integration into distribution systems presents both challenges, due to the additional constraints the EV charging can create, and opportunities, as smart charging and V2G can provide flexibility for improved operation and planning.

This chapter presents a literature review of EV grid integration into distribution systems from an holistic perspective. A review of the scientific literature and key European demonstrator projects was carried out using a methodological framework that considers technical, economic, regulatory and user-related aspects. In particular, this chapter analyzes four possible value frameworks (grid codes, connection agreements, tariffs and market platforms) to enable the use of flexibility at the distribution level, and their implementations with EV fleets in demonstrator projects. We identify remaining barriers for the active integration of EVs into power systems and identify research gaps which will lead the rest of this thesis.

1 Methodology

EVs will integrate the smart grid ecosystem, where they will interact with other emerging technologies, such as renewable energy resources (RES) and stationary batteries (BESS), as well as with various stakeholders, such as aggregators and system operators (DSOs, TSOs). The complex interactions between all these agents depend on many factors, including technological developments, economic relationships, regulatory frameworks and EV-user preferences and behavior. To properly analyze these interactions, a methodological framework, proposed in [17] for PV-EV synergies, was adapted and applied to the EV-distribution grid relationship.

By reviewing the scientific literature and the results and recommendations of main European demonstrator projects concerning smart grids and electric vehicle grid integration (VGI), key factors to address in order to exploit EV flexibility were identified, as shown in Figure 2.1. These aspects can be divided in technical, economic, regulatory and user-related aspects.

Technical aspects consist on the strategies adopted to use EV flexibility and how they are implemented. These strategies are applied in a given spatial configuration of the

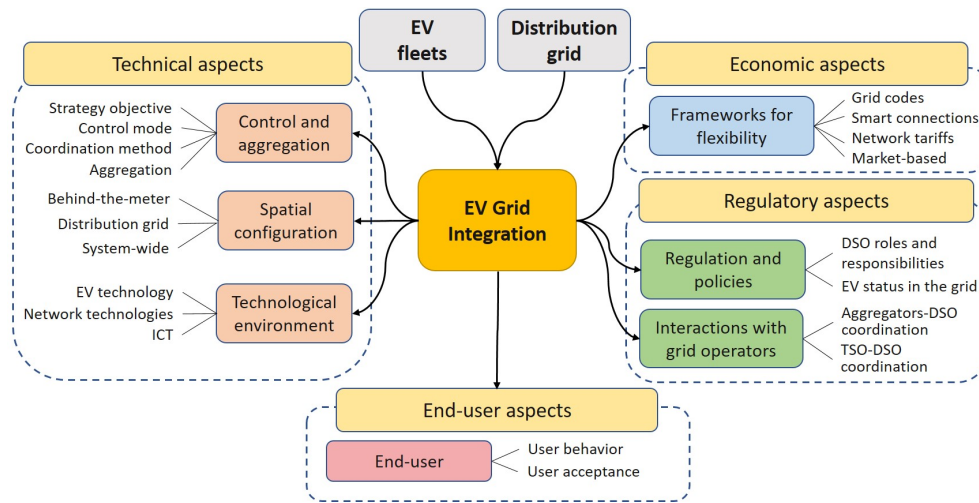


Figure 2.1: Analytical framework, adapted from [17].

electrical grid, from user-centered (behind-the-meter), to the local network (LV and MV distribution grids) or system-wide level (transmission level, wholesale markets). Additionally, VGI will be determined by the technological environment in which it develops, which encompasses the EV charging technology, the interaction with other DERs, and governing ICT standards and requirements.

Understanding economic and regulatory aspects is crucial for successful EV integration and robust business models for flexibility services. The main aspects are related to evolving policy and regulation to allow and encourage flexibility trading at distribution level, not only for EVs but for other types of demand response mechanisms as well, to how innovative frameworks for flexibility procurement can be implemented at the distribution level, and to the interactions between stakeholders.

Finally, the implementation of any flexibility service will depend on end-user behavior (how EVs are used and charged) and acceptance of the control strategy. While these aspects are often overlooked or misrepresented in academic studies, they are key to the success of its deployment [18].

2 Technical aspects

2.1 Control and aggregation

Smart control is the main lever to exploit EV flexibility and it refers to the technical implementation of EV charging strategies for flexibility provision. Key characteristics are the strategy objective, the control mode, the coordination method and aggregation issues.

Strategy objective

The strategy objective is the core of smart control. It sets the management of the EV charging process to respond to the user or another agent needs. The objective can represent a monetary or a physical quantity and may be directly tied to the flexibility services potentially offered to the agents. There are many proposed strategy objectives that may interest various stakeholders [19]:

- **For end-users:** Optimizing EV charging costs and management of electricity bills and assets (by means of V2H/V2B). This can consider increasing self-consumption of local renewable generation and optimizing the contracted power.
- **For DSOs:** Management of grid assets (congestion and voltage support), power losses minimization, valley filling and phase balancing (in LV grids).
- **For TSOs or Balancing Responsible Parties (BRPs):** Provision of balancing services (including frequency regulation), optimization of system-wide generation costs and RES support.

Several objectives can be targeted jointly, such as optimizing end-user costs while safeguarding the limits of the distribution grid operation, thus needing a hierarchy or common value system to discriminate among them. In-depth review of algorithms and objectives for smart charging and V2G have been carried out in [20][21].

Control mode

Control mode refers how the strategy objective is implemented in the EV environment. It sets a strategy objective with diverse constraints coming from end-users (charging requirements, EV technology), distribution grids (capacity limits, voltages standards) or other technologies (RES generation), all in a mathematical model. Control mode can be set through optimization, heuristics or hybrid techniques, and is applied in different time frames, either scheduling (day-ahead or intra-day) or in real-time.

Optimization techniques seek to minimize (or maximize) an objective function, representing the strategy objective of EV charging, subjected to a set of constraints. For example a charging strategy could search to minimize charging costs, constrained to a certain minimum state-of-charge (SoC) of the battery at the end of the charging process, or to respect the operating limits of the grid, such as current and voltage limits. Optimization techniques are usually used for day-ahead or intra-day scheduling of EV charging. According to the model employed they require forecast data, namely EV energy requirements, arrival and departure times, electricity prices, load profiles, RES generation, among others [22]. Most models are deterministic, assuming accurate forecasts. To represent uncertainty, stochastic optimization can be used by modeling several scenarios coming from different forecasts, though this technique is computationally more demanding [23]. Real-time optimization can be implemented to account for forecast errors, but it can be computational burdensome for large-scale fleets [24]

Heuristic techniques use a set of rules or algorithms to determine the charging process. These type of algorithms are usually used in real-time control, as they are easier to implement and often require less data or communication than optimization methods.

Heuristics techniques come in many forms, for example, [25] proposed a rule-based algorithm for thermal management of a neighborhood MV/LV transformer, [26] proposed a droop-based controller for real-time voltage and local congestion management using only local measurements and [27] proposed an algorithm based on game-theory to jointly reduce transformer overloading, grid losses and charging costs for the end-user.

Finally, hybrid techniques combine both optimization and heuristic approaches, usually in a two-stage process. In [28], the authors implemented a two-stage hierarchical control strategy, where the upper stage runs local congestion management using optimization over an aggregated EV fleet, and the lower stage implements decentralized voltage support using heuristics. Similarly, [29] proposed a day-ahead optimal fleet management to minimize network charges for DSOs, followed by a real-time fuzzy-logic control method that tries to follow the programmed schedule.

Coordination method

Smart control strategies often require the coordination of large EV fleets, which can be done in a centralized or decentralized manner. In centralized control, the entire fleet is commanded by a single central entity. This coordination method has the advantage of leading to globally optimal solutions, thus supporting higher EV penetration rates, but at a cost of higher communication, infrastructure, and data transfers requirements, as well as increasing computational requirements when the aggregated number of EVs increases. In decentralized control, charging decisions are taken by each EV, based on local measures or with limited information exchange with a central aggregator. This method can arrive at similar outcomes (near-optimal) to centralized control, especially at low EV penetration rates, and has lower ICT requirements. However, it may not provide optimal responses with higher EV penetration or under forecast errors [30][27].

Aggregation

The control strategy can be implemented by an aggregator who will act as the intermediary between EVs and electricity markets or system operators. The aggregator will be responsible for gathering the flexibility of distributed resources, offering it to markets/market agents, and then controlling the pool of resources accordingly (i.e., implementing the strategy, control, and coordination methods previously discussed).

Aggregators need to assess and propose a flexibility offer to market agents which transmits the ability to provide flexibility in a concise manner [16][24]. A flexibility offer is usually comprised by an expected load profile and a space of possible deviations from it, such as the amount of upwards and downwards flexibility. This requires advanced forecasting and modeling of the flexibility resources, which in the case of EV fleets means knowledge of the users' driving and charging behavior and modeling of technical constraints. Flexibility aggregation allows other market agents (DSOs, TSOs) to optimize their operations without facing all the technical constraints from the distributed resources.

2.2 Spatial configuration

The control strategy is applied within a given spatial configuration: behind-the-meter, distribution grid or system-wide. At each level, flexibility will be used to meet the requirements of different stakeholders and will require control over different EV fleet sizes.

Behind-the-meter

Behind-the-meter strategies consist on applications for end-users, behind the point of connection to the distribution grid. Applications have been proposed for homes (V2H), residential and work buildings (V2B) [21][31], parking lots, and more. EV flexibility can be used for bill optimization based on electricity tariffs, for load management based on maximum connection capacity, for increasing self-consumption of renewable energy (mainly from rooftop PV), and also as a backup power system (islanding capacity) [17][32]. These strategies are designed for households, controlling one or two EVs, and for residential buildings or commercial/industrial facilities, controlling small EV fleets.

Distribution grid

At the distribution level, EV flexibility can serve for local congestion management and voltage regulation in MV and LV grids. Phase balancing in LV grids (due to single-phase connections of end-users) as well as valley-filling or peak shaving services, can serve to improve quality of service and reduce active losses in the grid [33].

Flexibility at the distribution level can be used at various timeframes. At the medium- to long-term, flexible assets can defer or avoid grid reinforcements (such as transformers and feeders) by reducing congestion or voltage issues. At the operational time-frame, flexibility assets can improve reliability of the grid during congestion periods, for example due to seasonal peak load or high local renewable generation, during scheduled maintenance, which can temporarily reduce network capacity, and during post-fault (restoration) events [34][35][36].

Applications at the distribution level would need to manage dozens of EVs in LV grids, equivalent to tens to hundreds of kW (neighborhood scale in Europe), up to hundreds or even thousands of EVs in MV grids, equivalent to several MW (mid-size urban neighborhood or large rural areas).

System-wide level

At system-wide level, the main concerns are efficient and secure operation of the regional or national power system. For this, electricity markets are organized at various timeframes. At longer timeframes, capacity markets ensure sufficient generation is available to cope with peak demand. On operational time-frames (day-ahead and intraday) energy is traded among market participants. Finally, to ensure secure and reliable operation, TSOs implement balancing markets to procure reserves that can be activated in real-time if unbalances are detected between demand and supply.

EV flexibility can serve to provide system-wide services such as frequency containment reserves and energy arbitrage for BRPs, and can serve the capacity market as demand side

response. Provision of balancing reserves using EV fleets has been done commercially in the PJM interconnection (US) since 2013 [37] and in demonstrator projects such as Parker in Denmark [38] or GridMotion in France [39]. Energy arbitrage consists in adapting the charging process according to BRPs' strategies in the electricity markets, thus capturing value from price differences in the electricity market [40]. This can provide benefits for operation of the electricity system, reducing generation costs [41] and supporting the integration of renewable energy.

However, if not managed correctly, the activation of flexibility for system-wide purposes can create congestion at the distribution level. For example, EVs providing frequency response services to the TSO [42] or reacting to low electricity prices due to high renewable generation periods can increase congestion in the distribution grid due to synchronized charging of EVs [43].

Facilitating renewable integration by means of smart charging and V2G is a topic relevant to all levels of the grid. For end-users, EV-PV complementarities can help them reduce their energy bills, and self-consumption at the residential or district level can improve renewable grid integration [44]. The coordination of EV charging and local renewable generation can reduce voltage issues and congestion of grid assets at the distribution level, and at the transmission level it can improve the operation of the generation fleet, increasing RES hosting capacity and/or reducing RES curtailment [45].

Figure 2.2 summarizes the different flexibility services to be provided by EVs.

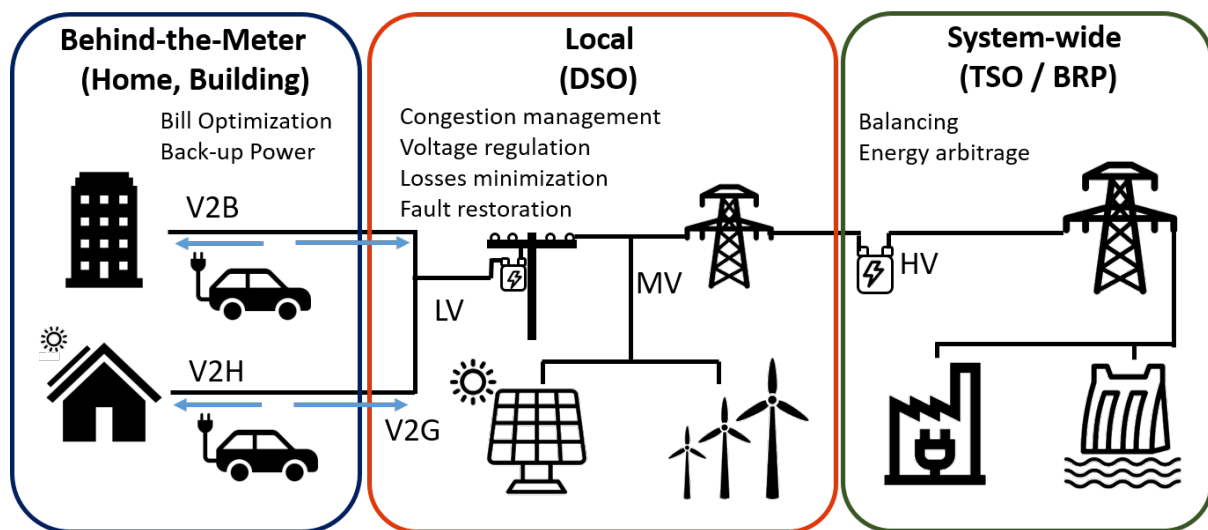


Figure 2.2: Main flexibility services to be provided by EVs

2.3 Technological Environment

EVs will integrate a rapidly changing environment as new technologies break through. The smart grid paradigm is changing the operation of distribution networks, opening up the possibility of synergies between EVs and other technologies. Core factors in the technology environment can be classified into EV charging technologies, network technologies and ICTs. OEMs need to know the technical requirements regarding charging equipment and ICTs that have to be developed and deployed in future EVs to make them smart grid compliant.

EV charging technology

Charging technology and its deployment have a direct effect on the impacts of EVs in power systems and in the flexibility services that they can provide.

An AC/DC converter system is required to charge the battery, which can be implemented on-board (inside the EV) or off-board (in the charging point, EVSE). To implement advanced smart charging and V2G, a dedicated EVSE is required for control and protection functions (mode 3 for AC or mode 4 for DC charging, according to IEC 61851-1 standard [46]).

Charging technology characteristics and capabilities will affect EV integration. EVs are large loads: a single-phase home charging station (3.7 to 7.4 kVA) is in the range of a typical household and can have significant impacts in LV grids. Increasing charging power (for example from 3.7 to 7.4 kVA) can create greater stress in the distribution grid [47], but it can also increase the flexibility potential of EV fleets. For example, moving from 3 kVA chargers to 7 or 11 kVA ones can increase the volume of power reserve for frequency response provision by EV fleets [25][40]. There are other technical characteristics that can affect the flexibility potential of EVs, such as accuracy to control signals, response times and efficiency of the charging equipment. The efficiency of charging equipment is extremely important, as high energy losses during charging and discharging processes may hinder the economic viability of V2G-based flexibility services [48]. Reference [48] characterized the efficiency of a V2G charger, which reached maximum one-way efficiencies of 90%, but which dropped drastically when charging at levels under 30% of the charger power, shown in Figure 2.3.

Capabilities of charging equipment will also determine the flexibility services that EVs will be able to provide. Proposed smart control strategies take advantage of various capabilities that are not yet universally deployed in EVs and charging infrastructures, such as bidirectional flows and reactive power provision. Bidirectional chargers are needed to exploit V2X and use EVs as distributed storage units, but currently there are few bidirectional chargers and compatible EVs available in the market. Technical challenges (in particular improving round-trip efficiency) and high costs still need to be overcome [18]. Controllable reactive power provision has been proposed for voltage regulation at LV and MV grids [49][50], but today's chargers do not provide this capability. This may change with ongoing R&D by OEMs, since this feature could be required by grid codes for bidirectional chargers. Renault, for example, tested a grid-code compliant on-board V2G charger [51].

Finally, battery degradation may represent a major impediment to V2G-based services, as V2G-induced additional battery cycling can reduce the battery's lifespan. Bat-

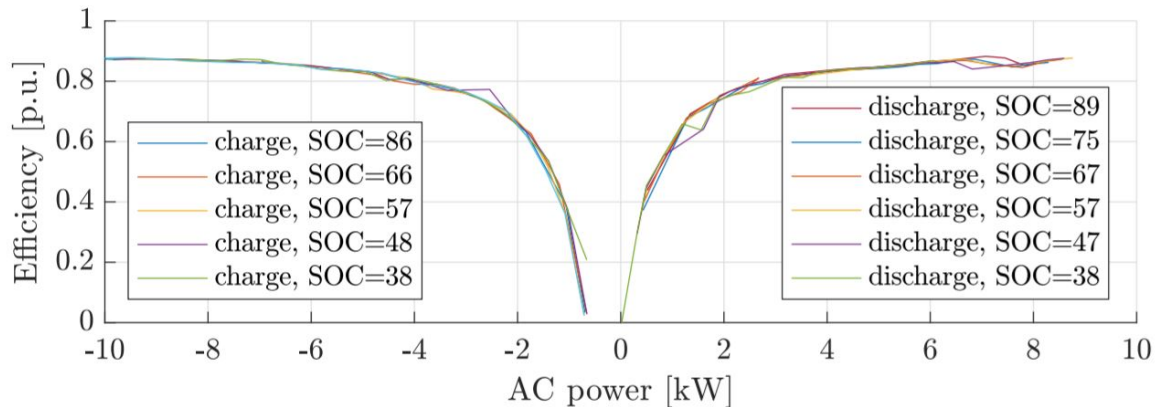


Figure 2.3: Charger efficiency during charge and discharge cycles at different SOC levels. From [48].

tery aging may significantly impact the viability of business models for flexibility services, and is a major factor in end-user acceptance of V2G [52]. Battery degradation is a complex process, ruled principally by two behaviors: calendar aging, dependent on temperature and SoC at storage, and cycling aging, dependent on power throughput, depth of discharge and other factors [53]. Recent studies, both experimental and simulation-based, have shown that V2G might significantly reduce battery life if not used properly [53], but have only minor effects if its usage is limited (20 times a year for energy-intensive services like peak-shaving, or for low-impact frequency response) [54]. If peak shaving services are used daily, they can have significant impact on battery degradation [55].

Smart grid technologies

EVs will interact with other technologies in future smart grids, including RES, stationary batteries, demand response, and network technologies that allow improved operation and control of grid topology (such as soft open points [56], LV on-load tap changers and other power electronics equipment [57]).

The interaction of EVs and distributed generation has been widely studied at different levels. By using renewable energy to charge the EVs, synergies may appear, allowing increased penetration rates of both technologies, and reducing curtailed renewable energy [58][45]. V2G-capable EVs can also increase the integration of other technologies, such as heat pumps in residential neighborhoods [59].

Other flexibility technologies such as BESS and demand response mechanisms can support EV integration, acting as complementary flexibility sources. Aggregators can group different assets together, such as EVs, BESS and demand response, to participate in local or wholesale energy and flexibility markets. This would enable aggregators to reduce risk, by relying on other resources when EVs are unavailable. Second-life EV batteries can be used for distribution grid support services, thus allowing increased EV penetration and fostering a flexibility asset ecosystem throughout the EV battery value-chain [60][61].

Information and communication technologies

Future smart grids need advanced ICT systems. The development of grid services requires advanced metering, control, and transactional communication involving several agents: EVs, aggregators, DSOs, TSOs, market operators, and other market players. Communication protocols and infrastructure need to be defined and deployed for the provision of flexibility services [22][62].

First, DSOs cannot develop flexibility services without greater visibility of their grids, i.e., grid status monitoring at near-real time resolution. This requires monitoring equipment, which include smart meters at customer locations as well as monitoring of distribution assets, state estimators, and accurate grid models [63]. Greater grid visibility will provide a better knowledge of grid utilization and flexibility services requirements. Smart meters are being deployed in many parts of the world, but with a variety of technical characteristics that may not be suitable for flexibility services settlement. In particular, smart meters frequency sampling should be aligned with flexibility trading periods and serve as settlement meters in order to avoid extra costs for participation in flexibility mechanisms [22]. Recent projects have found that requirements on settlement meters for DERs may undermine the economic viability of these solutions [64][18].

Second, communication protocols are required between different infrastructures and stakeholders: EVs, EVSE, flexibility aggregators, DSO/TSO, and commercial stakeholders such as charge point operators (CPO), e-Mobility service providers, in addition to OEMs or third party data servers and end-user interfaces [65],

The core EV-related communication protocols can be classified in *front-end* protocols, between the EV and EVSE, and *back-end* protocols, between EVSE and a third party such as CPO or aggregator (see Figure 2.4). EV flexibility requires the development of open (instead of proprietary) and widely-accepted protocols that support the advanced communication requirements of smart charging and V2G while keeping high standards for data security and privacy. However, recent smart charging implementations did not have access to relevant charging session information, such as SoC or battery sizes, limiting smart charging algorithms [66][67], and currently there are multiple competing protocols without full V2G support. Upcoming releases of open communication protocols, such as ISO 15118-20 standard (between EVSE and EV), and OCPP 2.0 (between EVSE and aggregator or CPO), will allow advanced communication between different stakeholders, including V2G support, and garner broad industry support [62]. While smart charging is already possible for most EVs, widespread commercialization of V2G-ready EVs and EVSEs is expected only for 2025 [68].¹ An in-depth discussion of EV-related protocols is done in [65] and [62].

ICT requirements may differ for different smart control services. Frequency regulation services require high-resolution frequency measurements and low latency communication to be able to respond according to frequency dynamics (in the order of seconds)². This may not be the case for distribution-level congestion management, as thermal dynamics work in slower timeframes, thus requiring flexibility activation within minutes. Coordination schemes also affect communication requirements: centralized schemes require

¹Currently, only EVs using CHAdeMO are V2G-compatible, which correspond mainly to Nissan Leafs.

²There are already some fast frequency response services that require sub-second delivery (UK, Finland [69]), which would require frequency measurement to be embedded inside the EV or EVSE.

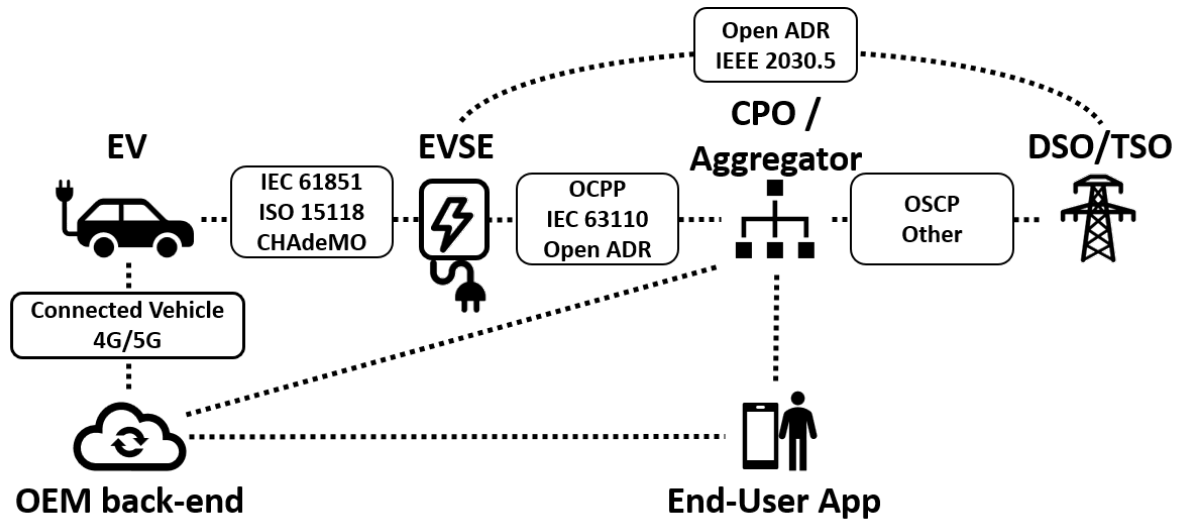


Figure 2.4: Main communication links for flexibility services, based from [65] and [62]

greater data exchange between the central controller (aggregator or other stakeholder) while decentralized control schemes work with less information exchange and may distribute computational capabilities.

Stakeholders should aim to identify the ICT requirements to monitor and control flexible sources in the grid, and work for common and open source ICT protocols and standards suitable for smart charging and V2G.

Table 2.1 overviews the main technical requirements for flexibility services.

Table 2.1: Technical requirements of EV flexibility services

Customer	Service	Charger capability*	Duration	ICT**
End-User	Bill optimization	SC	Hours	Smart meter, HEMS
	Self-consumption	SC, V2X	Hours	HEMS
	Back-up power	V2X	Hours, Days	None
DSO	Voltage regulation	Q, V2X, SC	Continuous	Low (decentralized)
	Congestion management	V2X, SC	15 min to 2h	Medium (DSO-Agg-EVSE)
	Fault-restoration	V2X	30min to 3h	Medium (DSO-Agg-EVSE)
BRP/TSO	Balancing	V2X	1-15min Fast activation	High
	Energy Arbitrage	SC	15min-hours	Depending on coordination

* SC: Smart charging (unidirectional). V2X: bidirectional charging. Q: reactive power compensation.

**Agg: Aggregator. HEMS: Home Energy Management System

3 Economic aspects

There are two main economic aspects that affect active integration of EVs into distribution systems: the value frameworks for exploiting flexibility at the distribution level, and the value of flexibility.

3.1 Flexibility procurement frameworks

EV flexibility today can be exploited where it can be monetized. This can be through the participation of EV aggregators in existing system-wide markets (wholesale or balancing markets), or through energy management systems to optimize electricity bills of end-users. However, there is still no widely accepted framework for the use of flexibility at distribution level. Different frameworks have been proposed in the literature and in demonstrator projects. According to CEER, models for flexibility procurement by DSOs can be divided in the following categories [70]:

Rules-based approach

This refers to grid codes that define the technical requirements for grid connection. They are used mainly to maintain the security and stability of the electricity grid, such as disconnection under fault conditions or harmonic distortion limits.

Imposing smart charging or V2G through grid codes might not be viable, as it may impose a barrier to the development of market-based flexibility services. However, reactive power compensation for voltage regulation (Volt-VAr regulation) has been proposed as a requirement for EV charging connections. While reactive power compensation as grid code has been proposed for of unidirectional EV charging infrastructure [71][50], it may unfairly burden grid access for EVs, as other loads do not have to comply with this requirement. Other solutions besides grid codes could be envisaged to develop reactive power compensation for unidirectional chargers. On the other hand, reactive power compensation can more easily be required for V2G-capable EVs, as it is already a requirement for power injecting DER (such as PV panels) in some countries [57][71] and is supported by the IEEE 1547 Standard [72].

Grid codes are defined at a regional or national level. While many aspects are shared across countries, there are still differences among requirements and varied treatment for emerging technologies, such as storage and EVs [73]. Compliance with diverse national grid codes may present a barrier for the massive deployment of V2G-capable EVs by OEMs with international presence, as well as creating issues with EVs that can move across national or regional borders (see Section 4.2). This calls for an uniformization of grid codes (specifically at the distribution level) at a large scale area, such as Europe.

Connection agreements

In this arrangement DSOs work with customers to form an agreement for the provision of flexibility. Connection agreements have been successfully implemented for congestion management using smart connections for renewable generation in Europe [74]. Generators with a smart connection are interruptible, which means they can be (partially) curtailed if there is local congestion, but benefit from lower connection costs and shorter delays.

Arrangements for EV charging infrastructure can take two approaches: interruptible contracts or variable capacity contracts (VCC).

Interruptible contracts, similar to those for renewable generation, can (partially) curtail EV charging infrastructure according to system conditions. This type of contract leaves direct control of the EV charging process to DSOs, and presents the risk of precluding EV mobility needs, thus potentially meeting with lower user acceptance. My Electric Avenue project tested an interruptible solution where a system temporarily curtailed EV charging to respect the limits on the local grid infrastructure [75].

VCCs provide the customer with a variable maximum power they can withdraw from the grid according to a schedule (either fixed or dynamic) set by the DSO, while benefiting them with lower network tariffs. For example, users can have a reduced maximum capacity during peak load hours but an increased maximum capacity during off-peak hours [76], as shown in Figure 2.5. This capacity can as well be periodically computed by the DSO (e.g., day-ahead based on load and generation forecasts) as proposed in [77]. This type of contract has recently been proposed for residential users in Spain, where customers can choose a higher subscribed capacity for off-peak hours (from midnight to 8 AM) [78].

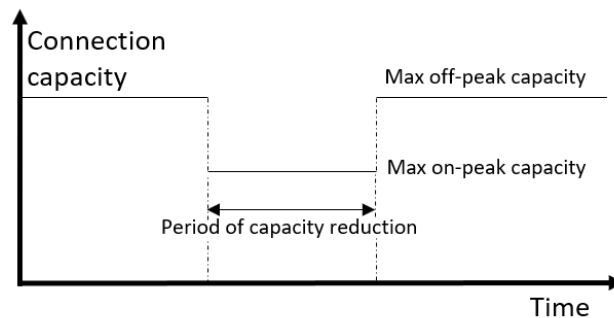


Figure 2.5: Illustration of variable capacity contract. Adapted from [76]

A VCC solution for EVs was demonstrated in the FlexPower project in Amsterdam for public charging infrastructure. In this project, charging points have a reduced charging capacity during the evening peak load time but benefit from increased capacity during the rest of the day, thus reducing congestion and optimizing EV charging times during the rest of the day. Results have shown minimal impact for users who charge during peak hours while increasing the energy charged by users who charge during off-peak hours [79]. In the Electric Nation project an aggregator-based VCC was implemented. The aggregator managed the charging process of fleets of over 250 EVs to follow a capacity limit curve provided by the DSO, that emulated the spare capacity on a MV feeder [66]. A similar aggregator-based solution was implemented for public charging infrastructure in one of the Invade project demonstrators [67].

These contracts have been proposed mainly to deal with grid congestion and investment deferral (by reducing the impact on peak load of new connections), but they could also be used for local voltage support, for example, by providing faster connections for EV charging infrastructure if they provide reactive power compensation.

Network tariffs

Network tariffs are used to recover the cost of operating and planning distribution and transmission grids, and they are one component of end-user retail prices along with energy costs and taxes and levies. Network costs represent an average of 25% of the electricity bill in Europe [80]. Tariffs should reflect the costs of the distribution system, giving incentives to develop of different forms of demand side response mechanisms [81], and they are one of the main levers to incite end-users to adopt smart charging or V2G strategies to reduce their energy bills in a behind-the-meter fashion.

Network tariff structure can be broken down into energy-based charges (related to the energy consumed by the customer, in €/kWh), capacity-based charges (related to the contracted or maximum power of a customer, in €/kW), and fixed charge (related to each point of connection, in €), with most countries in Europe presenting a mix of these charges (see Table 2.2). Differences in network tariffs will impact end-customer DER adoption and EV charging strategies [82][83]. Furthermore, tariffs can be temporally and geographically differentiated, with different rates for time periods, such as peak and off-peak, or grid zones.

Energy-based tariffs can depend on *when* the energy is consumed by the customer, such as Time-of-Use (ToU) or critical peak pricing tariffs, which provide lower prices during off-peak hours and higher prices during peak hours. ToU tariffs have been widely studied in the EV smart charging literature. Most studies conclude that simple two- or three-rate tariffs (on-peak, off-peak and super-off-peak) can reduce congestion issues in distribution grids in low EV penetration scenarios, by shifting the charging process to off-peak hours. However, in high-penetration scenarios they can create even higher peaks due to a synchronization of EV charging at off-peak periods [84][50][85], or with other controllable loads such as electric water heaters or heat pumps [86].

Retail tariffs can reflect both network and energy price signals with high temporal granularity. Dynamic electricity tariffs linked to (sub)-hourly wholesale electricity prices are already practised in several countries in Europe, such as Spain, Norway, [87] and the UK [88]. However, this type of dynamic pricing can still present high load peaks from EVs as they concentrate the charging process on low-price hours [89] and may not necessarily correlate to local congestion periods in the distribution grid. This is especially true in high-renewable systems, where wholesale electricity prices are not correlated to total (or local) demand [85], thus potentially further increasing the need for distribution network reinforcements [43]. Thus, challenges arise if only system-wide signals are passed to end-user tariffs.

Currently, significant research is being carried out on distribution locational marginal prices (DLMPs) [90][91], where the price of electricity reflects the costs of producing and delivering electricity at each node of the distribution grid (nodal marginal pricing). Depending on the formulation, DLMP-based frameworks account for line capacities, voltage limits, active losses and even reactive power. These frameworks can reflect the distribution grid conditions, but they are also difficult to implement in practice, especially in Europe where most countries do not even use nodal prices at the transmission level. Note that DLMPs can create issues for the transparency and stability of end-user tariffs [92][93]. Also, they can go against the equalization principles that exist in network tariffs in some European countries, like France [94] or the Netherlands [95], as DLMPs can make

customers connected in weaker, more congested grids, experience higher grid tariffs.

Capacity-based tariffs charge customers according to their contracted capacity or their maximum demand during a given period (demand charges). With this type of tariffs, users are given the incentives to adopt strategies to reduce their maximum consumption. If demand charges are computed at the peak-load period (coincidental demand charges), they can help reduce congestion in the distribution grid [83].

Currently, most network tariffs respond to system-wide criteria, such as system-wide peak load. This is shown in Table 2.2, detailing network tariffs for residential customers in selected countries in Europe (end-users tariffs need to account for energy costs and taxes and levies as well). Most countries have static network tariffs, with fixed on-peak/off-peak periods throughout the year and no geographical differentiation. It is thus necessary to develop tariffs with higher temporal and geographic granularity that can provide signals for a better utilisation of distribution grids [81][93]. For example, [96] proposed a network tariff for Spain based on compounded peak/off-peak tariffs at the different voltage levels, thus reflecting both transmission and distribution constrained periods. Likewise, New York utility ConEdison tested a residential retail tariff that considered dynamic day-ahead electricity prices for the energy component plus both transmission and distribution coincidental peak charges independently for network charges [97]. Network tariffs can provide incentives to end-users to reduce congestion in the distribution grid, but they might be less suitable for other flexibility services like voltage regulation or phase balancing in LV grids.

Table 2.2: Network tariffs for residential customers in selected countries (≤ 10 kVA or equivalent).

Country	Tariff type	Energy type*	Cap. type	Locational signal	Temporal signal
France [94]	E+C+F	Seasonal ToU (2)	Contracted cap.	Local (substation level)	Static
UK [98]	E+C+F	ToU (3)	Contracted cap.	Uniform within DSO	Static
Germany [99]	E	Flat	-	-	-
Netherlands [95]	C	-	Contracted cap.	-	-
Belgium [100]	E	ToU (2)	-	Uniform within DSO	Static
Spain [78]	E+C+F	Seasonal ToU (2)	Contracted cap.	Uniform within DSO	Static

E: Energy, C: Capacity, F: Fixed, ToU: Time-of-Use

* Parenthesis indicates the number of pricing periods.

Market-based

In this approach, DSOs explicitly procure flexibility services from a market, either via long-term bilateral contracts or via a short-term market platform. This approach is preferred by regulators [70].

Bilateral contracts can enable flexibility procurement for medium- to long-term horizons. In this case, DSOs identify in advance the flexibility requirements enabling to defer or avoid costly reinforcements or improve grid operation (for planned maintenance or fault-restoration) and procure flexibility through long-term contracts. This type of contract can be signed between DSOs and flexibility providers after a tender process, or through over-the-counter contracts if there are no sufficient conditions for market formation.

This approach has been adopted by the UK’s DSOs. UKPN, the London-area DSO, adopted a “flexibility first” policy towards all new investments in MV and HV (over 10 kV). They have identified grid sections where the use of flexibility during certain critical periods (usually in winter, during peak load) could help defer reinforcements, and have subsequently organized tender processes to procure flexibility from distributed sources since 2018. This market is supported by the flexibility platform PicloFlex, for which Figure 2.6 gives a screenshot depicting the flexibility requirements for a tender zone. Similar processes have been led by the other UK’s DNOs [101] and by French DSO Enedis [102], in an effort to contract flexibility for services including congestion management for investment deferral, reactive power compensation and fault-restoration services. Similarly, New York state utilities are using request for proposals for investment deferral though their non-wire alternatives (NWA) programs [103].

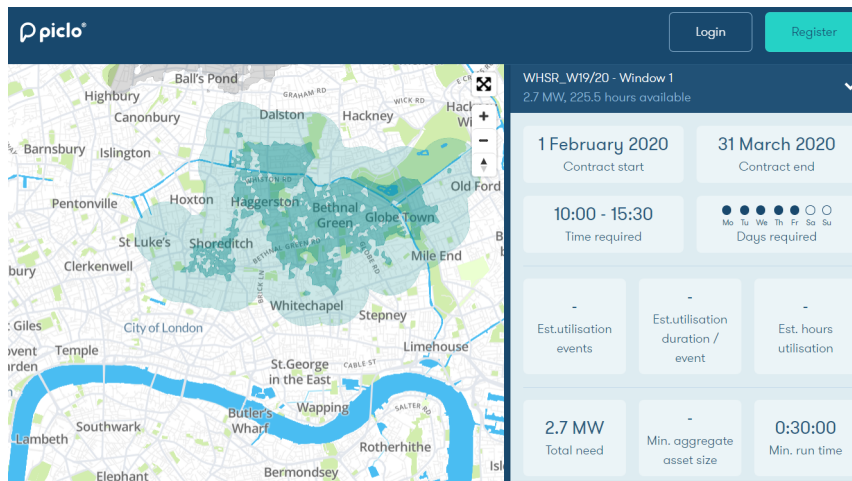


Figure 2.6: Screenshot of the PicloFlex flexibility platform, showing the flexibility requirements during winter 2020 in the London Area. (www.picloflex.com)

Flexibility trading within shorter timeframes, such as day-ahead or intraday, have been proposed in the literature and in various demonstrator and pilot projects in the form of flexibility market platforms and local energy markets, and there have recently been commercial implementations.

The first commercial implementations of short-term local flexibility trading are Enera (Germany) [104] and GOPACS (Netherlands) [105], where DSOs and TSOs procure flexibility to manage RES-driven congestion, supported by existing energy trading market platforms (EPEX Spot for Enera and ETPA for GOPACS). EV aggregators participating in these market platforms can provide flexibility to DSOs by offering location-specific bids.

The INVADe demonstrator project developed a flexibility management platform to control batteries and EVs to support higher penetration of renewable energy. Via this platform flexibility services are proposed for end-users (behind-the-meter services), DSOs (congestion management and voltage regulation) and BRPs (energy arbitrage) [106]. Likewise, the InterFlex project studied flexibility provision by EV aggregators at the LV level implementing a day-ahead and intraday local flexibility market in its Netherlands demonstrator [107].

A market-based approach raises the issue of product definition and procurement. For this, flexibility products should be defined, in particular the power (active or reactive), duration and location requirements. A settlement period according to the services and flexibility sources characteristics (ideally close to real-time to consider uncertainty) also have to be defined, along with consumption baselines for flexibility settlement that have to be accepted by all stakeholders [22]. Furthermore, the product definition should not pose barriers to entry to distributed flexibility resources, for example by setting over-high bid size thresholds or duration requirements [70].

Local market platforms also require advanced technical capabilities from DSOs, such as demand forecasting with high spatial granularity [108], LV state estimators to monitor the grid in (near) real-time to activate flexibility [109], and advanced optimization models for grid operation, such as AC optimal power flow (AC-OPF) [110].

Flexibility platforms have great potential to enable new business models to emerge. However, they are only possible where there are enough participants to create a competitive market, thus making them unsuitable to solve issues in small areas without many flexibility assets, or where a small market size can produce (prohibitively) high transaction costs [70].

Note that multiple alternatives can coexist, like flexibility market platforms, where aggregators would trade end-user flexibility to other electricity system actors (DSOs, BRPs, TSOs), alongside advanced electricity tariffs and flexible contracts that would incite customers to actively manage their consumption. Reference [111] analyzed nine mechanisms for congestion management at the DSO level using EV flexibility, based on combinations of four basic frameworks for flexibility (advanced tariffs, interruptible contracts, VCCs and flexibility markets). Their results showed that dynamic electricity tariffs coupled with flexible contracts or flexibility markets are able to solve DSO grid congestion with little to no impact on end-users.

Based on our analysis, Table 2.3 provides a summary of the value frameworks that can enable the provision of different flexibility services by EVs. Congestion management can be tackled through various solutions, including local flexibility markets and network tariffs. On the contrary, voltage issues require more research to develop flexibility procurement frameworks.

3.2 Flexibility value

The value of flexibility for the distribution systems will depend on the use cases for which it is used, and will be valued against the alternative solution that it will replace. Two complementary metrics can be considered to assess the value of flexibility: the variable value of flexibility, in €/kW/h, and the annual value of firm flexibility, in €/kW. The variable value of flexibility represents the value created by providing 1 kW of flexibility during one hour, at a specific time. This indicator can provide a comparison among different flexibility uses at a given time. The annual value of firm flexibility represents the value that can be created by a resource that can provide 1 kW of flexibility when needed during a whole year. It can indicate the maximum remuneration an asset can obtain from a given flexibility service.

Flexibility on the short-term can be used for congestion management, reduce RES curtailment and fault-restoration support. In [108], authors proposed a methodology to

Table 2.3: Flexibility services to be provided by EVs and the associated value frameworks.

Customer	Level	Service	Value framework
End-User	Behind-the-meter	Bill optimization	Grid tariffs
		Back-up power	End-user reliability
DSO	LV	Phase unbalance	Grid codes
		Voltage regulation	<i>Inexistent yet</i>
		Congestion management	Grid tariffs Flexible contracts LEM
	MV	Voltage regulation	Grid tariffs Flexible contracts
		Congestion management	Flexibility tenders Local flexibility markets
	MV/LV	Fault restoration	Bilateral contracts Flexibility tenders
TSO/BRP	System-wide	Balancing services	Balancing markets Energy markets
		Energy arbitrage	
		Imbalance compensation	

Table 2.4: Flexibility value ranges for different use cases.

Value case	Source	Variable value [€/MW/h]	Annual value [€/firm kW]
HV/MV substation reinforcements (NY, US) ^{2,3}	[19]	6300 ¹	756
MV reinforcements (US) ²	[112]	142-4370	11-125 ¹
MV reinforcements (FR)	Enedis [102]	-	0-24
MV reinforcements (UK) ²	UKPN tenders [113]	3-690	2-400
LV reinforcements (UK) ²	UKPN tenders [113]	22-1950 ¹	55
LV reinforcements (DK)	[114]	65 - 275	15
LV transformer loss-of-life (NL)	[108]	10-10000	-
RES curtailment	[115][116]	0-100	
Fault-restoration (VoLL) ⁴		9200	9.8
FCR (FR) ^{1,5}	[117]	3 - 10	55-79

¹ Own calculations from available data in the cited document.

² Values were converted to €, considering a 0.84 US\$/€ and 1.15 £/€ exchange rate.

³ Required downwards flexibility to be sustained for 8 consecutive hours.

⁴ Considering 64 minutes of average interruption per year (SAIDI), corresponding to Enedis 2019 reliability indicator [118]. Similar values can be found for most European countries [119].

⁵ Own calculations from FCR prices between 2017-2020 in France (data available at [117]). Annual value considers an ideal 1 kW bidirectional flexibility resource providing FCR services for a whole year (8760 hours).

define the willingness to pay of a DSO to reduce congestion in an MV/LV transformer, which depended on the loss-of-life of the transformer and the risk of a loss-of-load from transformer failure³. In this case, the higher the constraint, the higher the price the DSO is willing to pay to avoid lifetime reduction of the transformer and reduce the risk of a blackout. In the case of RES curtailment, the (economic) value of flexibility will be given by the avoidance of compensation payments for curtailed generators, which can go from 0 up to 100 €/MWh⁴. For fault-restoration cases, flexibility value can go up to the value-of-lost-load (VoLL), rated at 9200 €/MWh in France, albeit only needing it in rare occasions.

On the long-term, flexibility will be valued against the alternative investment costs. Thus, the value of flexibility will depend on the costs of the reinforcement solution and the expected magnitude (in kW) and duration (in h) of the constraints to be relieved by the investments. If the expected constraints are small or occur a few hours per year, flexibility can have, potentially, high value. However, as constraints increase in magnitude and/or time, the value of flexibility will decrease and the DSO will be more inclined to carry out the investment, removing the need for flexibility for the short- to medium-term.

In [114], a smart charging strategy was evaluated to defer reinforcements in a LV grid. Depending on the number of weeks that the smart charging service was needed, the variable value of flexibility varied by a factor of 4. Reference [112] proposed a methodology to value flexibility for reinforcement deferral in MV grids and applied it to a representative US MV grid, obtaining values ranging from 170 \$/MW/h to over 5000 \$/MW/h during constrained periods that occur only a few hours a year. Similarly, flexibility tenders in the UK have shown values ranging between 3-600 £/MW/h, amounting to 2-350 £/kW per year of firm flexibility. These values are consistently higher than frequency regulation services, for which variable prices in continental Europe average less than 10 €/MW/h.

We observe that the value of flexibility at the distribution system is highly dependent on the grid contexts (costs of alternative reinforcements, magnitude of constraints), but in favorable conditions it can provide significantly higher value than existing value streams (FCR for example, see Table 3.2). Moreover, distribution services can be complementary to other value streams, as these services are needed only a few hours per year. Table 3.2 summarizes the value ranges for different use cases, and provides the value ranges for FCR in France for comparison.

³The transformer was able to sustain up to 200% loading levels for short periods of time without increasing the risk of failure, but increasing the loss-of-life.

⁴Considering renewable tender prices in France until 2020 [115], and Germany and the UK until 2016 [116]. These costs can be reduced as renewable tender prices decrease.

4 Regulatory aspects

4.1 Regulation and Policy

DSO roles and responsibilities

Historically, the DSOs operated radial grids with unidirectional power flows from the transmission grid to end-users, where main concerns (congestion and voltage issues) were addressed by investing in grid reinforcements through a “fit-and-forget” approach. This approach was compounded by a regulatory framework that remunerated DSOs based on their capital expenditures (CAPEX), inciting them to invest in costly infrastructure to solve grid issues instead of using operational measures (OPEX).

However, the surge of DERs and digitalization is shifting DSOs roles and responsibilities towards more proactive grid operation [120][121]. With this approach, flexibility management at local level can provide more efficient use of existing assets, deferring or avoiding the need for costly infrastructure and reducing the risk of stranded assets in the event of uncertain load growth evolution [122]. This requires adapting current grid planning and operation practices to consider flexible assets.

Regulatory frameworks need to evolve to incite DSOs to implement smart and flexible solutions at local level as cost efficiency measures, thus moving beyond a CAPEX-based to a TOTEX-based (total expenditure) framework, with incentives to improve quality of service and innovation. This vision has been set out by a number of stakeholders, from academics [22][121] and regulators [123][124], to DSOs themselves [120][35]. An example of this shift is the UK’s performance-based network regulatory framework RIIO (Revenue=Incentives+Innovation+Outputs) that incites DSOs to create value for end-customers instead of just investing in new assets [125].

In particular, the European Clean Energy Package [126] represents an important step in policy evolution as it demands DSOs the active management of flexibility resources, which would significantly reduce network costs and improve reliability. European regulators see future DSOs as *neutral market facilitators*, similar to the roles taken by TSOs in Europe, enabling different DERs to participate in energy and flexibility markets, at both the local and system-wide level. It also restricts the actions of DSOs, as it bars them from directly owning or operating flexibility resources (including storage and EV charging infrastructure) [70].

The need for flexibility management is also acknowledged outside Europe. In the US, California’s Smart Grid [127] and New York’s Reforming Energy Vision [128] initiatives have pushed utilities to adopt DERs in their operation and planning phases and implement NWA as an alternative to grid investments [129].

The regulatory framework in the US, with vertically integrated utilities, allows utilities to have ownership and direct control of DERs, as well as direct contact with end-customers. However, their roles and responsibilities are evolving, with different views on the future utility, from expanding their roles to provide more grid and customer services, to setting them as market facilitators (like unbundled DSOs in Europe), or even completely separating the role of grid ownership from operation and planning (Independent DSO model) [130].

4.2 EV status in the grid

V2G-able EVs face great difficulties regarding their connection requirements and legal status as flexibility providers. Connection requirements can be burdensome, as V2G-capable EVs need to comply with requirements both as producers and consumers, as well as administrative procedures to declare and allow distributed sources to participate as flexibility providers. Legal status of V2G installations should also be clarified and aligned with that of storage, with tariffs and charges that prevent double taxation.

Regulators, system operators, and EV and EVSE manufacturers need to work to standardize interconnection requirements to ensure system and end-user safety, while easing administrative procedures. For example, the French regulator issued a series of recommendations regarding the interconnection requirements, mainly for the definition of the decoupling protection⁵, as well as simplification of administrative procedures [131]. In 2019, Delaware state passed legislation that defined the perimeter of V2G, defined clear interconnection procedures (adopting SAE J3072 safety for on-board bidirectional chargers [132]) and allowed net-metering to provide a level-playing field with utility-scale storage [133]. These measures have been suggested to other states as well [134].

4.3 Interactions with grid operators

An important aspect is how the different stakeholders interact along the flexibility value chain. There are interactions between flexibility providers and flexibility customers, in this case EV users and DSOs respectively, and interactions between DSOs and TSOs as potential flexibility customers, where their level of coordination and cooperation will affect how local flexibility is used.

EV users-DSO interaction

DSOs can procure flexibility from end-users directly or indirectly. As mentioned in Section 4.1, DSOs can procure flexibility using different solutions. By using direct obligations (grid codes) for flexibility provision or contract arrangements (such as interruptible contracts), DSOs will directly interact with EV users acquiring permission to directly control the EV charging process.

On the other hand, market-based procurement via flexibility platforms usually needs an aggregator that would gather multiple flexibility resources. This is currently the case for ancillary services and BRP energy arbitrage as done by existing EV aggregators. It could be expected that a growing number of EVs will become associated to an aggregator's program, therefore likely to meet communication and control requirements for the smart charging process. This will allow the provision of market-based flexibility services to DSOs by EV fleets.

DSO-TSO interaction

Currently there is only limited cooperation between DSOs and TSOs. As more DERs are connected into distribution networks and start providing ancillary services, like EVs

⁵This defines the conditions for EV/EVSE disconnection under local fault or islanding conditions.

providing frequency response, DSO-TSO cooperation will become increasingly important to guarantee the safe and reliable operation of the power system. This has been highlighted by the scientific community [74][135], industry and regulators [70], and was considered as a key aspect in the European Clean Energy Package.

SmartNet is a key demonstrator project that focused on DSO-TSO coordination, considering data exchange, monitoring and the provision of ancillary services from distributed sources [135]. Five possible coordination schemes for flexibility procurement by DSOs and TSOs were analyzed and different schemes emerged depending on the level of DSO-TSO cooperation, their roles and responsibilities definition and the level of integration of markets (centralized or decentralized). Higher coordination can present benefits on operational security and reliability and in asset efficiency, both in centralized and decentralized schemes, but it also carries higher computational and ICT burden, and poses regulatory issues.

In [74], authors analyzed possible cooperation between DSO and TSO according to the system state for congestion management, considering both operational issues and market issues. They found that cooperation can arise from forward stages (long- and medium- term), by harmonizing practices and data for capacity calculation, at day-ahead (short-term), by joint or coordinated flexibility procurement, and in real-time stages, by ensuring grid security in firmness and capacity allocation. Conflicts may arise if flexible resources (such as EVs) are required by the DSOs and TSOs concurrently. Reference [42] analyzed this issue in a context of distribution congestion management and primary frequency response services. Definition of priorities on flexibility procurement, activation and compensation will be needed in these cases.

5 End-user aspects

5.1 User behavior

To evaluate the impacts and flexibility potential of EVs it is necessary to have reliable data on user behavior and advanced models to forecast EV usages and electricity demand [47][136][137]. This requires to model the mobility patterns of EV users, i.e., how much and when they are driven, and how they EVs are recharged, i.e., how often, when, and where (at home, work, public charging, etc). Since EVs are a relatively new technology, data on user behavior is scarce or might not be representative of future trends. This make demonstrator projects hugely valuable since they provide insight into real data on EV usage and charging patterns. For example, My Electric Avenue [138], SwitchEV [139] and Electric Nation [66] projects have provided insights on residential EV user behavior in the UK, showing the behavioral diversity of EV drivers. Driving and charging patterns are affected by various factors, including driving purposes (commuting or other purposes), driving behavior (aggressive drivers have lower energy efficiency), driving conditions (topography, road congestion, outside temperature) [139]), plug-in preferences, battery sizes (EVs with bigger batteries tend to be connected fewer times per week) [47], and availability of charging infrastructure.

Flexibility provision will also depend on the use-case and charging infrastructure considered. At-home (overnight) charging has been widely studied [40][139][50][84][89], showing to have high flexibility potential. Studies analyzing charging patterns in public

charging infrastructure [140][141], and in workplace locations [142], have also found that EVs are idle (not charging) a significant amount of time, thus inducing inefficiencies in charging infrastructure utilization, but also opening an opportunity for smart charging. Therefore, understanding EV user driving and charging patterns is necessary to properly assess the impacts of EV integration and to identify opportunities for flexibility provision.

Understanding behavioral aspects is more important at distribution level, as clustering of EV users into a certain area or neighborhood can create issues at local level, even while overall EV diffusion remains low [143][144]. Usage patterns at local level (urban vs. rural usage), plug-in behavior [47], and weekly and seasonal variations in EV usage [136] will also impact the distribution grid and the flexibility potential of EV fleets.

EV user segmentation is also important to identify fleets with high flexibility potential. Identifying different types of usages/users can provide complementary sources of flexibility and should enable aggregators to better design flexibility offers around end-users needs. For example, the driving and charging patterns of commercial fleets are different than private ones [145], making them more suitable for certain flexibility services, and demonstrator projects like Parker [38] and GridMotion [39] have used company fleets to demonstrate V2G-based grid services. Likewise, [146] identified 32 typologies of EV users and their potential to provide V2G services. Users such as retirees or council fleets, which can be parked at the same location a significant amount of time, appeared as prime candidates for V2G.

5.2 User acceptance

Mobility is and will continue to be the primary purpose of EVs, so flexibility services will need to meet end-user mobility requirements and expectations. From a technical perspective, flexibility services should guarantee a sufficient range to fulfill travel requirements, and should not induce significant aging in the EV equipment, especially the battery, while also enabling users to retain control of the charging process (opt-out, cancelling any smart charging or V2G action if the user requires it). My Electric Avenue project implemented a local congestion management trial in a residential and workplace environment. They found that end-users opted out of controlled charging when the control process started to affect their charging requirements. Likewise, the Electric Nation project showed that an opt-out option was key for customer satisfaction, though rarely used (less than 5% of charging events) [66].

Providing economic incentives can help the acceptance of controlled charging, however they are not sufficient nor mandatory. Reference [147] conducted a survey on acceptance of night-time utility-controlled charging in Canada, and found potential support from between a half and two thirds of the population and economic incentives increased readiness to accept smart charging. Main concerns were loss of control and privacy. However, reference [148] found that economic incentives are expected, though not significant for acceptance, and that the main factor is an understanding for the need for grid flexibility and RES integration. In a more general case, the EMPOWER project found that key factors for end-user acceptance of flexibility services and local energy markets are: first, consuming local and renewable energy, and second, the financial incentives that can be gained (electricity costs reduction) [149].

Finally, awareness and knowledge of grid services, specially V2G, is still very low,

even among experts [52]. It is therefore critical to raise awareness and educate EV users about the utility of flexibility services to support the local grid and increase renewable energy penetration, while developing services around end-users needs and expectations. This shows that while economic incentives can help to increase user acceptance, other options such as raising awareness, sharing charging data and even gamification [150] can boost end-user engagement.

6 Discussion

EV grid integration is one of several challenges that face electricity systems. However, it presents a great opportunity to move towards distributed, decarbonized, flexible power systems. Exploiting EV flexibility can provide benefits for different actors in electricity systems, from supporting the grid by providing ancillary services and increasing renewable energy penetration, to reducing end-user electricity bills and providing energy autonomy as back-up power. In particular, for distribution networks, EV flexibility can help to defer or avoid costly reinforcements in highly uncertain scenarios, thus reducing the risk of stranded assets. Furthermore, EV flexibility can help to make more efficient use of existing infrastructure, by providing peak shaving services and voltage support, and by providing fault restoration or islanding services to reduce non-served energy.

The technical impacts of EV diffusion and the benefits of charging flexibility for distribution grids have been widely studied in the research community. These studies have mostly focused on developing new control algorithms and architectures for EV fleets, and have tested them in different use cases, most of them centered on LV residential grids. There has been less research on MV grids and rural or industrial/commercial environments.

The flexibility capability of EVs has been proven from a practical perspective. Demonstrator projects have successfully managed to provide system-wide services such as primary frequency response in the US (University of Delaware, PJM Interconnection) and in Europe (Parker, Denmark and GridMotion, France), and there are already EV aggregators that have commercial offers on the market, such as Nuvve and Jedlix. These actions show that communication and control of large EV fleets is possible.

There are, nevertheless, some technical barriers to the development of flexibility services at the distribution level. The main technical barriers are:

Observability in distribution grids: Need for increased observability by DSOs, ideally close-to-real-time, to enable forecasting and flexibility activation.

Battery aging: Battery aging is a major factor in the economic viability and user acceptance of grid services. This effect should be thoroughly studied in the context of distribution grid services, which can be more energy-intensive than frequency response services.

Charging technology: Bidirectional chargers are still not a mature technology. They remain expensive and round-trip efficiency can be an issue. However, costs are expected to fall and they could include additional capabilities, such as reactive power compensation.

However, the main barriers to develop EV flexibility are not technical but economic and institutional. These are:

Active management of distribution grids: DSOs should move from a "fit-and-forget" approach towards proactive management of their grids. This includes DSOs developing new roles and responsibilities for grid operation and planning (including forecasting and grid observability), as well as putting in place mechanisms that procure flexibility in a cost-efficient way. Regulators need to work on providing DSOs with the incentives for innovation and cost-efficiency.

EV status in the grid: V2G-able EVs face significant regulatory and technical burden to provide flexibility. Simplification and standardization of connection procedures and adapted metering options are recommended.

DSO-TSO cooperation: Need for increased cooperation and coordination to enable flexibility coming from all levels of the grid and to maintain secure and reliable operation of the power system.

Value frameworks for flexibility: The mechanisms for exploiting flexibility at the distribution level remain limited, but they are emerging, both in demonstrator projects and real-life implementations like flexibility tenders and NAWs.

Value of services: Since the use of flexibility at the distribution level is just emerging, the value that can be extracted from providing flexibility is still unclear. The additional value that V2G can provide with respect to smart charging still needs more research.

However, in recent years there have been several advances in this regard. Regulators have shown increasing interest in exploiting local flexibility from different sources and encouraging smart management of DERs. The European Commission Clean Energy Act made a first step, acknowledging the benefits of flexibility to reduce network costs and the need for regulators to introduce incentives to prompt DSOs to better manage and plan their grids and foster innovation. Note that European regulators (CEER) have also addressed the evolution of DSO roles, the associated incentives, and the use of local flexibility.

Considering EV flexibility, regulators like OFGEM (UK) and CRE (France) have seriously taken on the task of analyzing the challenges of EV integration (see [151] [131]), and several V2G demonstrator projects have been funded, especially in the UK [152]. The Netherlands has run several DSO-led projects where they test new solutions for hosting EVs, with active involvement of DSOs through Elaad, an association for EV development.

In this regard, demonstrator projects play a crucial role by addressing all four key aspects: technical, economic, regulatory and user-related. Table 2.5 summarizes the analyzed demonstrator projects in smart grids and VGI, including possible services and frameworks in which they can be implemented.

Most vehicle-grid integration projects have focused on proving the technical feasibility of EV flexibility and creating new technical solutions for EV grid integration without considering value mechanisms (Electric with a solution for LV voltage and congestion management [153], My Electric Avenue with a solution to handle overloading in LV residential

grids), or their economic viability on existing value mechanisms (balancing markets in Parker, balancing markets and energy arbitrage in GridMotion, balancing markets and demand response incentives in Invent). An exception is the FlexPower project, which has proven the benefits of the variable capacity connections as an innovative mechanism for public charging infrastructure. Similar solutions could be tested for other services, such as voltage regulation, where charging infrastructure could benefit from lower connection costs or a higher capacity contract if it actively regulates voltage, either using active or reactive power compensation.

Other projects have focused on short-term market solutions, such as flexibility platforms with varying levels of coordination with TSOs (SmartNet, InterFlex, INVADE), or local energy markets (EMPOWER). However, this kind of solution is not yet ready to be implemented, as flexibility resources need to become more abundant to allow competition at the local level. For this reason, the first implementations have been in the form long-term contracts (tenders in the UK and France, NWAs in the US). Nevertheless, long-term contracts for flexibility provision has been less studied in the literature.

Future smart grids will feature all four frameworks mentioned. Grid codes are needed to ensure grid reliability, for example by defining requirements for protection under fault conditions, or to reduce power quality issues [154]. The deployment of smart meters will allow the implementation of dynamic tariffs with higher temporal and geographical granularity that will incite users to adopt smart charging strategies, reducing the burden on distribution grids. The implementation of dynamic tariffs should help dealing with most day-to-day grid issues. However, contingencies can still occur in the distribution grid. Flexibility procurement through mid-to-long-term auctions or flexible contracts can improve distribution grid reliability and planning, by ensuring a minimum amount of flexibility available for contingencies or extreme events. In the operational timeframe, flexibility can be procured at lower costs through local flexibility markets in coordination with balancing flexibility for the TSOs.

Table 2.5: Demonstrator projects analyzed

Project	Period	Region	EV-related	Research Topic	Flexibility services	Value framework
evolvdSO	2013-2016	Europe	No	DSO future roles, tools and methods	CM	-
IDE4L	2013-2016	Europe	No	Automation and ICT for distribution grids	CM, fault-restoration	LFM
SmartNet	2016-2018	Europe	No	DSO-TSO coordination	CM, balancing	Market-based
EMPOWER	2015-2017	Norway	No	Local energy markets	P2P trading	Local energy markets
BienVenu	2016-2018	France	Yes	Smart charging in residential buildings	Residential building bill optimization	Grid tariffs
My Electric Avenue	2013-2015	UK	Yes	EV integration in LV grids	LV CM	Interruptible contract*
INVADE	2017-2019	Europe	Yes	Distributed storage management (EV & BESS)	LV CM	LFM
InterFlex	2017-2019	Europe	Yes	Flexibility for distribution grids	LV CM	LFM VCC via agg.*
Electric Nation	2017-2019	UK	Yes	Large-scale smart charging trial	MV CM	VCC via aggregator*
FlexPower	2017	Amsterdam	Yes	Smart charging on PCI	Peak shaving RES integration	VCC for PCI
Electrific	2017-2019	Europe	Yes	Solutions for e-Mobility (including VGI)	LV CM and VR	*
Parker	2016-2018	Denmark	Yes	Grid services using commercial EVs	FR	Balancing markets
ACES	2017-2019	Denmark	Yes	Large-scale VGI	*	*
GridMotion	2018-2020	France	Yes	EV Grid Services	Energy arbitrage FR	Energy and balancing markets
Invent	2017-2020	California	Yes	VGI in a university campus	V2B, DR, FR	Grid tariffs Existing markets

CM: Congestion management. VR: Voltage regulation. FR: Frequency regulation. DR: Demand response. LFM: Local flexibility market. PCI: Public charging infrastructure

*Value framework not explicitly addressed in the project

Research gaps have been identified, which should be further addressed in the literature:

- A thorough characterization of flexibility requirements for distribution grids, i.e., the frequency, duration and amount of flexibility needed to solve grid issues. The models to provide flexibility will differ according to whether the service is required only a few days a year to cope with peak demand, or if it is needed all-year-round. It can also affect the fleet size required to provide these flexibility services and the impact on battery degradation.
- Quantification of the value of different EV services. As most studies analyze each service separately (congestion management, voltage regulation, losses reduction), there is no common valuation of these services. This can help prioritize the services that EVs can provide.
- Quantification of the value of V2G with respect to smart charging. While this has been addressed in the frequency response framework (for example in [155]), it has been less thoroughly reviewed at distribution level.
- The coordination of EV flexibility provision within different frameworks still needs further research. For example, the coordination of flexibility provision through market frameworks in the presence of dynamic tariffs for end-users, or the coordination between EVs providing ancillary services to the TSO and to the DSO.
- Studies should consider **realistic driving and plug-in behavior**. Most studies assume that EVs are plugged-in every day, which overestimates the potential flexibility that EV fleets can effectively provide. Also, **spatial distribution** of EVs and **local local mobility patterns** (urban vs. rural conditions) are not taken into account. Advanced data-driven models can help overcome these issues.

7 Partial conclusions

This chapter analyzed the technical, economic, regulatory, and user-related aspects that arise for the proactive integration of EVs into distribution grids. This integration takes place against a broader backdrop of cross-sector electrification and decentralized generation that poses serious challenges to distribution grids operation and planning. EVs, through smart charging and V2G, can provide flexibility to electricity systems reducing the impact of their integration and even creating value for different stakeholders along the value chain, such as end-customers, aggregators and system operators, and help the integration of renewable energy.

EVs can provide DSOs with various services, including investment deferral on the planning timeframe, and congestion management, voltage regulation and back-up power in operational time frames. The ability to provide these services has been proven technically, but the technologies (bidirectional chargers, reactive power control) and communication protocols needed to exploit the full potential of EV flexibility are not yet widespread.

The main barriers for EVs to provide flexibility services to distribution grids are economic and institutional. DSOs have only recently started to change operational and planning practices to move from a "fit-and-forget" approach to an active management of their grids, so there are no widespread value frameworks under which EVs can provide flexibility to DSOs. This chapter analyzed four possible value frameworks (grid codes, connection agreements, tariffs and market platforms) to use flexibility at the distribution level, and their applications with EV fleets in demonstrator projects. In future smart-grids, we expect that these frameworks will coexist, such as dynamic tariffs for EVs that can incite EV-users to charge at low-impact hours, market platforms that can explicitly procure flexibility for DSO needs, and long-term contracts to provide flexibility in the case of unexpected events.

The adoption of smart charging and V2G will ultimately depend on end-user acceptance. The flexibility services covered in this paper will only be possible if they are built around end-users primary need of mobility. Understanding users' mobility and charging habits will be key for flexibility development.

7.1 Positioning with respect to the state-of-the-art

In the remainder of this thesis we will center on two of the research gaps identified: how EV user charging and driving patterns affect EV integration, and what mechanisms/frameworks are emerging for flexibility procurement at the distribution level. In Chapter 3, we will analyze and model the charging behavior of EV users (i.e., how often they plug-in their vehicle). Then, in Chapter 4 we will study how local mobility patterns and the spatial distribution of EVs affect EV integration and the coupling with renewable energies. Finally, in Chapter 5 we analyze emerging flexibility mechanisms at the distribution level, with a particular focus on long-term tenders, and how EV aggregators can participate in them.

Chapter 3

Plug-in behavior of EV users: modeling, insights from a large-scale trial and impacts for grid integration studies

1 Introduction

A proper assessment of the costs and benefits regarding EV integration hinges on correctly modeling and evaluating EV-user driving and charging patterns. As noted in Chapter 2, EV charging impact and flexibility potential will be affected by a number of factors, including driving patterns (purposes, distances driven), charging patterns (when, where, and how often EVs are charged) and EV characteristics (battery sizes, driving efficiency).

Most EV integration studies consider a plug-in behavior called *systematic*, meaning that the EVs are plugged in every day. However, recent studies have evidenced that EV users do not plug in every day (here called *non-systematic plug-in behavior*) even if they have charging access at a regular location (at home, work or easily accessible public charging) [66][156]. The consideration of non-systematic plug-in behavior started to be considered in the scientific literature only recently, and available models present limits.

In this chapter we will present an agent-based model (ABM) to generate synthetic EV load curves that considers a probabilistic non-systematic plug-in behavior. This model will be the base of the simulations and analysis carried out in the rest of this thesis. The plug-in decision module is calibrated to match observed plug-in behavior of EV users using real-world data from a large-scale demonstrator project. Then, we analyzed the impact of non-systematic plug-in behavior through two aspects relevant for EV grid integration: the EV charging demand and the potential of EV fleets to provide flexibility.

The main results of this chapter show that it is important to consider realistic non-systematic plug-in behavior to correctly assess the impacts of EV charging, especially at the distribution level and when considering price-responsive (smart) charging. Considering systematic (every day) charging can largely overestimate the flexibility that EV fleets can provide to the system via smart charging and V2G, both in terms of power (kW) and storage (kWh) available to aggregators. Non-systematic plug-in effects are more im-

portant for large-battery EVs, both in terms of impact of EV charging and on available flexibility. Counter-intuitively, large-battery EV fleets can put flexibility aggregators at risk, as they offer lower flexibility potential due to lower plug-in frequency and less flexible time per charging session.

Section 2 analyzes relevant work on ABMs and plug-in behavior modeling. Section 3 describes the proposed model for simulating EV charging, including the plug-in decision module. Section 4 provides insights on plug-in behavior from the Electric Nation project, a large-scale EV trial in the UK, which we use to calibrate our model. Section 5 evaluates the impact of considering non-systematic plug in behavior in EV grid integration and flexibility studies. Finally, Section 6 present some conclusions for this chapter.

2 Literature review

2.1 Agent-based models

ABMs are a simulation method where many autonomous agents are simulated individually, allowing each agent to interact with its environment and make its own decisions. Stochastic ABMs account for variability in the agents parameters. In this way, the stochasticity of user behavior can be accounted for, while capturing the emergence of aggregated behavior patterns [157].

ABMs have been widely used to simulate EV–grid interactions, as they allow for better user behavior modeling by considering heterogeneous agents (i.e., each EV can have its unique mobility patterns and technical characteristics). In [158], authors developed a model to assess the impacts of EV charging at various locations (work, home, public charging) based on a trip chain mobility model. Reference [159] proposed a model to assess EV impacts on road transport and electricity networks. Reference [160] coupled an ABM framework with detailed geo-referenced data to evaluate EV charging infrastructure development in a Swiss city. Many studies have developed ABMs to generate synthetic EV load curves and evaluate the impact of EV charging at the LV [161][157], MV [137] or system-wide level [162].

ABMs for EV simulation are composed, at least, of two modules: a mobility module and a charging module. The mobility module simulates the driving patterns of the EV, defining arrival and departure times at the charging location(s) and distances driven. One approach is to sample these variables (i.e., daily driven distance, arrival and departure times) from probability distributions for each agent in each simulated day. In [137][40][163][161], each variable is sampled independently. More advanced probabilistic models, such as [29] and [164] used Copula functions to model the dependencies between these variables. Probabilistic models can be suited to assess EV charging at one regular location.

More advanced mobility models simulate the activity pattern of each agent defining the state of the vehicle at each moment of time (whether it is driving, at home, at work, or in other states). Several methods have been used to generate the agent activities, such as Markov chain Monte Carlo models [165] and trip chains [158][166], usually based on national travel surveys. These models can provide more accurate descriptions of mobility patterns and can allow the assessment of EV charging at various locations. Mobility models can also account for realistic driving conditions, differentiating the time and

energy spent for different types of trips, such as in [167].

The charging module of ABMs computes EV charging, which can follow one or several strategies. ABM models that do not provide co-simulation with the electricity grid can implement decentralized charging strategies to generate EV charging profiles. Common decentralized strategies include:

- **uncontrolled** charging where the EV is charged at full power as soon as it is plugged-in [168][162][157][137][166][159][160];
- **off-peak** charging where the EV is charged only during off-peak hours - such as during a window in night-time [157][162][137][166],
- **average** charging where the EV is charged at a constant power during the whole charging session, reducing the maximum power drawn from the grid [162][50][166];
- **costs minimization** charging, where the EV will be charged to minimize charging costs given variable electricity prices [43][89].

Alternatively, ABMs mobility modules can provide the basis to perform grid simulations and implementing more complex EV charging strategies such as: **system costs minimization** where charging costs of the whole EV fleet are optimized (this can include the grid constraints) [163], **valley-filling** where the charging of the EV fleet is optimized to fill low-demand hours [137] or to support local RES generation [29].

2.2 Plug-in behavior models

Most EV grid integration studies analyzing grid impacts of EV charging and the potential of smart charging and V2G as flexibility sources consider a systematic plug-in behavior. EV impact studies include [89] who investigated the impacts of uncontrolled and price-responsive charging at HV/MV substation level in Switzerland, and [43] who addressed the impacts of EV integration in the MV grid in the Netherlands. These studies showed that price-responsive charging can create larger constraints in the grid due to the synchronization of EV charging at low-price hours. [167] quantified the demand increase using detailed EV and household modeling based on US data, [50] that studied the impacts of EV integration on Belgian LV grids. [157][162][137] proposed tools for generating EV charging profiles and assessed their impacts on the electricity grid. All previous studies consider that EVs are plugged in every day at the regular charging location (usually at home).

The literature on EV flexibility includes [44] who analyzed the potential of increasing self-consumption in a PV-rich Italian village using V2G-capable EVs, with underlying assumption that EVs are plugged in every day and at all times (day and night) that they are not being driven, which can prove to be highly unrealistic. In another case study, [155] and [169] estimated the revenues of EV fleets participating in primary frequency regulation services every day. This hypothesis may be possible for highly reliable company fleets, but is less accurate for much more uncertain private user fleets.

Considering systematic charging was a valid assumption when small-sized battery EVs (16-25 kWh) were predominant [138][170]. However, plug-in behavior is evolving as larger battery EVs are entering the market. Recent analyses using real EV driving

and charging behavior datasets have shown that users do not recharge every day, even if they have access to charging infrastructure at a regular location [66], and that there is large heterogeneity among EV users charging patterns [171]–[173]. The Electric Nation project in the UK, which counted over 600 participants running different makes and models, including plug-in hybrid EVs (PHEV), range extenders (REX) and battery EVs (BEV), and at-home charge access, showed a median charging frequency of 3.64 times per week for all participants, and only 2.73 times per week for BEV users [66]. Similar results have been found in Dutch public charging infrastructure, where [156] identified typologies of EV users from a dataset consisting of over 28000 unique users and computed an average charging frequency for different EV user types of between 0.9 and 4.6 events per week.

Thus, considering a systematic (i.e., every day) charging behavior can bias the actual impacts of EV integration into the grid and significantly overestimate the flexibility potential of each charging session. As users only plug in their EV a few times per week, there are fewer EVs available (i.e., connected) to provide flexibility to the system.

Studies have found that the main factors that affect the plug-in decision (whether to connect or not the EV) when charging at the users’ regular charging location are expected kilometers to be driven in the next trip and the remaining range [174], [175], while still maintaining a ‘comfortable range’ buffer [176]. Recent studies have started to consider and model the non-systematic plug-in behavior of EV users, summarized in Table 3.1. Still, most do not consider all the factors that shape plug-in behavior.

A study done by the French transmission system operator RTE considered different levels of non-systematic plug-in to evaluate EV charging impacts and the potential to provide flexibility services at the transmission level, though only by defining different shares of EVs connected per day at the national level [177]. Plug-in behavior was explicitly modeled by [168] to analyze the impact of 24 kWh EVs on a LV grid using predefined plug-in probability curves based on user’s daily distances driven and EV state of charge (*SoC*) on arrival at home. In [163], authors extended this work to 40 kWh EVs to study the gains of optimal charging scheduling in the Danish island of Bornholm. However, there is no parametric model for the probability curves used by these papers, limiting their use in other studies and the extrapolation to different battery sizes. [178] proposed a fuzzy logic plug-in decision model that depended on EV battery size and SoC on arrival at the charging location to evaluate the impact of EV charging at a HV/MV substation in Paris. However, no data was supporting this model. [179] analyzed EV impact on residential load profiles considering a plug-in decision model based on a logistic function dependent exclusively on SoC on arrival. The parameters that define the logistic function can be made to vary to account for the heterogeneity in user charging behavior. [180] proposed a heuristic model that selects the minimum number of charging events all trips during a full week, by minimizing the inconvenience of EV charging. [47] then applied this model to evaluate the impacts of EV charging in distribution networks, considering different levels of charger power and battery sizes, and [45] analyzed the potential for mitigating wind curtailment with the minimal charging strategy compared to a systematic (every day) charging.

We find that despite the evidence from various demonstrator projects and EV usage analyses, most EV-grid integration literature still does not consider the non-systematic plug-in behavior of users. Some recent studies have started to consider and model non-

systematic plug-in patterns, but either the models are not readily extendable to different kinds of users or EV characteristics (e.g., only applicable to a given battery size), or they do not account for the heterogeneity of user charging preferences (all users behaving the same), or the decision models are not backed up by real-world data on EV user plug-in behavior. Furthermore, there has not been any study that specifically analyzes the impact of considering the non-systematic plug-in behavior in EV grid integration studies.

2.3 Contributions

This chapter presents three major contributions to the scientific literature.

- First, we propose an ABM for EV simulation that considers **non-systematic plug-in behavior**. In particular, the plug-in decision complies with several characteristics missing from the scientific literature: it is extendable, can capture heterogeneity, and is backed-up by real-world data.
- Second, we provide **insights on plug-in preferences from EV users using a large-scale dataset** that comprises a wide diversity of EV marks and models. This is of particular interest as most analysis come from have little diversity on EV characteristics (see [138][181][170][173]).
- Third, we explicitly evaluate the **impact of non-systematic plug-in behavior** on EV grid integration studies, in both impact of EV charging and flexibility potential of EV fleets. To the best of our knowledge, this analysis has not been previously carried out.

Table 3.1: Summary of main EV grid integration studies that consider non-systematic plug-in behavior.

Study	Model	Extendable ^a	Data-based ^b	Heterogeneity ^c	Model parameters		
					Next-trip distance	SoC at arrival	Comfortable range
[177]	Proportion of connected EVs	-	No	No	No	No	No
[168]	Plug-in curves for 24 kWh EVs	No	Yes	No	Yes	Yes	-
[163]	Plug-in curves for 40 kWh EVs	No	Yes	No	Yes	Yes	-
[178]	Fuzzy logic decision model	Yes	No	No	Yes	Yes	Yes
[179]	Logistic curve	Yes	No	Yes	No	Yes	Yes
[180]	Minimum number of charging sessions	Yes	No	No	Yes	Yes	No
This study	Probabilistic plug-in	Yes	Yes	Yes	Yes	Yes	Yes

^a A model that can be applied to other contexts or EVs with different characteristics.

^b A model that is supported by real-world data of EV usage.

^c A model that allows for heterogeneity on EV users plug-in preferences.

3 EV simulation model

3.1 Model

We developed a stochastic ABM simulation tool to generate weekly or monthly EV load curves for distribution system studies that considers charging at one regular location, such as home charging. The model described in this section consists of three sequential sub-modules: a mobility module, a plug-in decision module, and a charging module that runs for each EV in each day of simulation, as shown in Fig 3.1. It was implemented in Python 3, including the library *cvxopt* for the optimization of charging strategies.

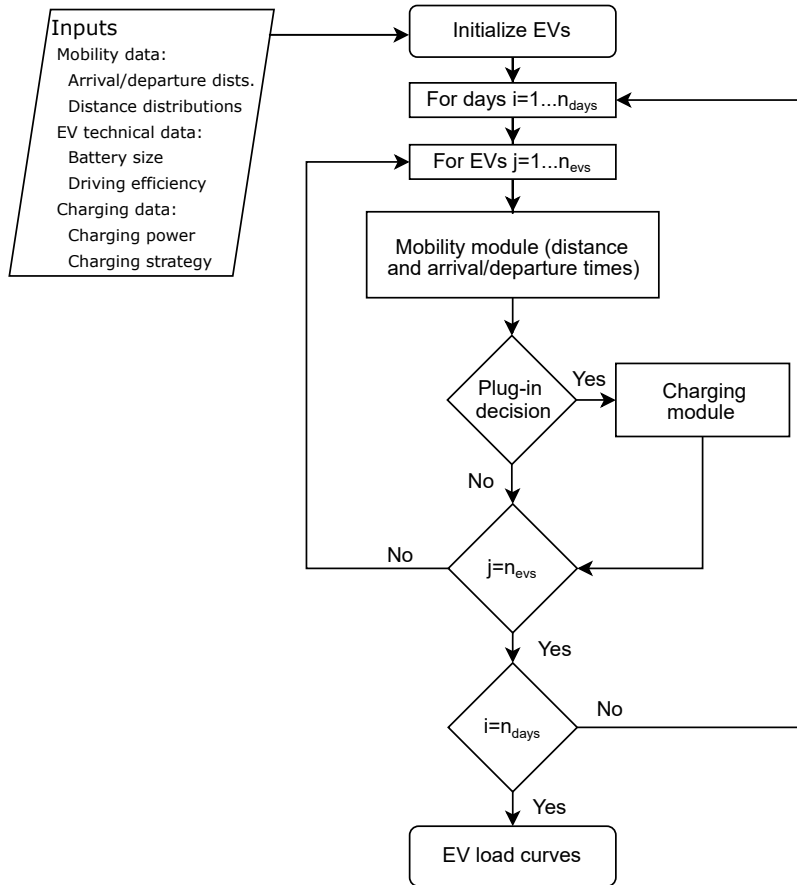


Figure 3.1: Flowchart of the developed ABM model

The mobility module computes daily distance driven (d_i) and arrival and departure times at the EV charging location. **It simulates commuters that travel the same distance to work every weekday and make variable trips on weekends**, with the possibility to include additional trips to increase the variability of daily distances driven. It follows a probabilistic approach, where arrival and departure times are randomly sampled from user-defined probability distributions for each day, which can be distinct for each day of the week. Finally, *SoC* levels on arrival at the charging location are computed based on distances driven, EV driving efficiency (η in kWh/km) and battery size (b in kWh), as shown in Eq. 3.1. ¹

¹The mobility module is a simple one, only sampling driven distances and arrival and departure times

$$SoC_i = SoC_{i-1} - \frac{d_i \cdot \eta}{b} \quad (3.1)$$

Second, a probabilistic plug-in decision module determines whether the EV is connected at each possible charging session. **The plug-in decision is based on three factors** identified in the literature, i.e., a **range anxiety factor** or comfortable range (ρ_i), the **expected next-trip distance** (d_{i+1}), and **SoC at arrival**, and detailed in Eqs. 3.2 and 3.3. The user will plug in if the remaining range (i.e., SoC on arrival) is lower than what is required for the next trip after allowing for a range anxiety safety margin (ξ_i), otherwise the probability of plugging in decreases with higher SoC levels. The α parameter modifies the user's plug-in preference, thus allowing to account for the heterogeneity of user choices. For α values close to zero, the user will plug in only if they need to cover next-day trips, whereas for high α values ($\alpha \gg 1$) the user will tend to plug in every day. Figure 3.2 gives an illustrative example of these plug-in probability curves.

$$\xi_i = \frac{d_{i+1} \cdot \eta}{b} \cdot \rho \quad (3.2)$$

$$\mathbb{P}(plugin_i) = \begin{cases} 1 & \text{if } SoC_i \leq \xi_i \\ 1 - \left(\frac{SoC_i - \xi}{1 - \xi}\right)^\alpha & \text{if } SoC_i > \xi_i \end{cases} \quad (3.3)$$

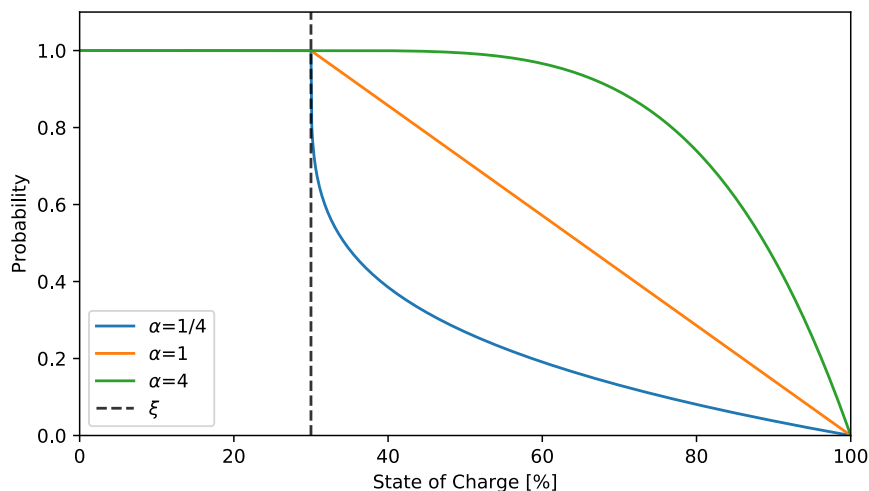


Figure 3.2: Plug-in probability curve according to SoC at arrival for three plug-in preferences (α), and for a required SoC for next trip (ξ) of 30%

Finally, if the agent decides to recharge the vehicle, the charging module will compute the charging profile needed to reach the desired SoC . Five decentralized charging strategies have been implemented: **uncontrolled**, **off-peak**, **modulated**, **costs-minimization** and **valley-filling**. A variable capacity limit (limiting the maximum from input probability distributions. However, it can also receive as input a schedule of availability times and driven distances which can be derived from more complex, activity-based mobility modules. However, this model can be useful to asses EV charging at the user's regular location, such as at home.

power that can be drawn from the grid) can be provided to the uncontrolled, off-peak and cost-minimization strategies. The valley filling strategy follows a decentralized approach based on the cost-minimization strategy, where each EV optimizes its charging schedule using the net load of the substation as the price profile. A central aggregator updates the net load profile after each new EV connection, and broadcasts it to the EV fleet². The four main strategies are shown in Figure 3.3. In this chapter we focus on **uncontrolled charging** and **price-responsive charging**³.

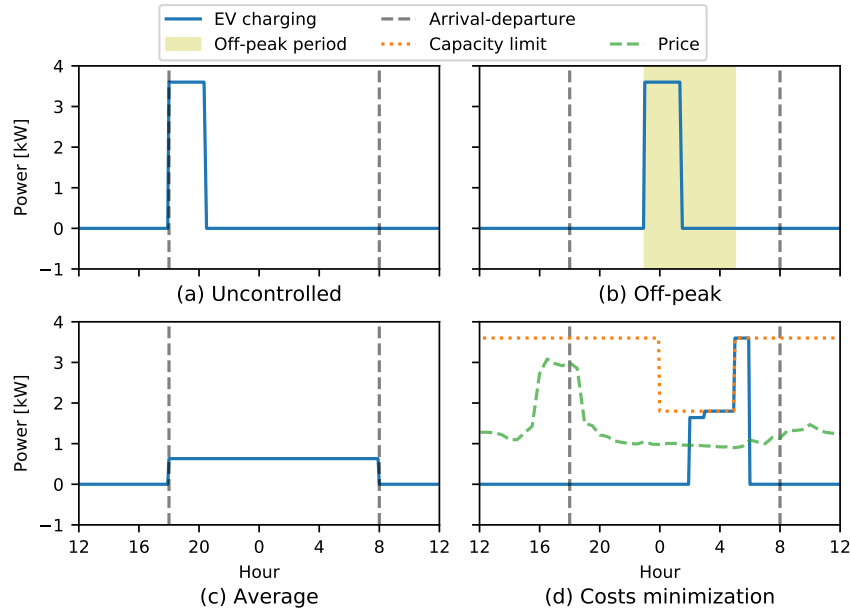


Figure 3.3: Illustration of implemented EV charging strategies. A variable capacity limit is included in the costs minimization strategy. 3.7 kVA charger.

²The optimization model for the cost-minimization strategy and the algorithm of the valley filling strategy are detailed in Appendix A

³Price-responsive charging includes both off-peak and price-responsive charging.

4 Insights from a large-scale EV trial and model calibration

4.1 The Electric Nation trial

We used real-world data from the Electric Nation project to calibrate the plug-in decision module. The Electric Nation project was a large-scale smart charging trial in the UK that ran from 2016 to 2018. The full dataset contains information for 153621 charging sessions, including starting time, ending time, and energy consumed for each session, by 601 unique users with a variety of BEVs, PHEVs, and REX marks and models.⁴

To calibrate the model, we only considered BEV users that stayed in the trial for more than 3 months. After cleaning the dataset, we obtained 52822 charging sessions for 265 unique users, encompassing a wide range of EV brands and battery sizes, as shown in Figure 3.4 and Table 3.2. Two distinct EV groups can be observed, the first composed of small EVs with battery sizes between 20–35 kWh, and a second group composed of large EVs with battery sizes around 75 kWh.

Table 3.2: Most popular BEVs in the Electric Nation trial (out of 265)

EV Model	Users	Battery size [kWh]
Nissan Leaf	79	24-30
Tesla Model S	74	75
BMW i3	43	33
Tesla Model X	20	75-100
Kia Soul EV	18	27-30
Renault Zoé	12	24

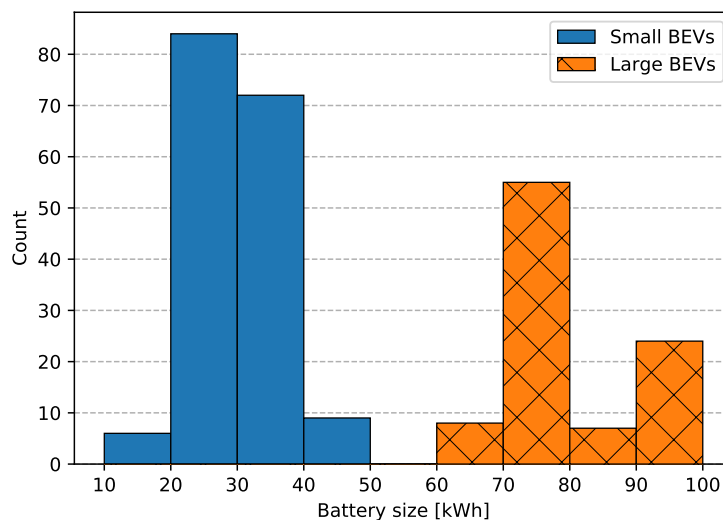


Figure 3.4: Distribution of battery sizes in the Electric Nation trial

⁴Dataset available [here](#) [182]

For each EV user, we computed three charging behavior indicators: the average number of weekly charging sessions, the average charged energy per session, and the average daily distance driven (d_{avg_e}). As the dataset does not provide the actual driven distances, we estimated them from the charged energy (E) and total permanence in the trial (nd_e , in days), as shown in Eq. 3.4. For this we considered a charger efficiency (ν) of 95% and a driving efficiency (η , in kWh/km) dependent on the battery size, shown in Eq. 3.5 [183].

$$d_{avg_e} = \frac{1}{nd_e} \sum_{s \in S_e} \frac{E_s \cdot \nu}{\eta} \quad (3.4)$$

$$\eta_e = (14 + 0.09 \cdot b_e) / 100 \quad (3.5)$$

The charging behavior indicators for all users are shown in Figure 3.5, and statistics are shown in Table 3.3. Some charging trends can be identified. Large EVs are plugged in less often (mean frequency of 2.79 sessions per week) than small EVs (mean frequency of 3.31 sessions per week) and charge a higher amount of energy per session (left-hand plot in Figure 3.5)), as larger battery sizes allow for longer periods without requiring to recharge. Furthermore, users who drive higher distances per day tend to plug in their car more frequently, and users with higher battery capacity drive longer distances for the same frequency of charging sessions (right-hand plot in Figure 3.5). This means that a small-EV user who plugs in 4 times a week will drive around 40 km/day, whereas a large-EV user will drive 60 km/day for the same charging frequency. A linear regression model between charging sessions and daily distances disaggregated by large and small EVs shows that an increase in daily distance driven of 7 km for small EVs and 14 km for large EVs requires one extra charging session per week. Note that the aggregated fleet can be seen as representative of car usage in Europe, where daily distances driven are around 40 km/day (similar results are found in [40] for France, [163] for Denmark or [166] for Belgium).

We observe as well a large heterogeneity in charging preferences among users. This reflects the different behavior that each user when charging their vehicle. Two users which share the same characteristics (battery size, daily driving distances) can have opposing charging behavior, one plugging in almost daily, whereas the other plugging in as least as possible.

Table 3.3: Charging behavior indicators of EV users from the Electric Nation trial. Results are shown for the aggregate EV user population and disaggregated for small (<50 kWh battery) and large (>50 kWh battery) EVs.

Indicator	Mean			Median		
	All	Small	Large	All	Small	Large
Weekly charging sessions	3.12	3.31	2.79	2.72	3.00	2.28
Charged energy per session [kWh]	18.5	13.2	28.3	15.2	13.2	29.3
Daily distance [km]	38.1	33.3	46.7	32.6	29.7	43.4

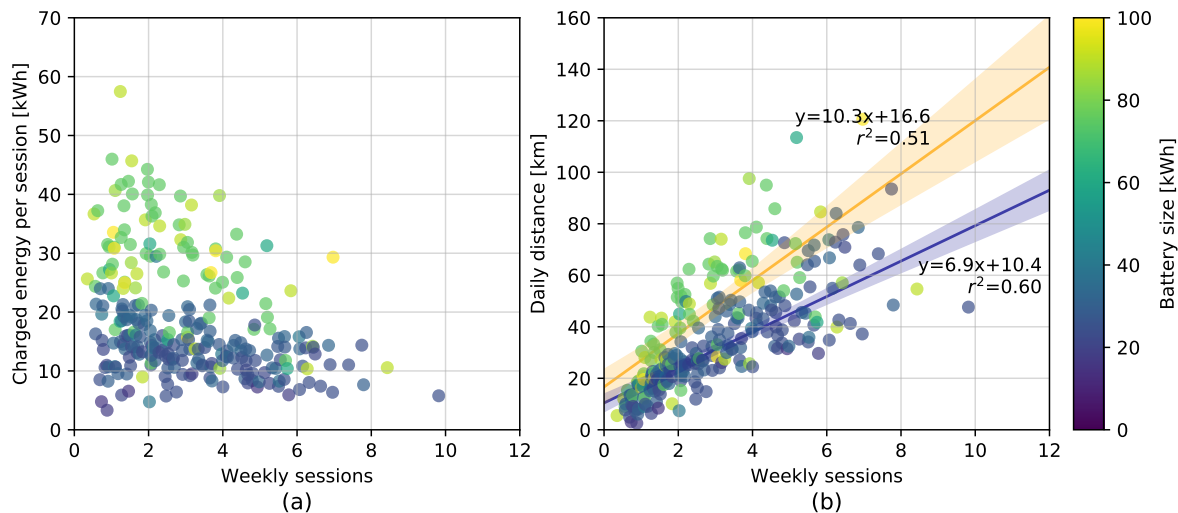


Figure 3.5: Charging behavior indicators in the Electric Nation trial. (a) Average charged energy per session and (b) daily distance driven according to weekly charging sessions. Each point corresponds to an EV user and is color-coded to battery size.

4.2 Plug-in decision model calibration

We calibrate our model to match the average plug-in frequency found in the Electric Nation trial for three cases representative of small (25 kWh battery), average-size (50 kWh), and large (75 kWh) EV fleets. Using the EV model presented in Section 3, a simulation for 1,000 EVs and 12 weeks was carried out with a range anxiety factor (ρ) of 1.5, and for levels of the plug-in parameter (α) varying from 10^{-2} to 10^2 . Each simulated EV has a daily distance sampled from a lognormal distribution, as in [40]. Table 3.4 shows the main parameters of the simulations used to calibrate the model, and Figure 3.6 shows the average frequency of charging sessions for a sweep of the α parameter for the three cases and the selected α value to match the observed data. The selected α parameter ranges between 0.89 for small EVs, to 1.31 for the average fleet.

Table 3.4: Simulation parameters for the three representative cases to calibrate the α parameter.

EV case	Battery size [kWh]	Average daily distance [km]	Average weekly plug in frequency
Small	28	33.3	3.31
Average	46	38.1	3.12
Large	79	46.7	2.79

To verify the quality of the model calibration, we computed the charging behavior indicators for the three simulated EV cases. We considered the heterogeneity of users' charging choices by sampling the α value individually for each user using a lognormal distribution centered on the α values previously found. We used a lognormal distribution due to the logarithmic behavior of the α variable (see Figure 3.6). For each EV group, the underlying normal distribution of the lognormal function has a mean (μ) equal to $\log \alpha$

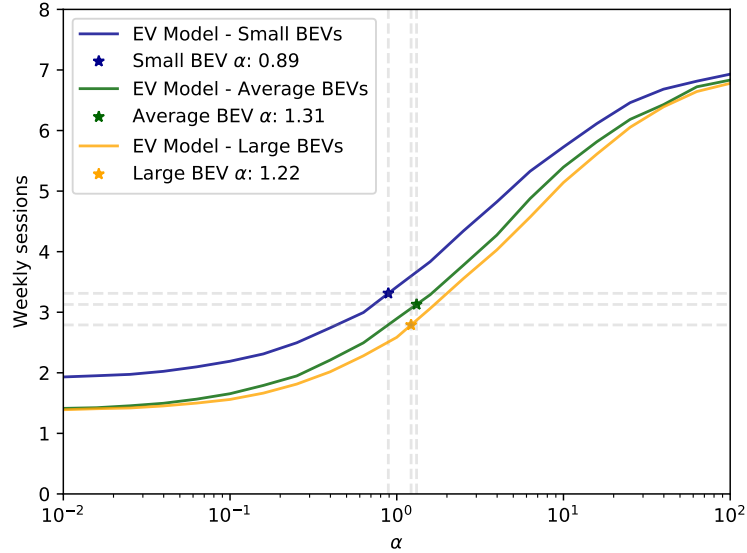


Figure 3.6: Average weekly charging frequency from EV model simulations varying the α parameter. α is selected to match the average charging frequency observed in the Electric Nation trial.

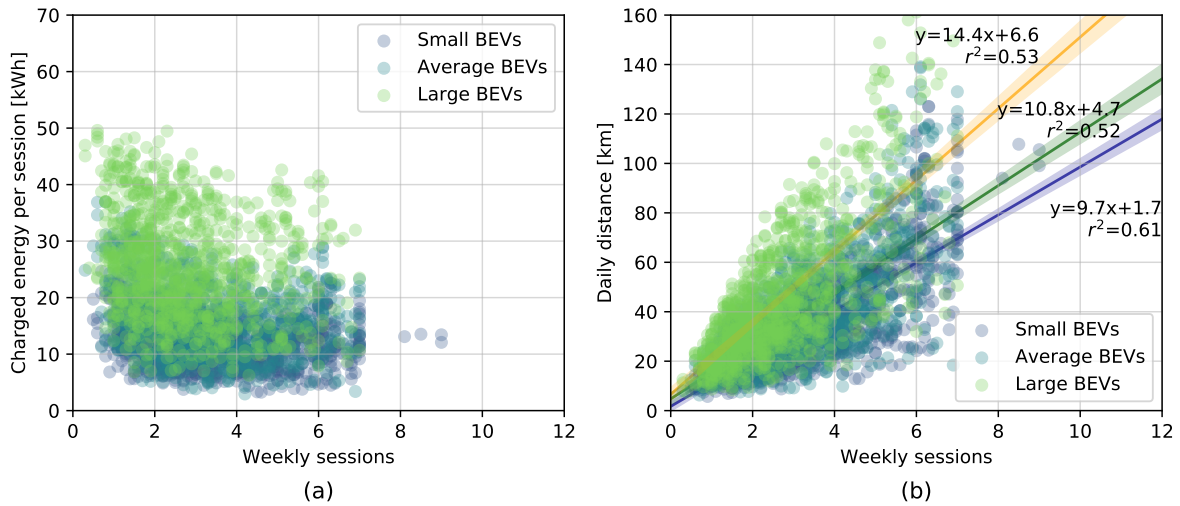


Figure 3.7: Charging behavior indicators for heterogeneous α simulation: (a) Average charged energy per session and (b) daily distance driven according to weekly charging sessions. Each point corresponds to an EV user.

and standard deviation (σ) of one.⁵ The charging behavior indicators of the simulations, shown in Figure 3.7, are similar to those observed in the trial, both qualitatively and quantitatively. The simulations reproduce the same EV-group patterns that in the trial (lower charging frequency, higher energy per session, and higher distances driven for large EVs). A group of users with significantly higher charged energy per session and a low charging frequency is also found, as observed in the Electric Nation trial. The model is also able to capture the large heterogeneity on charging choices among users. Quantitatively, the linear regression models of daily distances vs. charging frequency for small and large EV groups present similar coefficients to those observed in the trial, thus demonstrating the validity of the model calibration.

5 Impact of non-systematic plug-in behavior on EV grid integration studies

We evaluated the impact of considering non-systematic plug-in behavior in EV grid integration studies. For this purpose, we analyzed two aspects: the impact of EV charging in power systems through the peak load created by EV fleets, and the flexibility potential to assess the time and accessible storage capacity that EV fleets can use for smart charging or V2G-based flexibility services.

Simulations using the EV model were carried out for a fleet of 10,000 EVs and combinations of battery size, charging power, plug-in behavior, and charging strategies. We considered three battery sizes, i.e., **small (25 kWh)**, **medium (50 kWh)** and **large (75 kWh)** in line with current trends, and three charging power levels, i.e., **3.7 kVA** and **7.4 kVA**, reflecting standard single-phase chargers, and **11 kVA** three-phase charger, all with a 0.95 power factor. Charging choices were considered via **systematic plug-in** (i.e., every day) and **three non-systematic plug-in behaviors**, an average case given by the calibration with the Electric Nation trial ($\alpha=1.31$), a high plug-in case ($\alpha=3.4$), and a low plug-in case ($\alpha=0.5$) to account for different charging choices. Two charging strategies were analyzed: uncontrolled charging, where EVs are charged as soon as they are plugged in, and smart charging, where EVs charge during an off-peak period between 10pm and 6am. Finally, arrival and departure times at the charging locations are given by joint probability distributions derived from the Electric Nation trial (probability distributions shown in 3.8).

⁵For a lognormal distribution centered in x , the underlying normal distribution has a μ of $\log(x)$

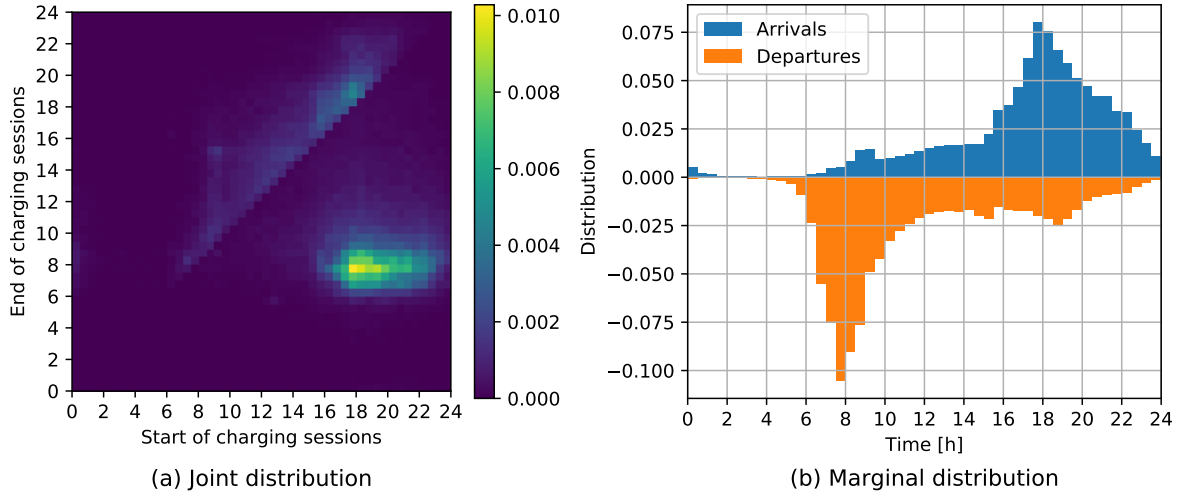


Figure 3.8: (a) Joint probability distribution and (b) marginal distribution for arrival and departure times derived from the Electric Nation trial.

5.1 Impact on peak load

To quantify the impact of EV charging at different levels of the grid, peak load was computed for fleets of varying sizes between 1 and 10,000 EVs, as the impact of EV charging at LV feeder level (tens of EVs) will not be the same as in the LV transformer (up to hundreds of EVs) or HV/MV substation (hundreds to thousands of EVs). 500 iterations for each fleet size were carried out to obtain statistically significant results. For each iteration, corresponding to a 3-month EV charging simulation, the peak load is computed, and then for each fleet size the average EV peak load is reported. This is defined in Eq. 3.6 where $PeakLoad_{fs}$ is the peak load for a fleet of size fs , and $\mathbf{x}_{i,j,t}$ is the load profile of the j^{th} EV of iteration i at time t .

$$PeakLoad_{fs} = \frac{\sum_{i=1}^{500} \max \sum_{j=1}^{fs} \mathbf{x}_{i,j,t}}{500} \quad (3.6)$$

Uncontrolled charging

In Figures 3.9 and 3.10 the load curves for uncontrolled charging of 20 EVs and 1000 EVs fleets are shown, for both systematic and non-systematic charging behavior and different battery sizes. Average demand reaches around 1 kW/EV for the different cases, however due to high variability of EV demand for small sized fleets, peak load reaches almost 4 kW/EV. Non-systematic plug-in has limited impact in both peak and average demand for small battery EVs, however, for large-battery EVs demand is shifted to later hours as each charging session requires more energy. It can be seen as well that with larger fleet sizes, charging variability is reduced, tightening around the average load curve.

Results for the uncontrolled case, depicted in Figure 3.11, show the decreasing coincidence of EV charging as EV fleet sizes increase due to the natural diversity of charging sessions, both in start times and in energy requirements. This effect is higher for higher charger power, as each charging session requires less time, and thus there is less coinci-

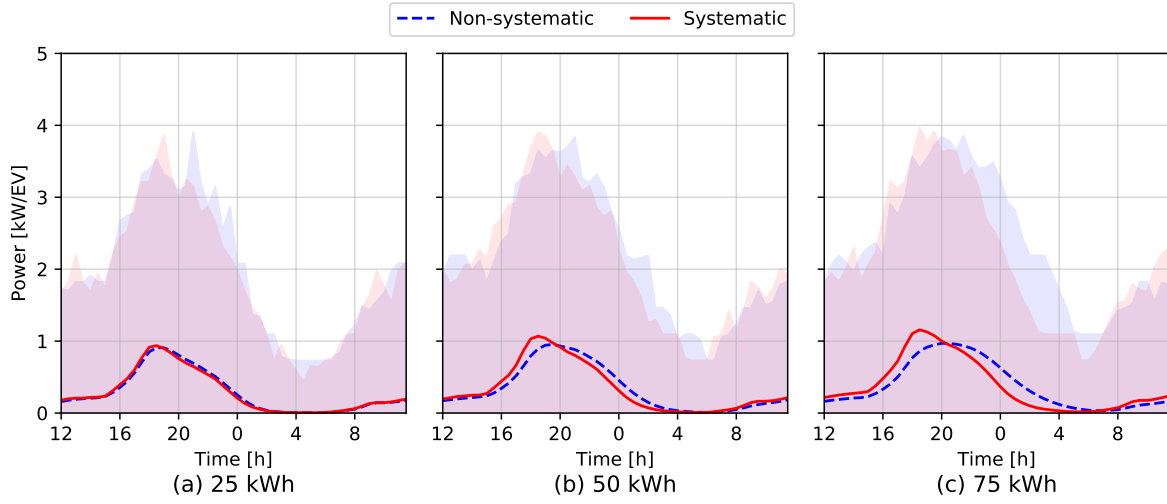


Figure 3.9: Load curves for uncontrolled charging [kW/EV]. **Fleet of 20 EVs**, 7.4 kVA charger, and systematic and non-systematic ($\alpha=1.31$) plug-in. Central lines plot average EV demand, and shaded areas show the variability of EV demand.

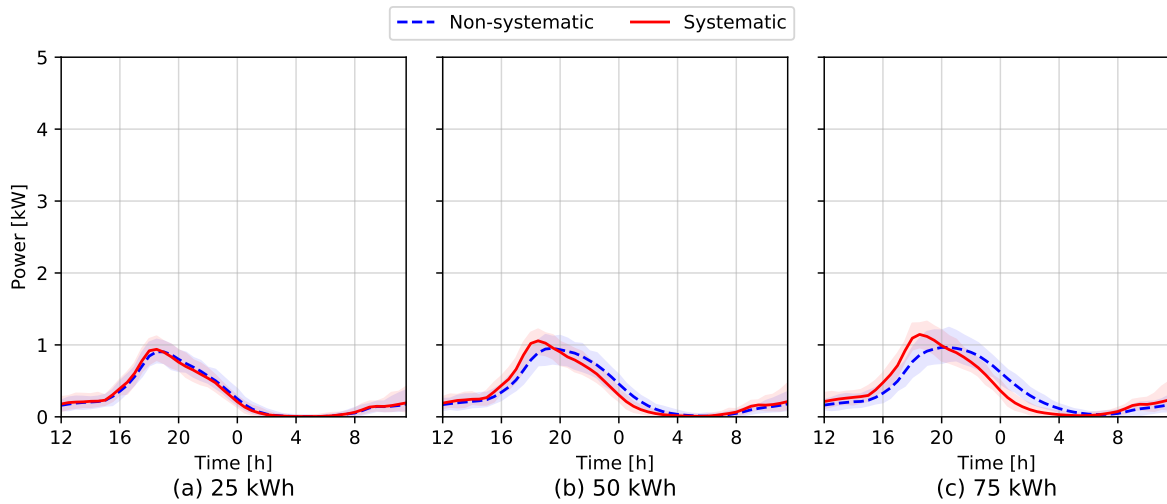


Figure 3.10: Load curves for uncontrolled charging [kW/EV]. **Fleet of 1000 EVs**, 7.4 kVA charger, and systematic and non-systematic ($\alpha=1.31$) plug-in. Central lines plot average EV demand, and shaded areas show the variability of EV demand.

dence in EV charging, with a drastic drop in 11 kVA chargers for fleets above 7 EVs. The coincidence factor of EV charging, summarized in Table 3.5, reaches 70% for fleets of 10 EVs (LV feeder level) with 3.7 kVA chargers but only 21% for fleets of 10,000 EVs (HV/MV substation level). The coincidence factor decreases as charging power increases, reaching only 12% for a 7.4 kVA charger (0.9 kW/EV) and 9% for an 11 kVA charger for fleets of 10,000 EVs. Therefore, increasing charging power will have a more significant impact on distribution grids, especially at the LV feeder level. For 10 EVs, moving from 3.7 to 7.4 kVA chargers represents an increase of 66% in EV peak load, whereas for 10,000 EVs (HV/MV level) the same increase in charging power represents only a 13% in EV peak load.

More importantly, results show **almost no difference in peak load for uncontrolled charging for different battery sizes and plug-in behaviors** for each of the three charger power levels. This means that even though there are fewer vehicles connected every day, the peak coincidence factor of EV charging remains the same due to higher energy requirements per session. Increasing battery sizes does not modify peak load, even though it represents a higher energy consumption due to lower driving efficiency. However, the EV load shape is altered as charging shifts towards later hours due to each charging session lasting longer. This effect is higher for large-battery EVs, which is in line with results found in [47]. Therefore, current trends of increasing battery sizes require to consider non-systematic plug-in behavior in EV grid impact studies.

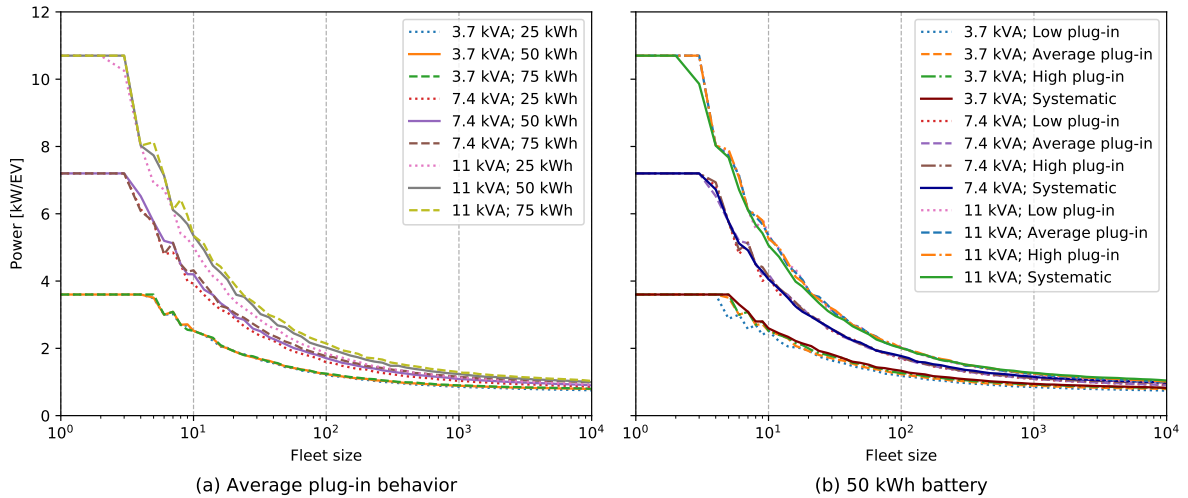


Figure 3.11: Peak load for varying fleet sizes [kW/EV] for the uncontrolled charging strategy. (a) Different battery sizes with average plug-in behavior ($\alpha=1.31$), and (b) different plug-in behaviors with 50 kWh battery EVs.

Off-peak charging

Widespread uncontrolled charging is unlikely to be the norm. EV users can adapt their charging strategy based on electricity tariffs to reduce their energy bills, and price-responsive (smart) charging is already possible with time-of-use tariffs such as peak/off-peak and dynamic tariffs that follow (sub) hourly market prices, as found in numerous

Table 3.5: Peak power per EV [kW/EV] and coincidence factor for fleets of 10, 100 and 10,000 EVs for the uncontrolled case.

Charger Power	Power [kW/EV]			Coincidence factor		
	10	100	10,000	10	100	10,000
3.7 kVA	2.52	1.23	0.79	70%	34%	22%
7.4 kVA	4.20	1.71	0.90	58%	24%	12%
11 kVA	5.35	2.02	0.99	50%	18%	9%

countries [17],[184]. While smart charging can benefit the (local) system by shifting load to off-peak hours, there is a risk of synchronizing EV charging in low-price periods that can create even higher congestion at the local distribution grid, as noted in [85].

Results for the smart charging case, depicted in Figure 3.12, show the synchronization of EV charging at low-price periods, with a greater peak load created under this case than under the uncontrolled case. Peak load for a fleet size of 10,000 EVs and non-systematic plug-in behavior increases between 107% for 3.7 kVA chargers and 377% for 11 kVA chargers, with respect to the uncontrolled case (see summary in Table 3.5. At the LV level (between 10 to 100 EVs), the coincidence factor of EV charging remains high, especially for small-sized EVs which are plugged in more often.

Considering systematic (every day) plug-in behavior highly overestimates the impact of price-responsive EV charging into the grid (see bottom plots in Figure 3.12), as it considers that all EVs will charge at the same moment. This may have little effect at the LV feeder level, as a high coincidence of EV charging can be expected for low numbers of EVs in all plug-in behavior cases (though not everyday). However, it has significant effects at the MV or HV level (fleet sizes above 100 EVs) as coincidence factors are double than those obtained for the non-systematic case. This can lead to overestimate the congestion created by EVs in the distribution grid, and wrongly estimate infrastructure reinforcements⁶. Price-responsive charging prompts a larger difference from plug-in behaviors than in the uncontrolled case, with lower peak loads for the low plug-in case, as fewer EVs are connected simultaneously, and with a greater impact of high-power chargers. However, the differences among non-systematic cases remain low compared to the systematic case highlighting the importance of considering non-systematic plug-in behavior, even with a roughly tuned parameter, on top of getting the model parametrization correctly fine-tuned (i.e., setting the correct α). We also observe a positive effect (i.e., reducing the peak load) of larger battery sizes, as lower plug-in frequency from larger EVs results in a lower coincidence of price-responsive EV charging.

Note that even though smart charging can create higher EV peak loads than uncontrolled charging due to the synchronization of EV charging events, it does not necessarily translate into higher peak loads at the distribution or transmission system. Well-adjusted price signals can shift EV load to low-demand periods where the system can absorb the extra load, and the non-systematic plug-in behavior of users reduces the risk of creating excessive additional demand during these periods. EV grid integration studies are still

⁶See [43] for an example of a smart charging impact assessment that showed high infrastructure requirements at the MV distribution level to cope with price-responsive EVs under high wind power penetration scenarios.

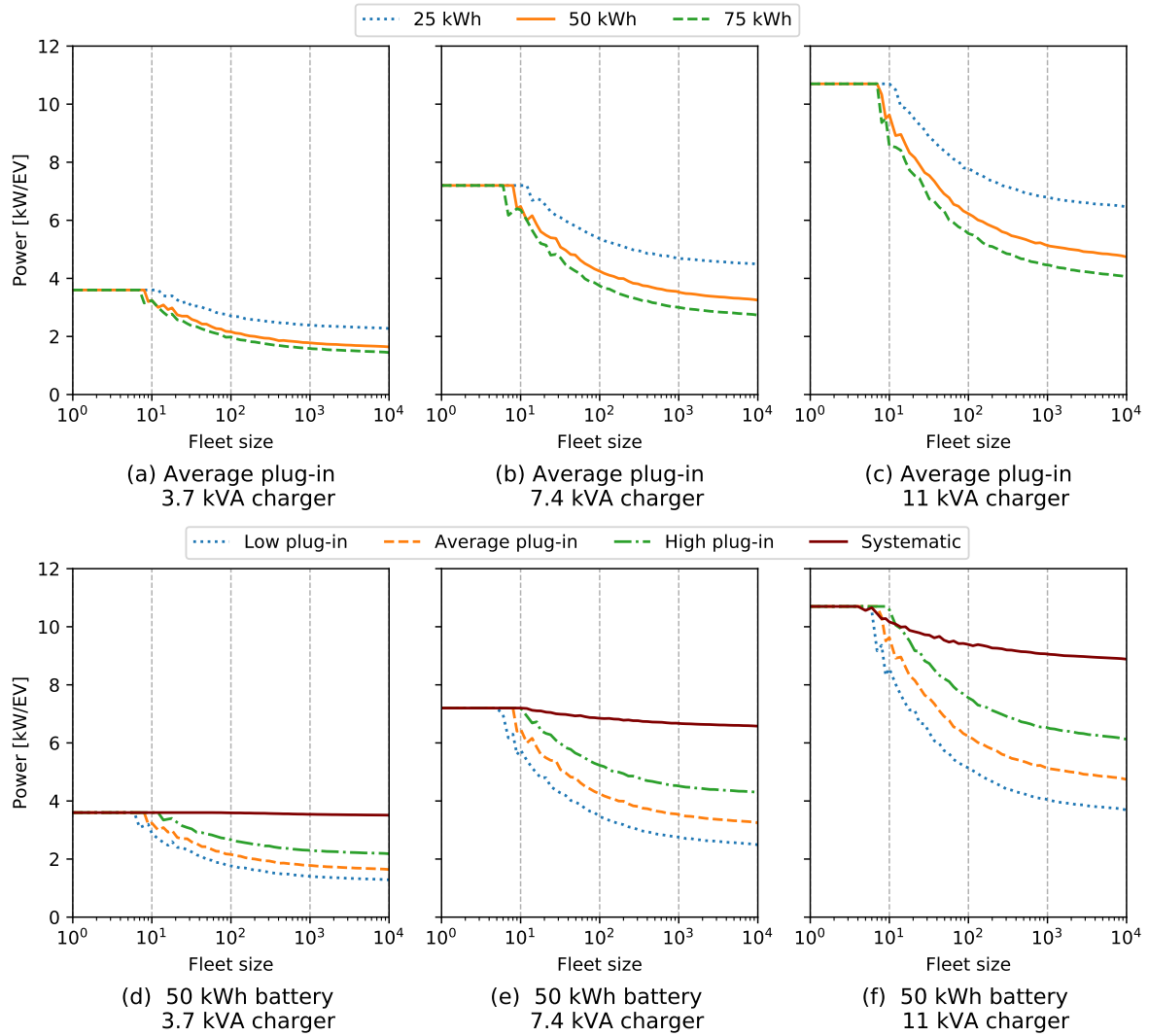


Figure 3.12: Peak load for varying fleet sizes [kW/EV] for price-responsive charging strategy (off-peak 10pm-6am). Top: different battery sizes with average plug-in behavior ($\alpha=1.31$). Bottom: different plug-in behaviors for 50 kWh battery EVs.

Table 3.6: Peak load for price-responsive charging and 10,000 EV fleet. Peak power per EV [kW/EV], coincidence factor (CF) and increase with respect to the uncontrolled case for the average plug-in and systematic cases and 50 kWh battery size.

Charger Power	Average ($\alpha = 1.31$)			Systematic		
	Power	CF	Increase	Power	CF	Increase
3.7 kVA	1.64	46%	+105%	3.51	97%	+338%
7.4 kVA	3.27	45%	+261%	6.57	91%	+630%
11 kVA	4.73	44%	+373%	8.88	83%	+788%

needed to assess the impact of EV charging, especially at the LV distribution grid, to analyze voltage deviations and unbalances, and they should consider non-systematic plug-in behavior, as longer charging sessions can create grid issues at different timeframes, an effect that is increased with current trends of increasing battery sizes.

5.2 Impact on flexibility potential

We assessed the impact of non-systematic plug-in behavior considering the three dimensions of flexibility: time, power and energy [16], as explained in Chapter 1. We considered three indicators: the flexible time of charging sessions, and the available connected power and accessible storage of an EV fleet from an aggregator point of view.

We analyzed three indicators to assess the flexibility that can be provided by V2G-capable EV fleets from an aggregator’s point of view, covering the three dimensions of flexibility: the average charging and flexible time of charging sessions (in hours); the average flexible power per EV (in kW/EV); and the average accessible storage capacity of an EV fleet (in kWh/EV).

While we report average values for the flexibility indicators, an aggregator will also require knowledge on the tails of the distributions to assess the risk of (non) availability of their flexibility assets. This will be mainly dependent on the utilization patterns of EVs (when and how often are connected) and the fleet size. These aspects will be addressed in Chapter 5.

5.3 Flexible time

The average duration of charging sessions and their charging and flexible times for different battery sizes and plug-in behaviors are shown in Figure 3.13. The average duration of charging sessions remains constant for the different cases (10.2 hours), as it is given by the arrival and departure times of users and not for how often they plug-in, but the time spent charging depends greatly on battery size and the user’s plug-in behavior. Under the systematic plug-in assumption, the average charging time per session is between 2 to 3 hours with a 3.7 kVA charger and around 1 hour with a 7.4 kVA charger, leaving more than 12 hours of idle time to provide flexibility. However, **when considering non-systematic plug-in behavior, users charge less often and require more energy in each charging session, increasing the charging duration and reducing the flexible time.** This effect is higher for larger battery sizes, as they tend to plug in less frequently and have higher energy requirements. For users with a 3.7 kVA charger and battery sizes above 60 kWh, average charging times are above 5 hours (average plug-in case), thus reducing flexible time accordingly. As these indicators are average values, there may be cases where charging time exceeds connection time, thus creating the possibility that large-battery EV users will adopt high-power chargers to reduce these risks. This can be a more significant issue in countries where residential dwellings already have three-phase supply, such as Germany or the Netherlands, easing the installation of high-power chargers at home, unlike France or the UK where residential dwellings have primarily single-phase supply. Nevertheless, average flexible time remains high, at above 8 to 10 hours per charging session for most cases and battery sizes under 60 kWh, which can be ample margin to shift charging to off-peak hours or provide even a few hours of

bidirectional power to the grid.

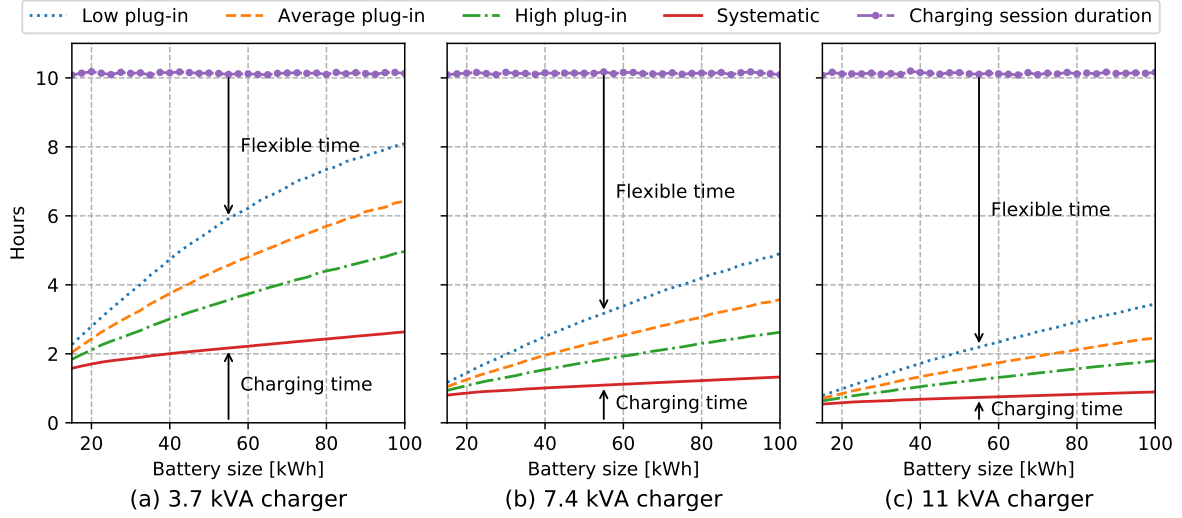


Figure 3.13: Average charging and flexible times of charging sessions. Arrows indicate charging time for the case systematic plug-in and flexible time for the case of non-systematic low plug-in.

Flexible power

The power that EV aggregators can access depends mainly on the number of EVs connected to the grid, which varies along the day, as shown in Figure 3.14. As our case study refers to home charging, EVs are mostly connected during nighttime, i.e., between 8 pm and 7 am. We computed the flexible power seen from an aggregator’s perspective, shown in Figure 3.15, as the average charging power of connected EVs between 10pm and 6am, i.e., the period in which the share of connected EVs is higher. An aggregator that controls fleets that are systematically connected can be certain that all EVs will be available as flexibility resources, thus offering access to the full charger power of the whole EV fleet. However, when considering non-systematic plug-in behavior, fewer EVs are connected per day, and so the aggregator has a lower amount of power flexibility to control. **With a fleet of 25 kWh EVs, an aggregator will only have access to 60% of the fleet power on average, and this figure drops to less than 40% for battery sizes above 60 kWh.** Therefore, large-battery EVs can present risks to flexibility aggregators, as they will have to contend with fewer EVs connected daily and less flexible time per charging session.

Accessible storage

Finally, the flexibility that V2G-capable EVs can provide also depends on the storage capacity that they can access (i.e., the energy aspect of flexibility). To assess the flexibility storage capacity that an EV aggregator can control we defined the accessible storage of a V2G-capable EV as the space of feasible charging trajectories, depicted in green in Figure 3.16. The accessible storage of a charging session for one EV will depend on its

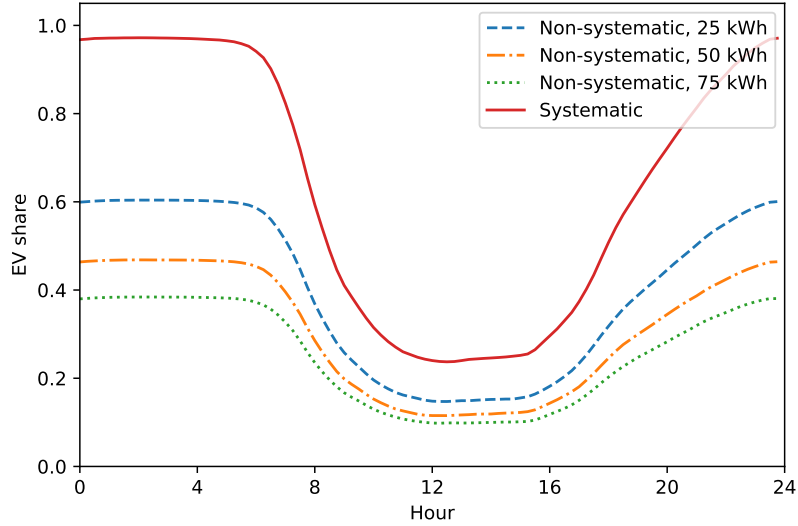


Figure 3.14: Average share of connected EVs along the day. Average plug-in behavior for non-systematic cases.

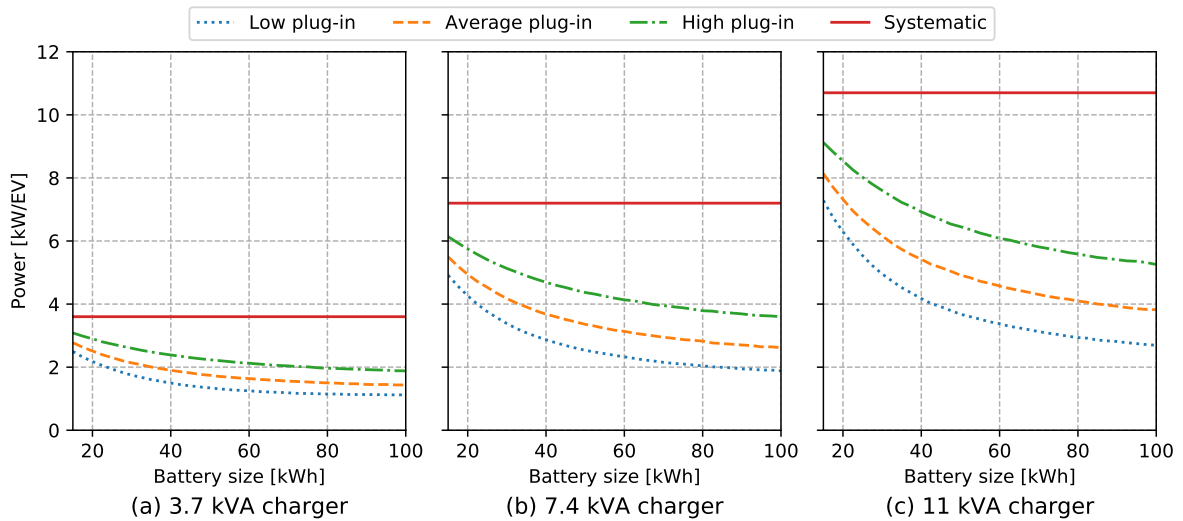


Figure 3.15: Average flexible power [kW/EV] during high-availability hours (10pm-6am) for a 1,000-EV fleet

battery size, charging power, and connection duration. The accessible storage of an EV fleet (AS_f) is then computed as the sum of accessible storage of all EVs for an average charging period, as shown in Eq. 3.7, where ts_{avg} is the average charging session duration of 10.2 hours and n_{evs} is the number of EVs in the fleet (we express this indicator in kWh/EV to make it independent of fleet size).

$$AS_f = \frac{\sum_{e \in EV} \int_t AS_e(t) dt}{n_{evs} \cdot ts_{avg}} \quad (3.7)$$

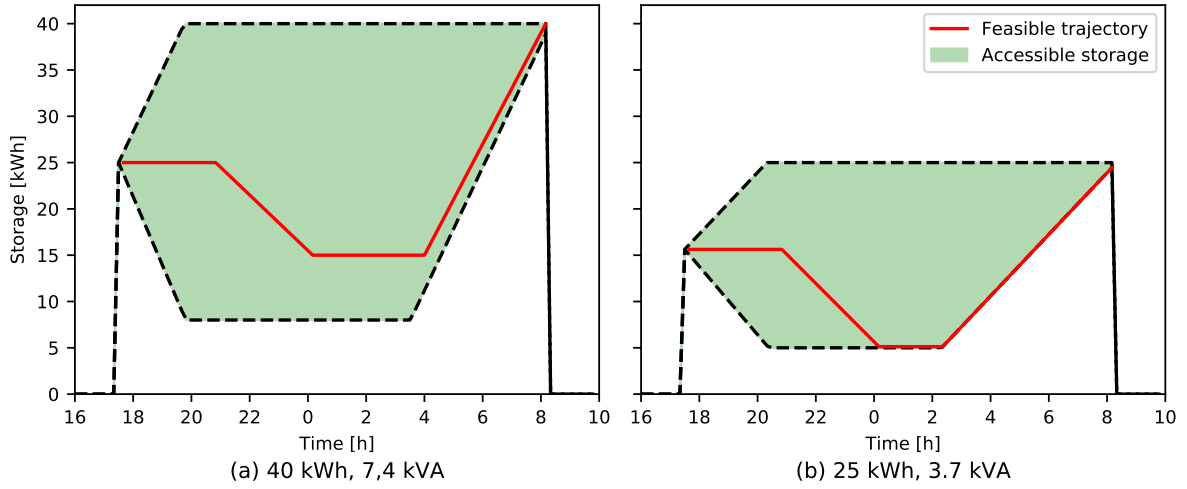


Figure 3.16: Example of the accessible storage of a charging session of a single EV ($AS_e(t)$) with a feasible charging (and discharging) trajectory, for (a) a 40 kWh battery and (b) 25 kWh battery. A minimum SoC of 20% was considered for computing the accessible storage.

The results for average accessible storage per EV for different battery sizes and plug-in behaviors, shown in Figure 3.17, point to several conclusions. First, when considering systematic plug-in behavior, which is the ideal case where EVs are plugged in every day, larger battery sizes increase the accessible storage per EV, but only up to a given battery size dependent on charger power. This means that **increasing battery sizes above a certain threshold does not increase the accessible storage capacity of a fleet**, as this additional storage capacity is not accessible during the charging session time.⁷ For a 3.7 kVA charger, the maximum accessible storage is 15.7 kWh, reached with 40 kWh batteries, which can be increased to 30.5 kWh with 7.4 kVA chargers, reached with battery sizes larger than 80 kWh. In both cases the accessible storage represents around 4.5 hours of bidirectional power injection to the grid. Thus, to fully access EVs' storage capabilities of large-battery EVs requires an increase in charging power. However, increasing charger power can have a significant impact on the distribution grid, as shown in Section 5.1.

⁷For a 10 hour charging session of a 50 kWh EV with a 7.4 kVA charger, and disregarding charging requirements, it can, at most, discharge during 5 hours and then charge during the remaining 5 hours, having a maximum accessible storage of 37 kWh. Increasing the battery size does not provide additional flexibility.

Second, when we consider non-systematic plug-in behavior, the accessible storage of the whole fleet is reduced by at least 50%, as fewer EVs are connected and they have reduced flexible time. Moreover, we observe a peak in accessible storage, at around 25 kWh for a 3.7 kVA charger, and around 60 kWh for a 7.4 kVA charger, after which increasing battery sizes reduces accessible storage. This is due to lower plug-in rates and higher energy requirements per charging session for larger battery sizes. Therefore, increasing battery sizes can present high risks for EV aggregators wanting to offer flexibility services to the grid, as larger-battery EVs actually decrease the accessible storage. Increasing the charger power can increase the accessible storage, but this increase is much less significant than with systematic charging. Providing incentives to plug in (i.e., changing from an average plug-in behavior to a high plug-in one) could be equally or more effective in increasing accessible storage than increasing charger power.

Third, a fleet composed of small-battery EVs that is systematically connected can provide greater flexibility than a fleet of large-battery EVs with non-systematic plug-in. This can be the case for company fleets (see, for example, the Parker project demonstrator that used 21 kWh EVs [38]). From the results shown in Figure 3.17, for 11 kVA chargers, a fleet composed of 20 kWh EVs with systematic charging can offer greater accessible storage than a fleets with an average plug-in behavior for any battery size.

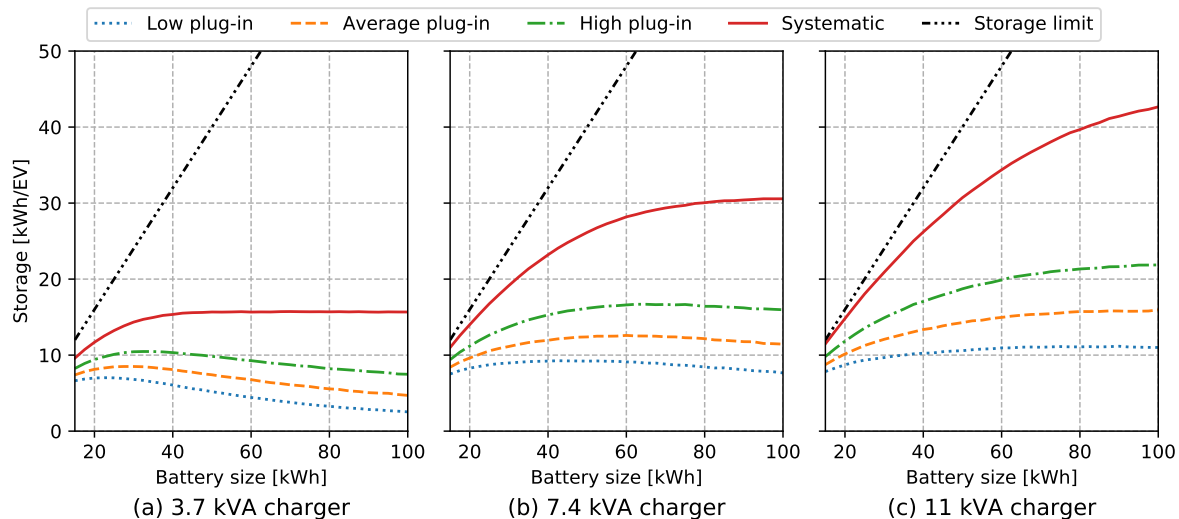


Figure 3.17: Average accessible storage [kWh/EV] for a 1,000 EV fleet and for three charger power levels. Storage limit is equal to 80% of the battery size.

These results demonstrate the significance of EV users' plug-in behavior as a factor in the flexibility that can be provided to the system. EV fleets with high plug-in frequency can provide increased flexibility, both in power and energy, compared to regular EV users. EV aggregators should consider providing incentives for end-users to plug in on a regular basis to maximize the flexibility they can harvest.

6 Partial conclusions

To correctly assess the impact of EV integration into the grid and the flexibility that EVs can provide to the system, models should appropriately reflect EV users' real driving and charging behaviors. Studies have evidenced the fact that EV users do not plug in their vehicle every day, yet few EV grid integration studies have considered this real-world behavior pattern, and the models available present several limitations.

In this chapter we presented an agent-based EV simulation model that considers a probabilistic plug-in decision module. The model parameters were then calibrated to match the charging behavior observed in the Electric Nation project, a large-scale smart charging trial in the UK that covered a wide range of EV marks and models. Our model correctly captures the heterogeneity of users' charging preferences and can be used to generate load curves for a wide array of EV conditions, including different battery sizes and driving patterns. On average, users tend to charge their vehicle between 2 to 4 times per week, with large-battery EVs having reduced plug-in frequency and higher energy requirements per charging session.

We then evaluated the impact of the non-systematic plug-in behavior of EV users charging at home through two aspects: the peak load that EVs generate at different levels of the grid, and the flexibility potential that can be offered during charging sessions.

Results show that to correctly assess EV charging at the distribution level it is important to factor in non-systematic plug-in behavior, especially considering the current trend towards increasing battery sizes. For uncontrolled charging, there is no significant on peak load between systematic and non-systematic plug-in behavior. However, large-battery EV load is shifted to later hours which can modify the grid impact of EV charging. For price-responsive charging, considering only systematic charging (i.e., every day) significantly overestimates the impact of load synchronization at low-price hours.

Concerning the flexibility potential, results show that non-systematic plug-in behavior can significantly reduce the accessible flexibility of EV fleets. This is more important for larger battery sizes as they have lower plug-in rates, less flexible time of charging sessions, and reduced accessible storage capacity. One route to cope with this reduction of flexibility is to increase charger power level, but at the expense of creating greater impacts on distribution grids from EV charging. Thus, a trade-off appears for increasing charging power between additional flexibility and higher grid impacts.

Aggregators wanting to make use of EV flexibility should consider providing the incentives to plug-in to end users to maximize the available flexibility, in idle time, power, and storage capacity. Indeed, increasing plug-in ratios can prove to be more beneficial than improving the technical characteristics of EV fleets (charger power, battery sizes).

Chapter 4

Assessing EV integration in distribution grids: a data-driven approach.

In Chapter 2 it was noted that user driving and charging behavior has significant impact on EV integration. Moreover, the local conditions of both the distribution grid and the spatial distribution of EV demand and renewable generation will determine the capacity of the distribution grid to host these new resources. Therefore, it is key to model local mobility patterns and the spatial distribution of EV charging at the local level, and evaluate the impacts of EV charging in realistic grid conditions.

We addressed the question of how the plug-in behavior of EV users affect EV integration into distribution grids in the previous chapter. We found out that non-systematic plug-in behavior can limit the impacts of price-responsive charging but also reduce the ability of EV fleets to provide flexibility, as they are connected less often.

In this chapter we will analyze how mobility patterns and the spatial distribution of EV users affect EV integration into distribution grids. In particular, we evaluate how rural and urban conditions affect the impact of EV charging at the local level, and how the complementarity between EVs and PV generation can be affected by their spatial distribution in the grid. To achieve this, we leverage several open-source datasets to build realistic case studies on French primary substations and medium voltage grids.

The remainder of this chapter is structured as follows: in Section 1, we present a literature review on spatial considerations and on local mobility patterns when analyzing EV grid integration. In Section 2, we present the methodology developed to build realistic case studies of distribution grids in France. Then, in Section 3 we study the impact of EV charging in representative French primary substations. Finally, in Section 4 we analyze the joint integration of EVs and PV generation in a mixed rural-urban MV grid in southwest France.

1 Relevant works on EV integration into distribution grids

1.1 EV integration in realistic grid conditions

The literature on EV integration into distribution grids is dense, with a significant amount of work carried out to simulate the impacts of EV integration in low voltage grids. There have been studies focused on the benefits of using smart charging [168][185][84][138], reactive power compensation [50][49], and V2G [33], mainly in residential grids. Test cases consist of standard test grids, such as the IEEE European Low Voltage grid, or LV grids representative of local conditions, including the UK [138][181], Denmark [185][168], Belgium [50], and France [186].

There have been comparatively less studies regarding EV integration in MV grids.

At the primary substation level, [89] studied the impact of residential EV charging at using real grid data from the Bern region in Switzerland, and [178] presented the case of EV charging at a French urban primary substation, considering at-home and at-work charging. [187] mapped the spatial distribution of EV and rooftop PV using detailed census data to evaluate the impact their joint integration at the primary substations in Portugal, showing different diffusion patterns among the studied substations.

Some studies have analyzed the impacts of EV charging at detailed MV grids, including the interaction with renewable energy generation. In [43], they analyzed the impact of price responsive EV charging in Dutch MV grids, considering electricity prices dependent on wind generation. In [188], authors studied different coordination schemes for EV charging to improve wind generation integration, and demonstrated their effectiveness using grid data from a real rural feeder in a Greek island. A similar approach was taken in [189], evaluating the benefits of V2G to support wind generation, with an evaluation case study in a simplified MV feeder. [190] studied the case of joint high rooftop PV and EV integration in a mixed urban-rural grid in Sweden. A highly detailed study case was built using LiDAR data to map potential buildings for PV installations, coupled to an EV model that considered at-home, work, and public charging. Finally, [191] studied analyzed MV distribution grid planning strategies under uncertainty on PV and EV penetration, with case studies on the MV grid of Grenoble city center.

1.2 Local mobility patterns

As detailed in Chapter 3, Section 2, several models have been proposed to simulate the mobility patterns of EV users. However, most of them are based on mobility surveys at the national level, such as [192] for the UK, [43] for the Netherlands, [166] for Belgium, [89] for Switzerland, and [190] for Sweden, and [168] for Denmark. These studies do not consider local mobility patterns, such as differences between urban and rural areas. Travel surveys and the scientific literature have evidenced that people in rural or peri-urban areas travel longer distances for their daily trips than people in urban areas, and with a higher share of car usage [193][194].

Table 1.2 provides a summary of relevant literature on EV integration into distribution grids that consider realistic grid and mobility patterns. We observe that studies do not consider the impact of local mobility patterns, at most calibrating their models based

on national travel surveys. An exception is [160], where authors developed an agent-based model to evaluate the requirements for additional public charging infrastructure in a small city in Switzerland. Their model simulates each EV in their travel schedules around the city, allowing to account for local mobility patterns and identifying the spatial distribution of EV charging. However, the model has only been applied in a small city context.

Table 4.1: Summary of relevant literature on simulation of EV integration into distribution grids.

Paper	Level	Test case	Mobility model	Mobility data	Charging case	Charging strategy	RES
[138]	LV grid	Real English LV grids	Probabilistic	EV trial data	Res.	Uncontrolled	No
[181]	LV grid	UK urban, rural grids	Probabilistic	EV trial data	Res.	Uncontrolled	No
[168]	LV grid	Danish LV grid	ABM with non-syst. plug-in	Danish NTS	Res.	Uncontrolled Off-peak	No
[50]	LV grid	Flemish LV grid	ABM	Flemish NTS	Res.	Uncontrolled Modulated	No
[89]	HV/MV SS	Switzerland (Bern area)	ABM	Swiss NTS	Res.	Uncontrolled Price-responsive	No
[178]	HV/MV SS	French urban area	ABM	French NTS	Res., W	Uncontrolled	No
[187]	HV/MV SS	Portugal (Porto area)	No model	-	Res., W	Predefined load curve	PV
[191]	MV grid	Urban grid (Grenoble)	Probabilistic	French NTS (urban case)	Res., W	Uncontrolled	No
[43]	MV grid	48 Dutch grids	ABM	Dutch NTS	Res.	Uncontrolled Price-responsive Valley filling	No
[188]	MV grid	Rural feeder (Greece)	Probabilistic	-	Res.	Uncontrolled Valley-filling	Wind
[189]	MV grid	Rural feeder	Probabilistic	US NTS	Res.	Uncontrolled Valley-filling V2G	Wind
[190]	MV grid	Mixed urban-rural grid (Sweden)	Markov-chain ABM	Sweden NTS	Res., W, PC	Uncontrolled	PV
[160]	LV transformers	Swiss city (St. Gallen)	ABM	City level	Res., W, PC	Uncontrolled	No

SS: Substation, NTS: National travel survey,
Res.: Residential, W: Work-place charging, PC: Public charging

1.3 Contributions

This chapter builds on the existing literature, mainly from the data-driven methodologies of [187] and [190], to provide two main contributions to the scientific literature. First, we analyze the impact of local mobility patterns on EV charging at the primary substation level considering residential and workplace charging, and considering non-systematic plug-in behavior (see Chapter 3). Case studies on real urban and peri-urban French substations exemplify the results. Second, we develop a data-driven methodology that leverages data from several open-source datasets to evaluate EV integration in realistic MV grids which considers the spatial distribution of EV users. We apply this methodology to a mixed urban-rural MV grid in south west France to study the joint integration of PV systems and EV charging.

2 A data driven methodology to build realistic case studies

The spatially detailed models developed in [187], [190] and [160] have shown that the importance of mapping the spatial distribution of distributed energy resources into the grid and the need to consider real case studies, going beyond standard test grids.

A bottom-up methodology to assess the joint integration of EVs and PV integration into realistic cases in France was developed. It exploits several high-resolution open-source datasets. These datasets provide information at the infra-communal level, called *IRIS* cells, which are the smallest aggregation units for statistical purposes in France [195], grouping between 1500-5000 residents in each cell.

The developed methodology consists of four modules, as depicted in Figure 4.1: a grid reconstruction module, an EV module, a PV module and a simulation module. The grid reconstruction module uses the cartography of existing medium voltage networks to reconstruct the grid to carry out power flow simulations. The EV module uses travel survey and census data to define local mobility requirements and generate EV demand time-series at the infra-communal level, using the EV model presented in Chapter 3. The PV module defines the distribution of PV generation systems, including small-scale and mid-size rooftop PV systems and ground-mounted PV farms. Finally, the simulation module evaluates the impact of EV and PV integration by performing power flow simulations using the *pandapower* Python tool [196].

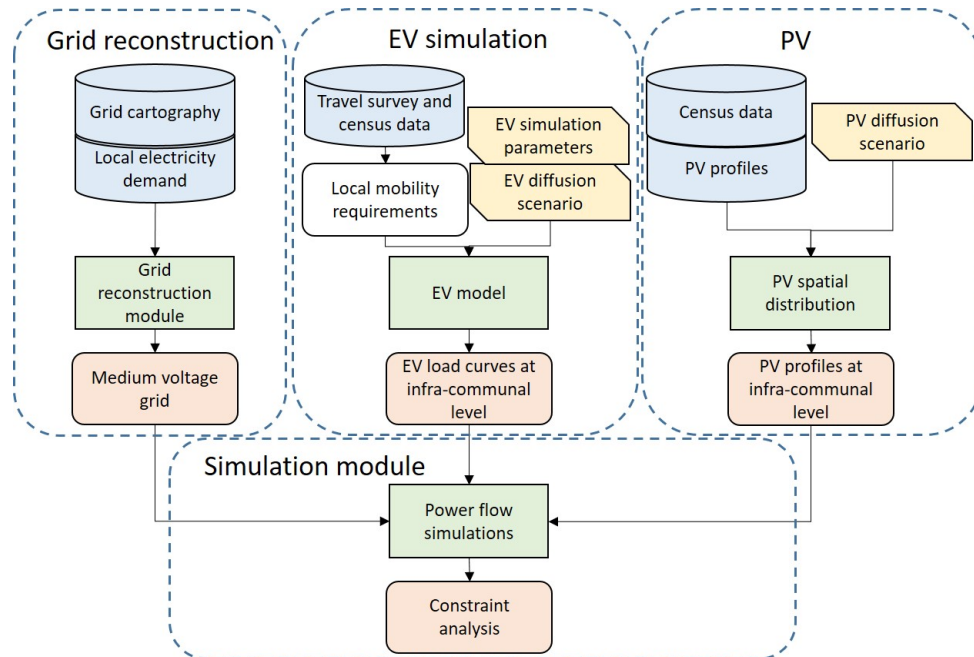


Figure 4.1: Flowchart of implemented methodology to analyze EV and PV integration into MV grids

2.1 Grid reconstruction

The cartography of Enedis' network is publicly available at [197]. It contains the positions of the main network elements: HV/MV substations, overhead and underground MV lines, MV/LV transformers, and LV lines. However, no connectivity among the grid elements nor any technical information of lines or transformers is given.

A methodology was developed to reconstruct the MV grid served by a HV/MV substation from the position of network elements. A detailed explanation of the methodology can be found in the Appendix B. The main steps are:

1. **Determine grid connectivity.** Here is determined how each line segment or transformer is connected to each other, defining all grid nodes. An algorithm was developed for this purpose.
2. **Define service area of a HV/MV substation.** This step determines the area served by the substation under normal operation conditions, by defining open/closed lines considering that the network is operated in with a radial topology, without closed loops or loads being alimented by two or more HV/MV substations at the same time. This step mimics operational processes of distribution grids [191].
3. **Include loads at MV/LV transformers.** Using annual electricity demand per customer type (residential, commercial, industrial) at the *IRIS* level, a demand time-series is generated for each *IRIS* cell. This load is distributed among the MV/LV transformers in each *IRIS* cell.
4. **Determine technical characteristics of lines** (resistance, reactance and ampacity). An algorithm defines the smallest conductor section for each line segment from a set of possible conductor types, considering thermal and voltage drop constraints during peak-load hours.

At the end of the methodology, we obtain the necessary files required to perform power flow simulations for a base case without the integration of renewable energy or EVs.

2.2 EV module

The EV module generates EV load curves at the infra-communal level considering local mobility patterns. First, the mobility requirements at the communal level are defined using census data, which are then used as input for EV charging simulations.

Local mobility patterns

We used the professional mobility dataset provided by the French Statistics Institute (INSEE), issued from the 2015 census [198]. It provides the commune of residence and workplace for 25 million workers in France and the share of transport mode (walking, bike, car) for each commune. We compute commuting distances using *OpenStreetMap* route planner for each arrival-departure commune pair. For each commune, we obtain two histograms for the probability distribution of commuting distance, one for residents of the commune and one for workers of the commune. The average commuting distance by

commune of residence is shown in Figure 4.2. Residents of city centers drive, in average, less kilometers per day, whereas residents of peri-urban areas drive significantly longer distances. This pattern can be seen in major French cities such as Paris, Lyon, Toulouse or Bordeaux. This analysis allows to identify zones with different dynamics. Zones like Paris attract a great number of people, which also can come from far away, while residents have shorter commuting distances since a they tend to work in the same zone, as shown in Figure 4.3.

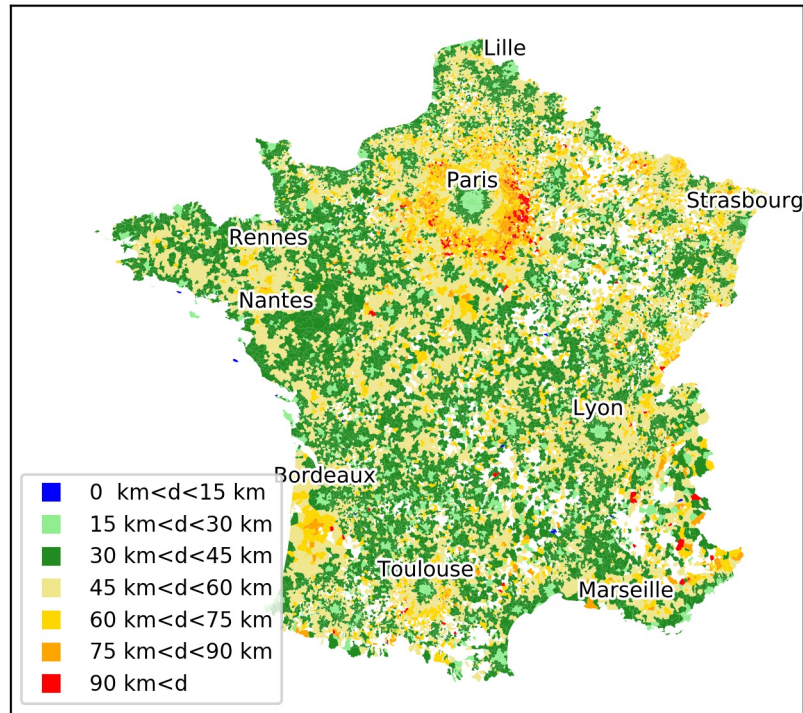


Figure 4.2: Average daily commuting distances by commune of residence [km]

EV model simulation

We use the EV model presented in Chapter 3 to simulate EV charging at the infra-communal level. EV simulation parameters are defined according to the case studies, namely charging power, battery sizes, driving efficiency, plug-in behavior and charging strategy.

We considered residential charging and work-place charging. At each infra-communal cell i , we obtain the total number of vehicles of residents (people that reside in the area, $TotNev_{h,i}$) and of workers (people that go to work to the area, $TotNev_{w,i}$), and then determine the number of EVs doing home ($Nev_{h,i}$) and work ($Nev_{w,i}$) charging considering two factors: the EV diffusion scenario (δ_{ev} and the work-place charging ratio (wr), as shown in equations 4.1 and 4.2. The EV diffusion scenario represent the percentage of EVs among the total vehicle fleet, and the work-place charging ratio represents the share of drivers that have access to a charger in their workplace (which can include public charging, if available), and will prefer to charge at this location instead of at home.

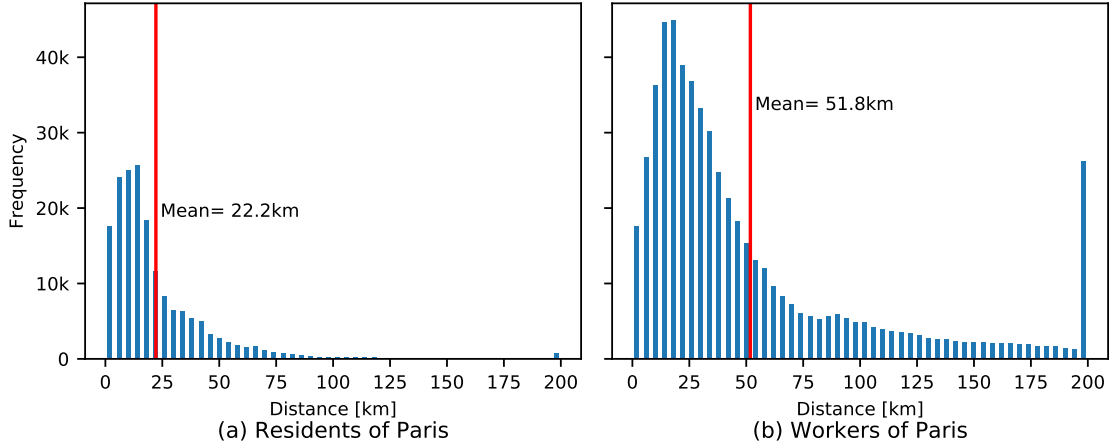


Figure 4.3: Histogram of daily commuting distance for car users in Paris commune (*Paris intramuros*), for (a) residents and (b) workers. Total car users: Residents 173,600, workers, 564,700

$$N_{ev_{h,i}} = TotN_{ev_{h,i}} \cdot \delta_{ev} \cdot (1 - wr) \quad (4.1)$$

$$N_{ev_{w,i}} = TotN_{ev_{w,i}} \cdot \delta_{ev} \cdot wr \quad (4.2)$$

2.3 PV integration

We considered three types of PV installations possible: small-scale, medium-scale and large scale. Small-scale PV represents residential PV systems <36kW, medium-scale represents larger rooftop installations, such as ones that can be found in large buildings or industries, and large-scale represents ground-mounted installation with an installed capacity larger than 250 kW. In France almost half of PV installed capacity has been done by large scale installations with an average size of 3 MW, as shown in Table 4.2. The distribution of types of PV installations varies strongly with the region, shown in Figure 4.4, with large-scale installations are more concentrated in southern regions. In northern regions, rooftop PV installations are more predominant than large-scale ones, though the total installed capacity is less important.

Table 4.2: Installed capacity of PV systems in France, by end of March 2021. Own elaboration from [199].

Type	Capacity [kW]	Average size [kW]	Total installed capacity [MW]	Share [%]
Small-scale	<36	4.3	1,976	29.6
Medium-scale	36-250	110	2,826	20.7
Large-scale	>250	3,005	4,740	46.7

We integrate each type of PV installation in a different manner in our case studies, as their diffusion dynamics will depend on the characteristics of each infra-communal cell.

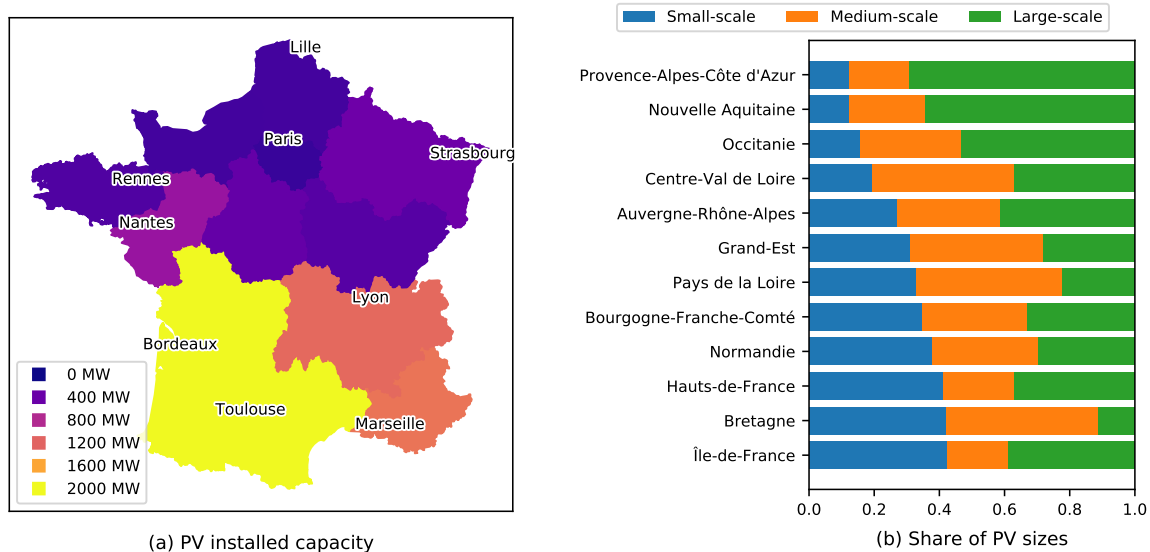


Figure 4.4: (a) Installed capacity of PV systems in France and (b) share of PV types per region, by March 2021. Own elaboration from [199].

Small-scale rooftop will be installed as a share of the number of single dwellings of each infra-communal cell, medium-scale rooftop will be installed as a share of the number of large buildings, and ground-mounted PV will be installed only in rural cells. The number of single dwellings, large buildings and the type of infra-communal cell (rural, urban) is determined from census data.

Finally, we obtain year-long PV profiles for the studied area from *renewables.ninja* tool [200]. This tool provides electricity generation profiles from PV panels considering historical weather measurements. PV panels characteristics include orientation, azimuth, losses, tilt and tracking devices.

2.4 Simulation module

The simulation module gathers the results from the grid reconstruction, EV and PV modules to build the grid model in the pandapower environment for Python. Loads, EV charging and PV generators are assigned to MV/LV transformers of each infra-communal cell, distributing the total load in equal measure among the MV/LV transformers.

We perform year-long power flow simulations with 30-minute time resolution. The simulations allow to assess the impact of EV and PV integration for different penetration scenarios. Simulations integrate control functions for grid operation, implemented within the pandapower environment. We considered an on-load tap changer at the HV/MV transformer that maintains the voltage in the MV side between 0.99 and 1.01 pu, and reactive power compensation (Volt-VAR regulation) for large-scale PV plants according to Enedis' operational standards, as defined in [201].

3 EV charging impact at the primary substation level

In this section we will discuss the impact of EV charging at the primary substation level, in order to understand different patterns that emerge when considering the spatial distribution of EVs and local mobility patterns.

We carried out simulations at the substation level considering residential and work-place charging, with a EV penetration of 50%¹ and 30% access to work-place charging (this means 30% of people will be charging during day-time), in line with the base-case scenario from French TSO [177]². Three battery sizes were considered, small (25 kWh), medium (50 kWh), and large (75 kWh), with a distribution among users of 25%, 50% and 25% respectively, in line with current trends. Charging power ranged between 3.7 and 11 kW, with different shares for residential and work-place charging, considering overall higher charger power at work-place than at home, as shown in Table 4.3.

Table 4.3: Charger power for residential and work-place charging

Charger power	Residential	Work-place
3.7 kVA	32.5%	0%
7.4 kVA	50%	50%
11 kVA	17.5%	50%

A non-systematic plug-in behavior was considered, in line with the findings of Chapter 3 (average case, $\alpha=1.31$), with the additional condition that users will charge at least once during the weekend. This is to study the capacity of EV charging to be shifted to low demand days, as currently there are EV-oriented electricity tariffs with lower prices during the weekend.

3.1 Urban and rural trends

Two contrasting substations are shown in the following results, one substation in Paris city center, with an average distance driven (d_{avg}) of 22.2 km, and another in the rural area of Seine-et-Marne *département*, in the eastern outskirts of Paris, with a d_{avg} of 70.6 km. The number of EVs in each of the substations are shown in Table 4.4

Table 4.4: Number of EVs in simulation for urban and rural substations

Charging place	Urban	Rural
Residential	4480	3867
Work-place	6023	810

Figure 4.6 shows the EV loads at the urban and rural substations considering uncoordinated charging, evidencing the impacts that differences on local mobility patterns have

¹This represents 16M EVs in circulation in France, which is in line with the most optimistic scenarios by 2035 from the French industry and system operators [177]. However, even if this EV diffusion level is not reached nation-wide, it can still be reached at the local level due to clustering of EV adopters.

²Scenario Crescendo. A 30% access to day-time charging still requires a strong development of public and work-place charging infrastructure, as current studies found that over 80% of EV charging is done at home[151].

on the substation load. **The urban area attracts population, experiencing high day-time charging with high peaks on weekdays at the beginning of working hours.** Residential charging is less significant, as **residents of city centers tend to drive fewer kilometers per day** and have a use alternative transport modes in a higher proportion. This allows them to displace a high share of EV charging along the week, in this case towards the weekend where 42% of the EV load is charged.

On the contrary, **the peri-urban/rural substation experiences mostly residential charging**, as the area attracts less commuters, thus having lower demand during day-time. Additionally, **high daily distances driven by residents require a high plug-in frequency of EV users** (mean plug-in ratio of 4.8 times per week, see Figure 4.5), with a high share of users plugging-in almost daily. This creates an EV load that remains relatively stable along the week, having low capacity to shift load towards weekends, charging only 23% of the EV load during the weekends.

We observe as well that work-place charging creates high peaks around 9am due to high synchronization of the arrival at work, which is in line with results found in the literature, such as [47]. Residential charging is less *peaky*, as arrival at home tends to be more spread along the day, with a greater effect on weekends. This can make residential charging during weekends attractive for reducing the impacts on the grid.

The total load at the substation for the peak demand week is shown in Figure 4.7. In the urban case, the high demand created by work-place charging is synchronized with the morning peak. However EV demand remains low compared to total demand at the substation. Peak demand (in power) is increased by 3.5%, and annual demand (in energy) by 2.9%. For the rural case, EV load represents a higher impact at the substation, increasing in 22.0% the annual demand and peak load by 22.6%.

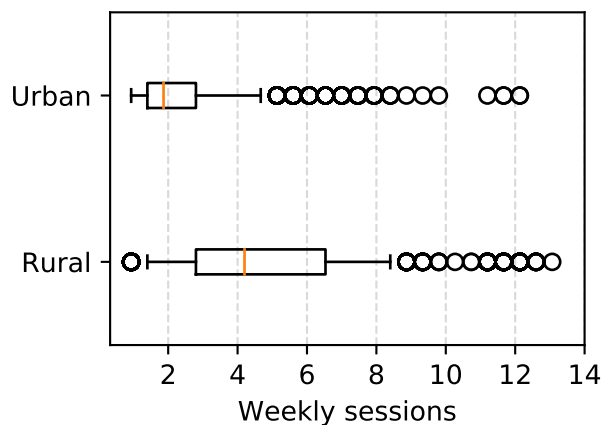


Figure 4.5: Plug-in frequency distribution of EVs in the urban and rural substations. Box covering 2nd and 3rd quartile of data, whiskers at 5 and 95 percentiles and orange line indicating median value.

The impacts of EV charging can be reduced by shifting charging to low demand periods. We studied a case of a simple control strategy. In this strategy, residential users implement off-peak charging, with non-synchronous off-peak periods for each user starting between 10pm and 3am, to avoid charging at peak hours and avoid synchronization effects

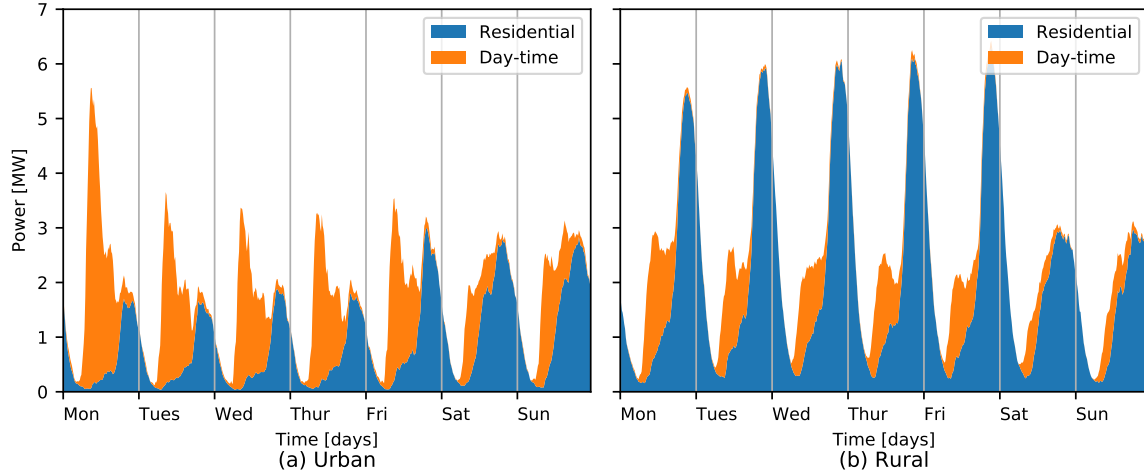


Figure 4.6: EV load at (a) urban, and (b) rural substations for uncontrolled charging.

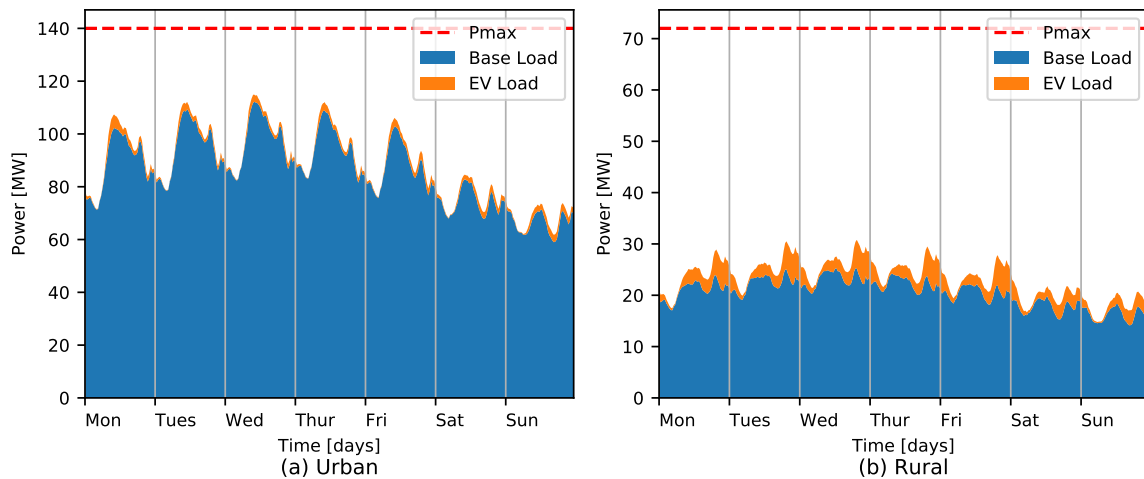


Figure 4.7: Total load at (a) urban, and (b) rural substations for the peak demand week for uncontrolled charging. P_{max} represents the installed transformation capacity at the substation.

of EV charging³. Day-time chargers implement an average charging strategy (charging at a constant power during the whole connection period), to avoid synchronization of EV charging at maximum power at the beginning of working hours. Results at the substation level are shown in Figure 4.9. For the urban case, work-place charging impact is reduced, increasing peak load in only 1.9% with respect to the case without EVs. However, for the rural case, the benefits are limited as the additional load that can be accommodated during off-peak hours without increasing peak load is smaller than the amount of residential charging needed. Thus, a simple off-peak charging strategy creates a new peak demand at 2am with total peak demand increasing by 19.1%. Nevertheless, there are still operational margins in both studied substations.

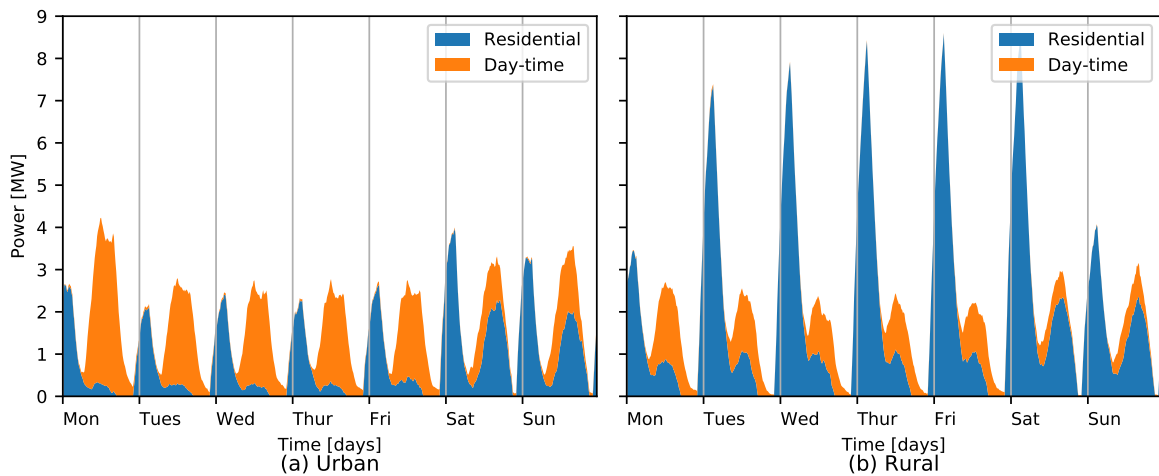


Figure 4.8: EV load at (a) urban, and (b) rural substations for off-peak charging.

3.2 A nation-wide study

The methodology was applied to 2063 HV/MV substations of Enedis service territory, with simulations carried out for uncontrolled and off-peak charging⁴. The integration of 50% EVs would increase substation energy demand by 12.8% in average (see Figure 4.10), and peak load by 11.8% with uncontrolled charging (see Figure 4.11), albeit with high variability among substations. The increase in peak load can be reduced to 8.7%, in average, with an off-peak charging strategy. However, this strategy presents higher effectiveness in substations where EV demand represents between 10% to 15% of total demand. For substations where EV charging represents a share of total demand above 20%, the effectiveness of the off-peak charging is reduced, as EV charging creates a new peak at the off-peak period, evidenced in the rural substation case study in the previous subsection.

We further study the urban/rural characteristics of the service areas of the substations. We use the classification of *urban areas* from INSEE, which consist of urban poles providing at least 10,000 jobs. Each municipality can be assigned to an urban area and

³This type of asynchronous off-peak definition is implemented in France by DSOs.

⁴Computation time aspects can be found in Appendix C

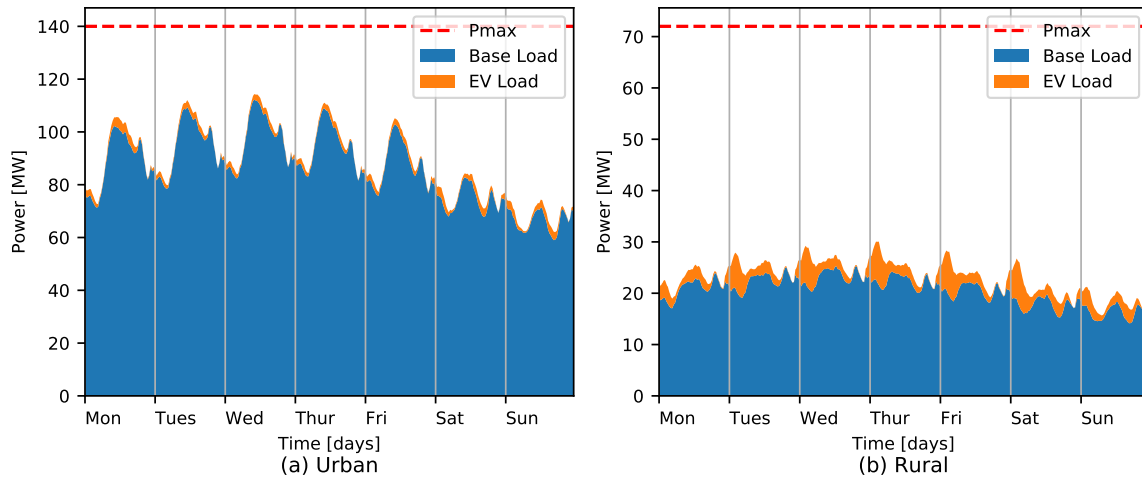


Figure 4.9: Total load at (a) urban, and (b) rural substations for the peak demand week for the off-peak charging case. Pmax represents the installed transformation capacity at the substation.

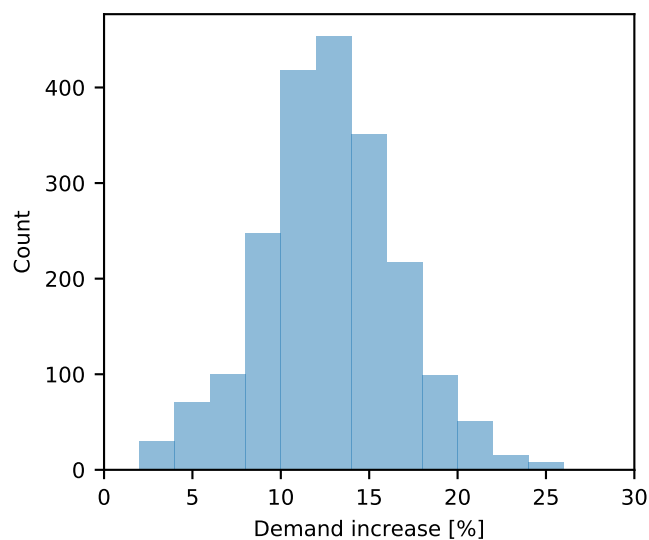


Figure 4.10: Histogram of demand increase (in energy) due to EV integration in Enedis' substations.

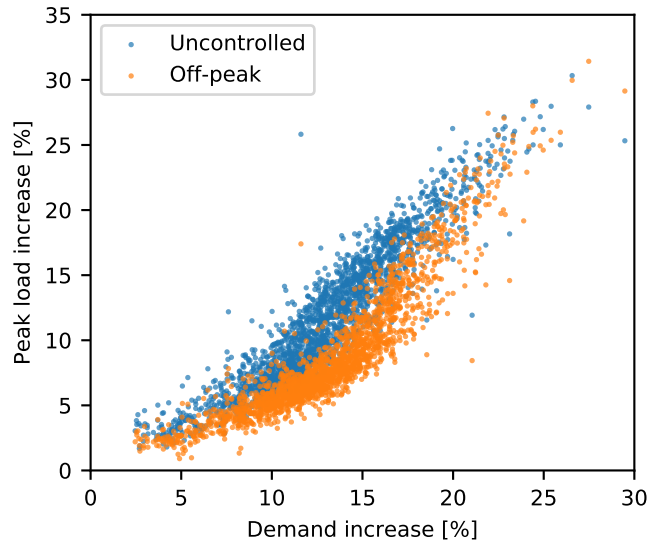


Figure 4.11: Increase in peak load vs. increase in total demand due to EV integration in Enedis substations.

can have different roles (municipality belonging to the urban pole, municipality belonging to the surrounding area of an urban pole, rural municipality). We define eight types of urbanity for each municipality, according to the role of the municipality in the urban areas (urban pole, agglomeration belt or rural area) and the size of the urban areas (large (>500k residents), medium (between 100k-500k residents) and small (<100k residents), as shown in Table 4.5 and Figure 4.12. For example, large urban poles (LUP) represent city centers and adjoining urban municipalities of major French cities, including Paris, Lyon, Marseille and Bordeaux, and agglomeration belts (AB) represent the peri-urban area around the economic centers of these cities. We then defined the category of each substation based on the predominant type of urban tissue of its service area⁵.

The peak load increase with respect to the demand increase due to EV charging for three contrasting urban tissue cases (large urban poles, agglomeration of large urban poles and rural areas) is shown in Figure 4.13. While a high variability among substations appears, there are clear trends among them. EV charging impacts are less significant in urban city centers than in rural and peri-urban areas. On the contrary, peri-urban areas of large poles tend to suffer greater impacts, both in term of additional demand and peak load, than both rural and urban cases. The average demand increase and peak load increase for the eight urban tissue cases is shown in Table 3.2. These results show the importance of considering local mobility patterns in EV integration studies at the distribution level.

⁵We counted the number of infra-communal cells belonging to each type of urban tissue in the substation service area, and selected the type of urban tissue with the highest count.

Table 4.5: Categories of urban tissue and number of assigned substations.

Type of urban tissue	Abbr.	Category in urban area ^a	Size of urban area ^b	Number of substations
Large urban pole	LUP	Urban pole	>500k	352
Medium urban pole	MUP	Urban pole	100k-500k	208
Small urban pole	SUP	Urban pole	<100k	117
Agglomeration belt of large urban pole	LAB	AB	>500k	183
Agglomeration belt of medium urban pole	MAB	AB	100k-500k	239
Agglomeration belt of small urban pole	SAB	AB	<100k	127
Rural agglomeration belt of multiple urban poles	RMP	Rural	Multiple	136
Rural outside the influence of urban areas	R	Rural	-	710

^a The type of municipality is found in [202] under the CATAEU variable.

^b In number of residents of urban area [202].

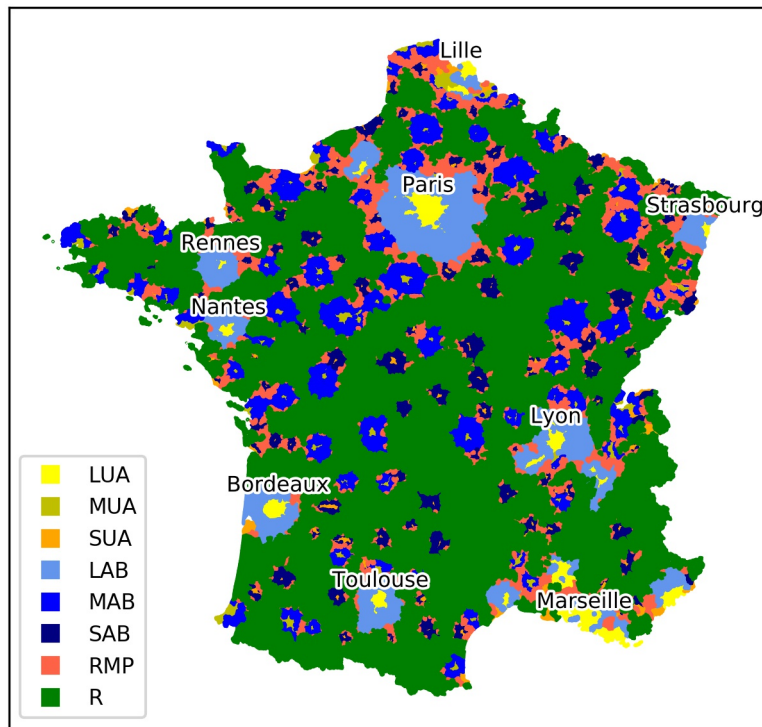


Figure 4.12: Urban tissue category definition.

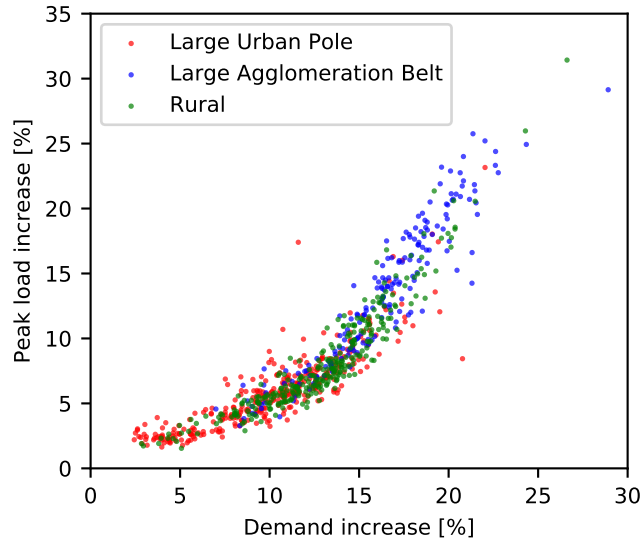


Figure 4.13: Increase in peak load vs. increase in total demand due to EV integration in substations serving large urban poles, agglomeration belts of large urban poles and rural areas, for the off-peak charging case.

Table 4.6: EV charging impacts at the substation level per type of urban tissue

Type of substation	Demand increase	Peak load increase	
		Uncontrolled	Off-peak
LUP	10.4%	8.4%	6.0%
MUP	12.4%	9.9%	7.6%
SUP	11.8%	9.3%	6.9%
LAB	16.6%	16.9%	13.5%
MAB	14.3%	14.1%	10.3%
SAB	12.9%	11.6%	8.5%
RMP	15.1%	14.6%	11.1%
R	12.9%	11.7%	8.1%

4 EV and PV integration in realistic MV grids

In this section we will present a study on the impacts of the joint integration of EVs and PV generation at the MV level, by performing year-long power flow simulations in a realistic case study⁶. We analyze constraints that can occur from asset overloading or voltage deviations (voltage at the MV level should be maintained between 0.95 and 1.05 pu).

We use infra-communal data to create a case study for the *La Boriette* substation in south-west France, which supplies part of the city of Brive-la-Gaillarde and the surrounding rural areas. This area corresponds to a mid-size urban pole (MUP, according to Table 4.5).

The substation is composed of three HV/MV 36 MVA transformers, which supply 20 MV feeders with nominal voltage 20 kV. There are 13 urban feeders with a total length between 5 to 10 km, all of them composed of underground cables (see Figure 4.14). The remaining 7 feeder supply rural areas, with total lengths going up to 70 km including ramifications, as shown in Figure 4.15⁷, with a mixture of overhead lines and underground cables. Peak demand for feeders ranges between 1.1 to 4.4 MW, with total peak demand at the HV/MV substation of 57.8 MVA.

We use the 2018 load profiles of different customer classes (residential, professional, tertiary, industry and agriculture) and annual consumption by customer class by infra-communal cell to define the load profiles at each infra-communal cell. We obtain yearly PV generation profiles from *renewables.ninja* for Brive-la-Gaillarde area for the same year. Capacity factor for ground-mounted PV reach 14.8% and for rooftop PV 13.3%.

4.1 Case studies

We place ourselves in the 2035 horizon and analyze three scenarios:

- **EV-only scenario.** EV integration with 50% diffusion.
- **Continuity scenario.** EV and PV integration following current trends.
- **Synergies scenario.** High EV and rooftop PV integration.

The **EV-only scenario** studies the impacts of EV integration in *La Boriette* HV/MV grid without PV adoption. It considers an EV diffusion scenario of 50% and 30% of work-place charging, as the precedent case studies at the HV/MV substation level. Residential EVs apply an off-peak charging strategy and work-place charging EVs an average charging strategy

In the **Continuity scenario** we evaluate the impact of PV integration following current trends of PV installations, with around 50% being ground-mounted. We consider the French government objectives, which envision between 35 to 44 GW of PV installed capacity by 2028⁸ [203]. We extrapolate the uptake to 2035 to arrive at 70 GW installed nation-wide in France, following [177]. We decline these values at the HV/MV substation

⁶Computation time aspects can be found in Appendix C

⁷Total length per feeder depend on the hypotheses from the grid reconstruction model. Actual operating conditions may differ.

⁸The French government objectives consider over 50% of PV installations as ground-mounted.

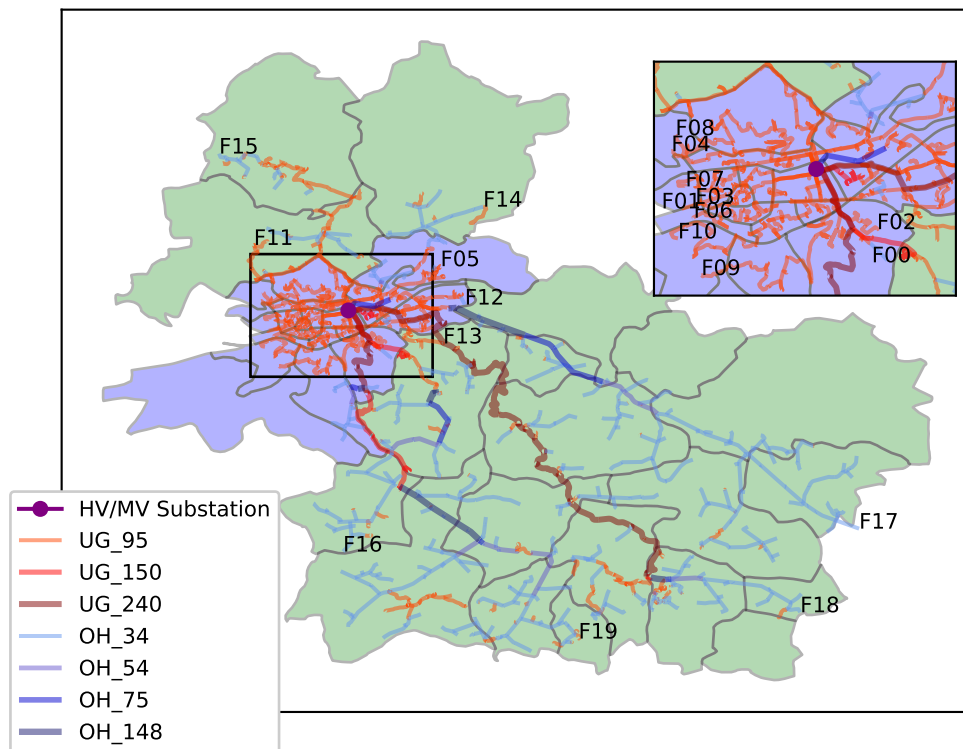


Figure 4.14: Service area and MV grid of *La Boriette* substation. A zoom on the urban area corresponding to Brive-la-Gaillarde city center is shown. Each polygon represents one infra-communal cell, with blue polygons corresponding to urban areas and green polygons to rural areas.

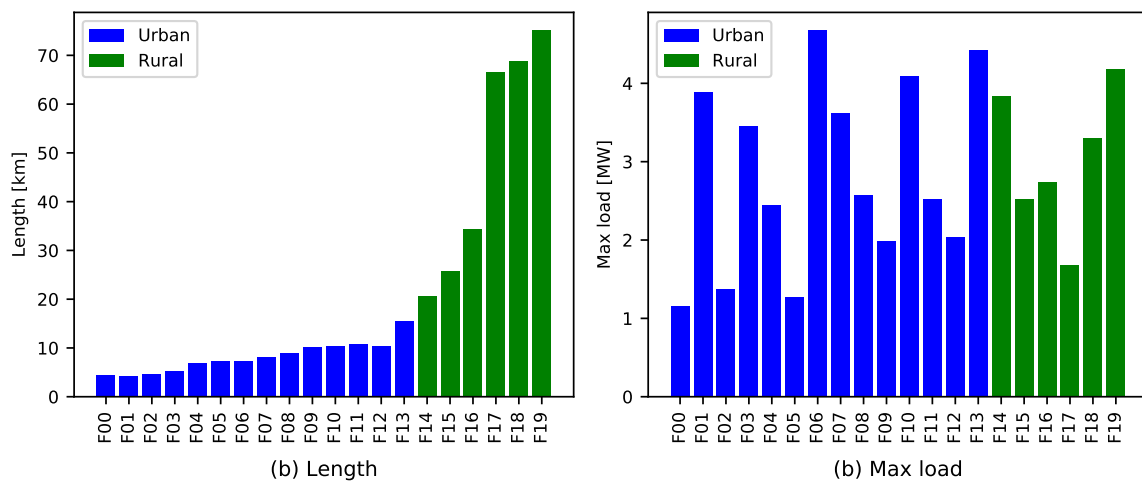


Figure 4.15: (a) Total length and (b) maximum demand for feeders of *La Boriette* substation

level, following the methodology described in the Appendix B, obtaining 69 MW of PV installed capacity.

The **Synergies scenario** analyzes a case with a high share of rooftop PV integration and high access to work-place charging, to evidence possible synergies between EV and PV installations. We consider a 100% EV adoption scenario with 50% work-place charging access. Both residential and work-place charging EVs apply a valley-filling strategy with respect to the load at the HV/MV substation. The key parameters for each case study are shown in Table 4.7.

Table 4.7: Main parameters of the three case studies.

Parameter	EV only	Continuity	Synergies
EV diffusion	50%	50%	100%
Workplace charging access	30%	30%	50%
EV doing residential charging	9,794	9,794	13,995
Residential charging strategy	Off-peak	Off-peak	Valley-filling
EVs doing work-place charging	4,387	4,387	14,625
Work-place charging strategy	Average	Average	Valley-filling
Installed rooftop PV	-	26.9 MW	60.5 MW
Installed ground-mounted PV	-	42.1 MW	9.3 MW

We map the spatial distribution of EVs per infra-communal cell, shown in Figure 4.16 for the EV-only and Continuity scenario⁹. It can be seen that day-time charging needs will be concentrated around Brive-la-Gaillarde city (see zoom at top right of each plot), as it attracts a lot of workers. Rural areas are less populated and attract less workers.

The installed capacity of EV connections per feeder is shown in Figures 4.17 and 4.18 (left hand plots). The total installed capacity for EV charging can reach over 20 MW in one feeder (Feeder 6, Synergies scenario, which hosts 1238 residential EVs and 1358 work-place EVs). While this may seem a lot, peak work-place and residential charging do not coincide, and from results of Chapter 3, we expect coincidence factors between 10-15% for 1,000 EVs (MV feeder level) and uncontrolled charging. Therefore, we expect around 2-3 MW of EV charging in high-demand feeders, e.g., feeder 6).

In Figures 4.17 and 4.18 (right hand plots), we show the PV installed capacity per feeder¹⁰. The spatial distribution of PV differs between the Continuity and Synergies scenario. In the Continuity scenario, PV installations are concentrated in longer rural feeders (feeders 14-19), as ground-mounted PV installations count for a high share of installed capacity. On the contrary, in the Synergies scenario, PV installed capacity is more evenly distributed among feeders, as rooftop installations are distributed all over the MV grid, with a higher share is installed in Brive-la-Gaillarde city area, which has a dense MV grid.

⁹EV spatial distribution for the Synergies scenario is shown in Appendix D.

¹⁰Spatial distribution of PV installation per infra-communal cells can be found in Appendix D

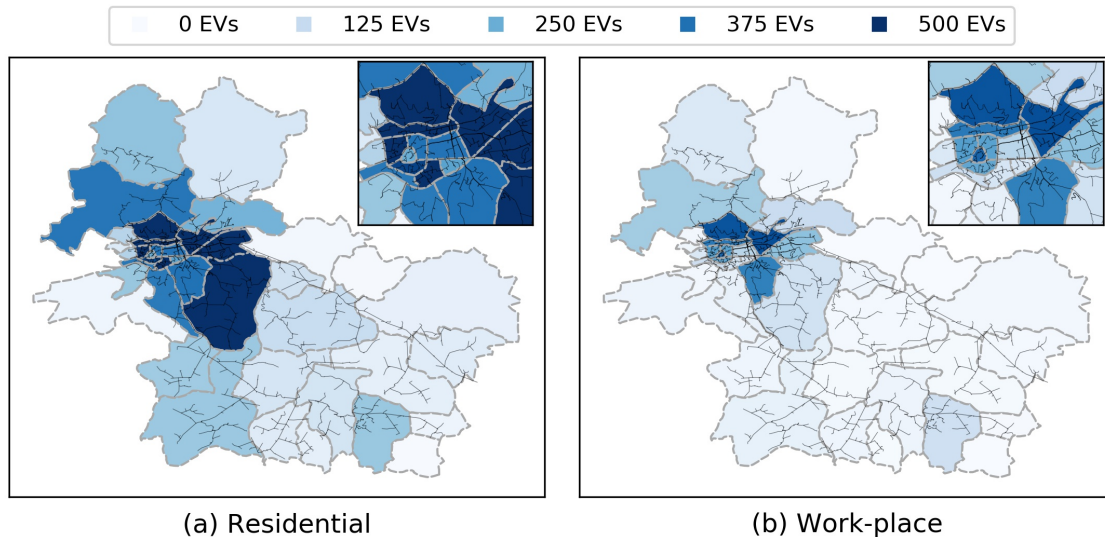


Figure 4.16: Spatial distribution of EVs per infra-communal cell, EV-only and Continuity scenarios (EV diffusion=50%, Work-place charging access=30%). Zoom on Brive-la-Gaillarde city center on top right corner of each plot.

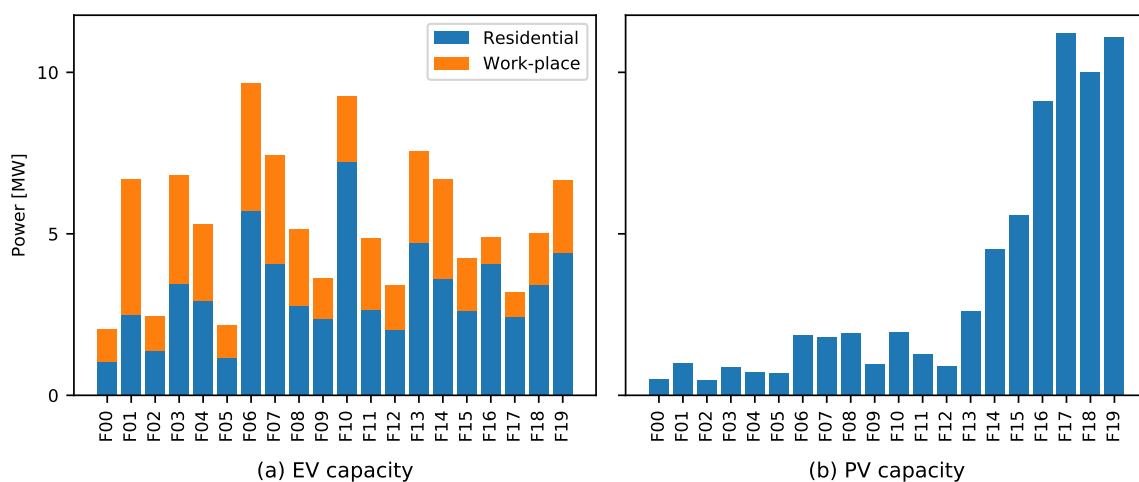


Figure 4.17: Installed capacity of EVs and PVs per feeder, Continuity scenario.

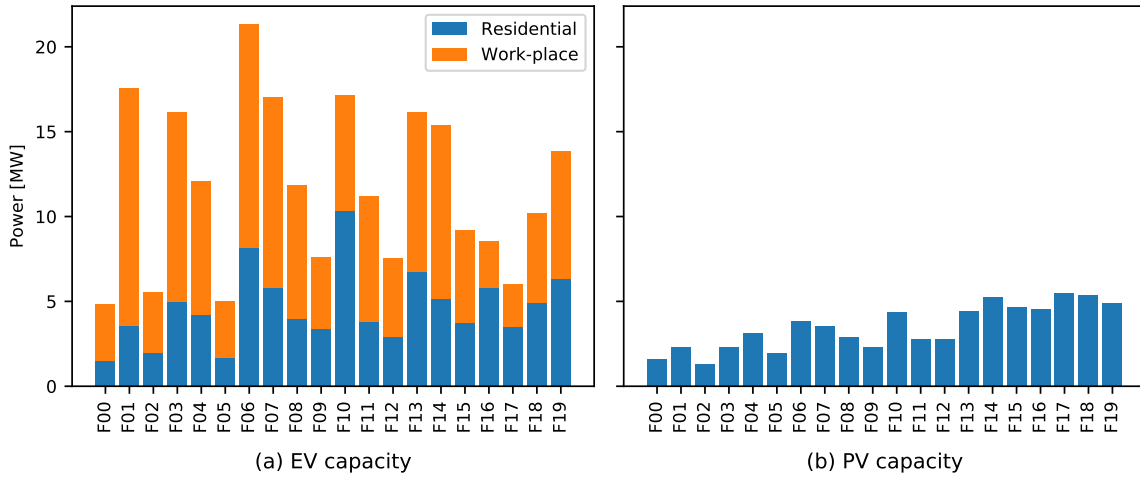


Figure 4.18: Installed capacity of EVs and PVs per feeder, Synergies scenario.

4.2 Results

General results

Key indicators for the results of simulations are shown in Table 4.8. In terms of additional demand (in energy), EV integration would represent an 11.4% increase (30.7 GWh) for the 50% EV diffusion case, and mounting up to 24% (64.1 GWh) in the Synergies scenario (100% EV penetration with high work-place charging access). **EV integration has little impacts on congestion and voltage deviations in the studied MV grid**, increasing maximum line loading by 4% and minimum voltage dropping by 0.09 pu (comparison between base case and EV-only case).

The integration of 70 MW of PV systems in the studied grid will generate over 80 GWh of electricity, which is more than the energy required to support 100% EV integration. However, under the Continuity scenario, more than 10% of it is exported towards the transmission system. This energy can be almost fully consumed locally (i.e., not exported towards the transmission system) in the Synergy scenario, due to an increased share of day-time charging and a valley filling charging strategy.

PV generation can have significant impacts on the MV grid, especially under current trends of high shares of ground-mounted PV installations. In the Continuity scenario maximum line loading reaches over 100% of the rated current for 5 section in Feeder 17 (rural feeder) and over-voltages occur at several nodes at the extremes of feeders 16, 17 and 18. On the other hand, in the Synergies scenario maximum line loading and voltage deviation issues are reduced, as PV installations are more evenly distributed among feeders and EV demand is coordinated with PV generation.

In Figure 4.19 and 4.20, the load at the HV/MV substation for the Continuity and Synergies scenario are shown for the winter peak load week (last week of February) and the lowest net load week (last week of August). It can be seen that PV generation will significantly modify the load at the substation level, with EV having a minor impact in comparison. However, complementarities between EV charging and PV can appear if day-time charging is incentivized, allowing to reduce exporting PV generation even in

Table 4.8: Key indicators for power flow simulation results.

	Base (no EV)	EV-only	Continuity	Synergies
Total annual demand [GWh]	263.8	294.5	294.5	327.9
-From Evs	0	30.7	30.7	64.1
PV generation [GWh]	0	0	85.8	82.3
-Exported to transmission system	0	0	9.1	<0.1
-Hours of export	0	0	1082	<10
Peak load [MW]	57.8	62.08	60.1	59.3
Min load [MW]	14.4	14.9	-22.7	-0.8
Max line loading	50.2%	54.4%	104.7%	54.7%
Min bus voltage [pu]	0.9652	0.9575	0.9575	0.9647
Max bus voltage [pu]	1.0100	1.0100	1.0984	1.0310

summer months (Synergies scenario), and allowing high levels of EV hosting with minimal grid impact.

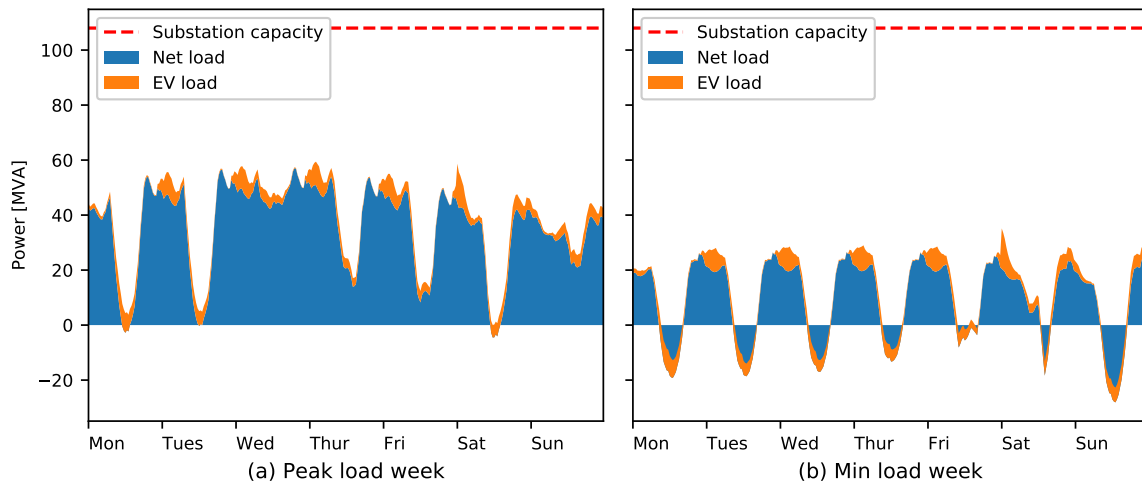


Figure 4.19: Net load (base load minus PV generation) and EV load at the HV/MV transformer for Continuity scenario. (a) winter peak load week, and (b) lowest net load week.

Line loading

The maximum line loading in the Continuity scenario is shown in Figure 4.21¹¹. Highest line loading occur in feeder 17 due to high concentration of ground-mounted PV systems and low demand (including from EVs), with significant loading (over 60%) in feeder 16. We observe as well relatively high loading in the city center, close to the HV/MV substation, but reaching at most 50%.

In Figure 4.22 we show the line loading for two critical segments, one of an urban feeder (feeder 6), and one of the critical rural feeder 17, during the peak load week in winter. The figure shows the influence of PV generation in line loading, as well as the

¹¹For the other scenarios, see the Appendix D

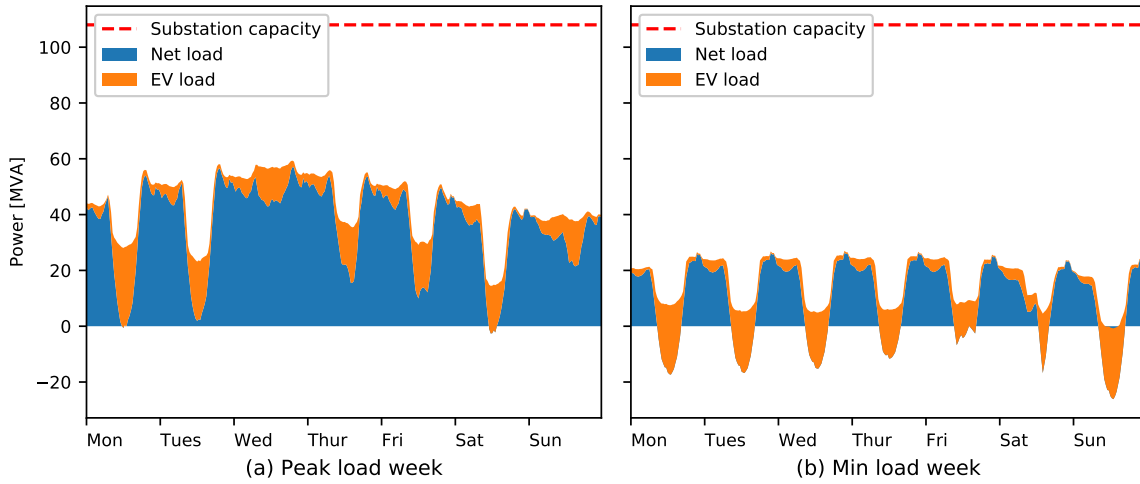


Figure 4.20: Net load (base load minus PV generation) and EV load at the HV/MV transformer for Synergies scenario. (a) winter peak load week, and (b) lowest net load week.

relatively low impact, in comparison, of EV charging. High line loading can occur due to PV generation even in winter months.

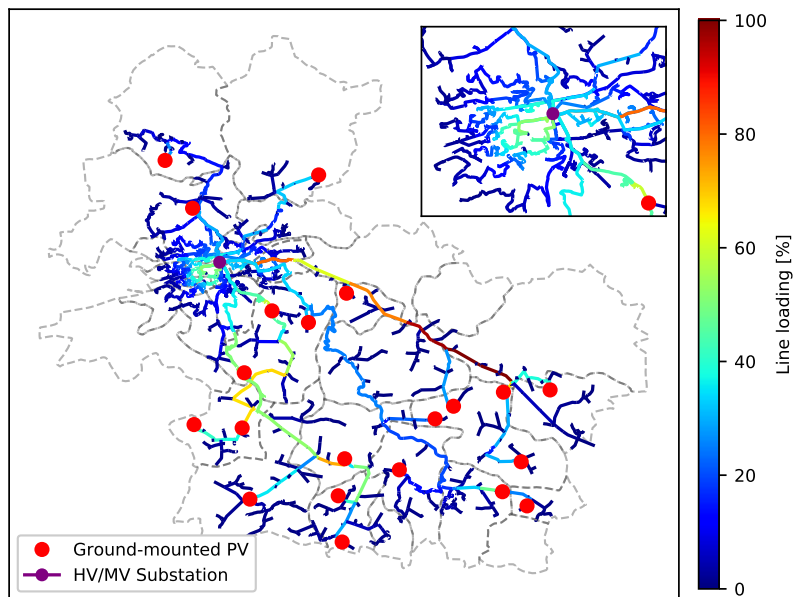


Figure 4.21: Maximum line loading in the Continuity scenario.

Voltage deviations

As shown in the general results, only the Continuity scenario experiences voltage deviations (over-voltages) outside the required limits. The percentage of nodes and time where there are nodes in constraint, per feeder, are shown in Table 4.9.

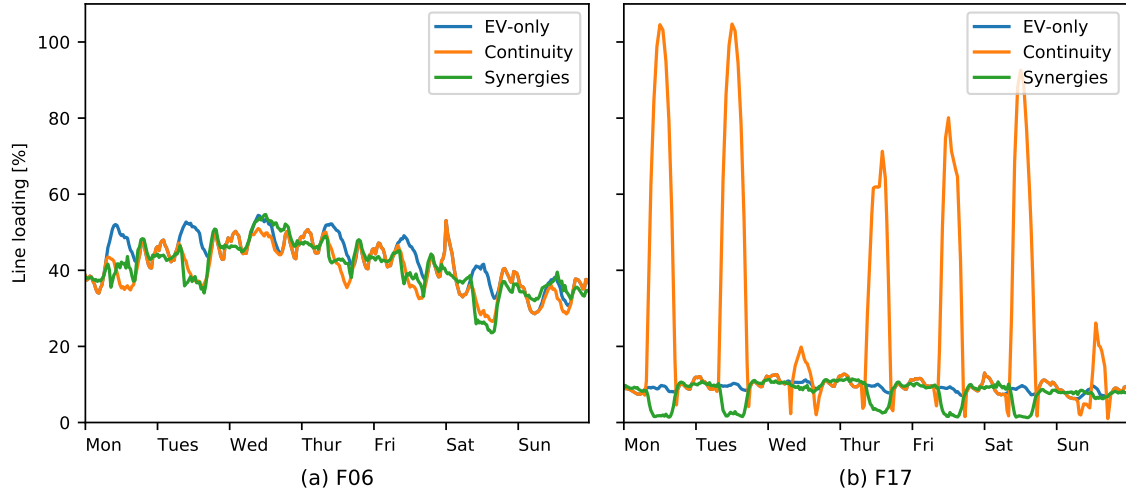


Figure 4.22: Line loading for two critical lines in winter week. (a) Feeder 6 (urban) and (b) Feeder 17 (rural).

Table 4.9: Percentage of nodes experiencing over-voltages and percentage of time where over-voltages occur, per feeder, Continuity scenario. Non mentioned feeders do not experience over-voltages.

Feeder	Nodes	Time
F16	28.0%	8.3%
F17	62.2%	17.9%
F19	9.5%	0.3%

In Figure 4.23 we show the voltage profile of two critical nodes in the peak load winter, one in urban feeder 6 and one in rural feeder 17, for the three scenarios in study. It shows the higher variability that the voltage in rural feeder experiences. This is due to the spatial distribution of PV installations. Under the Continuity scenario significant shares of PV installations are placed in rural areas with low population density, thus low availability of in-place EV charging to reduce constraints.

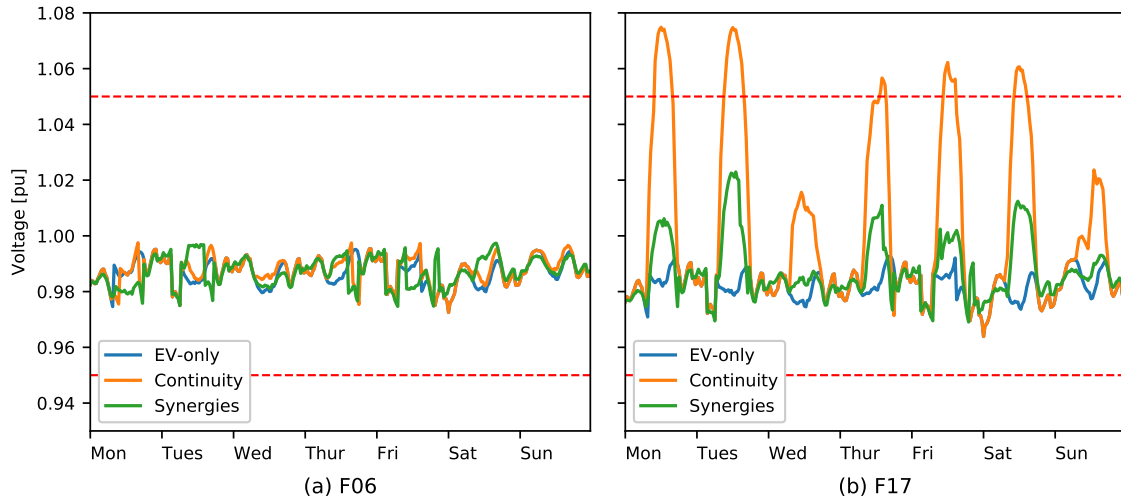


Figure 4.23: Voltage profile for further buses in winter week. (a) Feeder 6 (urban) and (b) Feeder 17 (rural).

5 Partial conclusions

In this Chapter we studied how local mobility patterns and the spatial distribution of EVs impact their grid integration. We based our case studies on high-granularity data sources (infra-communal level) from France.

First, we evaluated the impact at the HV/MV substation level, showing that local mobility patterns create different EV charging dynamics at the substation level. Large city centers can experience high demand for EV charging during day-time, as they attract a lot of population for work purposes, and relatively lower demand from residents during night-time who tend to drive short distances. On the contrary, peri-urban areas attract few workers and can experience high demand from residents during night-time, who drive longer distances and charge almost daily.

The integration of EVs with a 50% penetration, equivalent to 16M EVs in France, can increase peak load demand at the HV/MV substations in a range from 2% to over 25%. These impacts will be more significant in substations serving peri-urban areas of large cities, with lower impacts on substations serving large urban city centers. Off-peak charging can reduce the impacts on peak load, but only to a certain amount. For substations where EV demand amounts over 20% of base demand, an off-peak charging strategy creates little peak load reduction. Therefore, critical substations may require more advanced charging strategies to improve EV integration.

We then evaluated the impacts of the joint integration of EV and PV systems at the MV level. A case study in a substation in Brive-la-Gaillarde, a city in southwest France, showed that the MV grid appears robust in face of even a 100% EV penetration. Higher impacts can come from PV integration, in both voltage deviations and asset over-loadings, especially under current trends of high shares of ground-mounted PV systems located in rural, low population density areas. Incentivizing rooftop PV generation and day-time EV charging can create positive complementarities, reducing the integration impacts of both technologies. Thus, we see the need not only for *time* coordination of EV charging and PV generation, but as well a *spatial* coordination of these installations to reduce grid integration impacts.

This chapter shows the importance of modeling user driving behavior at the local level, going beyond nation-wide travel surveys. Further work should be carried to improve the mobility modeling of EV users, as this work only considered commuting purposes. Advanced transport simulation models, such as MATSim or others, could be used to improve EV integration assessments. Evolutions in mobility patterns, such as car-sharing, multi-modal transports and the influence of tele-working and delivery services should as well be considered.

It is also important to evaluate EV integration using realistic case studies, as EV and PV integration are extremely dependent on the local grid conditions. Studies considering integrated MV and LV grids should be carried next to completely assess the impact of EV and PV integration. Our study was also done only for normal operation conditions. Analyses on N-1 situations, used to dimensionate MV grids, are still required.

Chapter 5

Participation of electric vehicle fleets in local flexibility tenders: Analyzing barriers to entry and workable solutions

1 Introduction

As discussed in Chapter 1, the integration of distributed energy resources (DERs), including distributed generation, energy storage and electric vehicles (EVs), opens up the possibility of advanced operation and planning of distribution grids. These controllable assets can provide *flexibility* to distribution system operators that will allow for a more efficient use of grid assets. Several use-cases have been identified. In the operational timeframe, flexibility can be used to solve grid congestion, improve grid reliability during maintenance periods, and provide back-up power in fault events. In the medium-to-long-term, flexibility can reduce or avoid grid reinforcements or reduce the risk of stranded assets under uncertain load growth.

In Chapter 2 we analyzed four value frameworks that DSOs can use to procure flexibility: grid codes, smart connections, network tariffs and market-based solutions. In particular, market-based frameworks have garnered significant attention by industry and academia, and are favored by regulators. Market-based solutions enable competition, allowing for cost efficiency and innovation in flexibility procurement.

In recent years, a number of demonstrator projects have proposed and tested market-based flexibility solutions at the distribution level (see Chapter 2, Section 3), mostly in the form of local flexibility market platforms. Moreover, DSOs in the UK, France, Germany and the Netherlands have already started to implement market solutions to procure flexibility for their short- and long-term needs. Likewise, New York State utilities implement ‘non-wires alternatives’ where DERs can provide a cost-effective alternative to costly reinforcement investments [103].

In this chapter, we will evaluate the participation of EV fleet aggregators in market-based flexibility implementations. For that, first, we will analyze emerging flexibility implementations by European DSOs to identify best practices in market design. In a second step, we will quantify the potential gains that EV fleet aggregators can obtain

from long-term flexibility tenders and identify the main parameters that affect this remuneration.

1.1 Contributions

This chapter makes four main contributions. First, we analyzed the impact of local flexibility market rules on the participation of DERs. This includes both short-term initiatives as well as long-term mechanisms. To the best of our knowledge, no previous studies have tackled long-term market mechanisms at the distribution level. Second, we proposed a two-stage methodology for evaluating EV fleet participation in long-term tenders that can capture various specificities of the tender process. Third, we quantified EV fleet participation using real-world data from demonstrator projects in Europe, which makes the results representative. And fourth, we formulate policy recommendations based on best-practices to boost the participation of DERs in local flexibility markets.

This chapter is structured as follows. Section 2 presents five emerging flexibility markets in Europe and identifies key market rules that can affect EV participation. Section 3 explains the methodology developed to quantify EV participation in long-term distribution tenders and presents the case study. Section 4 reports the main results of the study on EV remuneration. Section 5 completes this chapter with key conclusions and policy recommendations.

2 Looking for decentralized flexibility markets

Market-based solutions for the provision of flexibility at the distribution level has gained a lot of attention in recent years. [204] categorized three main approaches for flexibility contracting:

- **Local trading in the wholesale market:** Where the DSO contracts location-specific flexibility through existing markets (day-ahead, intraday) at the same time as generation.
- **Local exchange:** Where a local market runs in parallel to existing energy and balancing markets.
- **Reserve-like local market:** Where DSOs use long-term contracts to ensure availability of flexibility resources. Then, flexibility is activated in real-time. Flexibility providers are paid an availability fee and an activation fee.

Several academic studies have focused on short-term flexibility provision that allow DSOs to solve congestion in (near-) real time. In [205], a day-ahead flexibility market that runs in parallel to energy markets allows DSOs to relieve congestion. A comprehensive framework to alleviate congestion in distribution grids was proposed in [206]. It considered a combination of dynamic network tariffs, a day-ahead flexibility market, and demand curtailment in real-time. Similarly, [74] analyzes congestion management at the distribution level with a *traffic light* approach. In the green system state, distribution grid operation is normal and no action is needed to be taken by the DSO. If congestions

are expected, the system passes onto the orange state and the DSO can procure flexibility from a local flexibility market. If the DSO is unable to resolve congestions through the local flexibility market, the system goes into the red state and load curtailment can be carried out to maintain system security. Additionally, examples of local flexibility trading platforms can be found in the Invade [207], SmartNet [135] and Interflex [108] demonstrator projects. See as well [208] for a review of methods and models.

However, DSOs can face high risks if they rely solely on short-term markets. Short-term local flexibility markets may suffer from a lack of liquidity due to their limited size, thus exposing DSOs to high flexibility prices or even endangering grid reliability since DSOs would have limited options if the market fails. Reserve-like local markets can allow DSOs to procure flexibility for investment deferral purposes, as they provide a long-term perspective on flexibility availability. Long-term contracts can provide an appropriate way to manage risks between participants [209]. In this case, they provide a degree of certainty to both contractors: DSOs are guaranteed that flexibility will be available if needed¹, and flexibility operators are provided with secured future revenue streams.

As discussed in [210], long-term contracts also can mitigate gaming in short-term markets. Gaming can be serious issue in local flexibility markets where the limited number of market participants can reduce competition and where a participant with sufficient knowledge of expected grid bottlenecks can aggravate congestion and then get paid to solve the problems created by itself.

Long-term contracting of flexibility for the distribution system has been less studied in the literature. In [85] analyzed several congestion management mechanisms, including a capacity auction for congested lines which could be run in a yearly basis, however they did not define how this auction would take place. In [211], a model to enable DSOs to procure flexibility for investment deferral is proposed. A regulated tariff for flexibility is set, destined to compensate flexibility providers for their investments.

2.1 Emerging flexibility markets

We have identified five European initiatives surrounding the implementation of local flexibility markets, each taking a different approach according to their local requirements. Two of them, UKPN and Enedis (DSOs), propose mid- to long-term tenders (i.e., reserve-like markets) to procure flexibility ahead of time, as their major use-case is to defer grid reinforcement. The other three, Enera, Nodes and GOPACS, are short-term (intraday) market platforms whose main use-case is to reduce renewable energy source (RES)-driven congestion at transmission or distribution level. [210] analyzed four of these projects through the lens of controversies around local flexibility market design, including level of integration of local markets into existing structures (day-ahead, intraday, and balancing markets), roles and responsibilities of DSOs in market operation, standardization of flexibility products, and level of coordination between DSO and transmission system operator (TSO).

First, UK Power Networks (UKPN, the London-area DSO) has implemented local flexibility tenders since 2018 to contract flexibility for the medium- to long-term in sections of the grid where they expect congestion, allowing them to reduce investment costs

¹Or reducing the risk of stranded assets in case the expected load growth does not materialize.

[212]. UKPN identifies periods of time during which they expect congestion, usually winter evening hours due to peak load, and the amount of flexibility required to solve them. Flexibility is required to be available at these periods ('availability windows') but not necessarily activated each day, as activations are expected to happen only a few hours per year.

The last tender process carried out in April 2020 comprised 62 medium voltage (MV) zones and over 60 low voltage (LV) zones, awarding contracts for 42 MV and 15 LV zones, for up to 7 years duration. EV companies won a significant share of the flexibility contracts, for a total 36 MW out of 52 MW awarded in the HV tender [213]. HV tenders were a competitive process, where participants bid an availability fee (in £/MW/h) and a utilization fee (in £/MWh) for a given amount of flexibility. Results for the April 2020 tender, shown in Figure 5.1, show that prices vary widely depending on participant strategy and tender conditions. Availability payments (left plot) can go from 3 to over 4500 £/MW/h, which is significantly higher than payments for frequency regulation services in continental Europe² and the UK³ which are under 10 €/MW/h or 10 £/MW/h. Equivalent payments per firm kW (right plot)⁴ average 61.3 £/kW/year but can exceed 300 £/kW/year in certain areas, showing the potential high value of flexibility for investment deferral. To simplify flexibility procurement at LV level, the LV tender provided only a fixed service fee of 47.6 £/kW/year, which is close to the average payments for their HV tender.

Additionally, contracts were signed with flexibility providers to deal with other grid requirements, such as managing outages. Flexibility activation for these additional services occurs in real-time according to grid conditions, but the flexibility providers have no obligation to provide the flexibility. These contracts therefore only entail utilization payments.

²Payments for frequency containment reserve (FCR) in the FCR Cooperation averaged 7.4 €/MW/h between January 2017 and August 2020 [117]. FCR Cooperation is a common reserve market for FCR between TSOs in France, Germany, Switzerland, Belgium, the Netherlands and Austria

³Most of the firm frequency response services contracted by NGESO (UK's TSO) are between 0–4 £/MW/h [214].

⁴Service payments per firm kW are computed for each accepted bid considering the number of hours during which flexibility should be available and a total of 10 one-hour activations per year.

$$Serv.Payment[\text{£}/\text{kW}] = Act.Payment[\text{£}/\text{kWh}] * 1[\text{h}] * 10 + Avail.Payment[\text{£}/\text{kW.h}] * Avail.Hours[\text{h}]$$

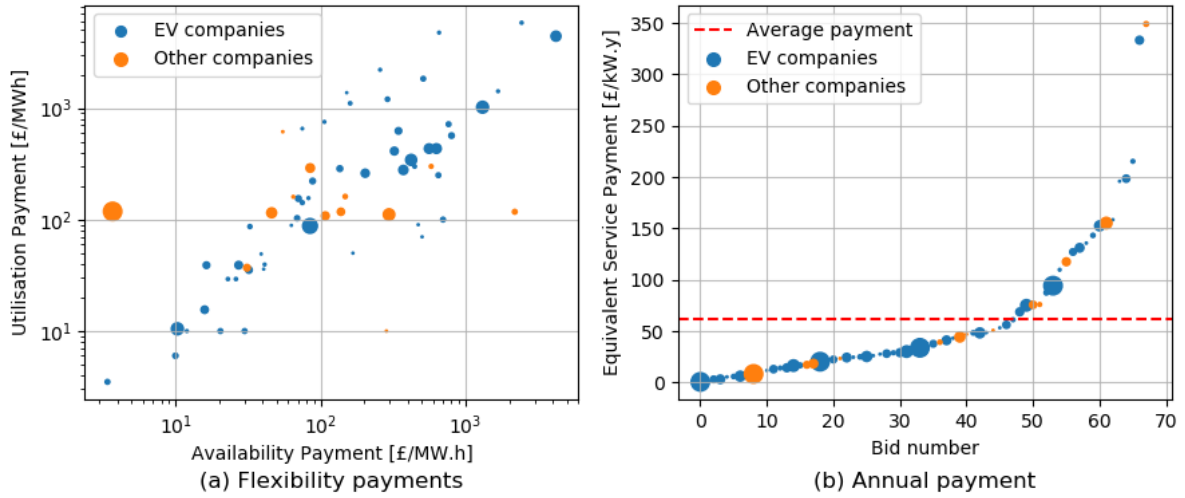


Figure 5.1: Results for accepted bids during the UKPN April 2020 HV tender. (a) Availability and utilization prices, and (b) equivalent service payments per firm kW. Marker sizes are proportional to bid flexibility [kW]

Second, Enedis, the French DSO supplying 95% of continental France, launched its first tender process during 2019–2020. The tender covers six zones in their medium voltage (MV) grid, each with different use-cases. Three zones require flexibility for investment deferral, with availability and utilization payments in much the same way as the UKPN HV tenders, and three zones require flexibility on the operational timeframe (fault-restoration), with only utilization payments. The use-cases for investment deferral are also varied, with one case dealing with peak load, a second one dealing with voltage regulation due to high PV penetration and requiring reactive power, and a third one to guarantee reliability under fault conditions, thus requiring flexibility to be available at all times [215]. The 2020 tender process did not provide awarded any contracts. The process continues with a second tender in 2021 that considers three zones, one for investment deferral (with availability payments) and two for fault-restoration use-cases (without availability payments).

Third, GOPACS is a collaboration between Dutch grids operators, TenneT, the TSO, and four DSOs. It can be categorized as a local trading in wholesale market, as it provides a platform that serves as an intermediary between grid operators and the intraday market platform ETPA, operational in the Netherlands. Participants of the ETPA trading platform can respond to GOPACS requests by submitting bids with a locational tag. It has so far only been used to solve transmission-level congestion [216], as an alternative to redispatching, but they expect to use it for distribution-grid needs in the near future.

Fourth, Enera is a German pilot project allowing DSOs EWE NETZ and Avacon and TSO TenneT to reduce uneconomic curtailment of excess RES generation. It proposes intraday trading based on the existing market platform Epex Spot [104]. Likewise, NODES run two pilot projects in Germany in an effort to reduce curtailment in wind-saturated regions by providing an intraday marketplace [217]. Both of these projects thus require load increase to absorb extra renewable generation.

These projects illustrate how solutions are tied to problems faced by DSOs. Enera

and NODES face a problem of excessive RES generation where the current solution is un-economic curtailment, so they proposed a short-term platform to improve grid operation. UKPN and Enedis mainly face issues that require grid reinforcements, and so they implemented tender processes to ensure flexibility availability and improve grid planning.⁵ Fault-restoration services are also procured through long-term contracts, as an intraday market solution is not adequate for that purpose. Physically, flexibility needs are related to load reduction or load increase (active power) or reactive power exchanges. For these local needs, the flexible resources must be well located to bring an efficient solution.

2.2 Can DERs participate in emerging flexibility markets?

A modular framework, originally proposed to identify entry barriers for DER aggregators in reserve markets [40], was adapted to assess the participation of DER aggregators in local flexibility markets. The modular framework serves to classify market rules and identify best practices and room for improvement. The framework is composed of three hierarchical modules, each with a set of parameters, as shown in Table 5.1.

Table 5.1: Modular framework to evaluate the participation of DERs in local flexibility markets

Module	Parameter
Administrative rules	A1 Technical discrimination
	A2 Flexibility platform interoperability
	A3 Perimeter evolution
Product definition	B1 Distance from real-time and availability window definition
	B2 Minimum activation time
	B3 Minimum bid size
	B4 Location
Payment scheme	C1 Nature of payment
	C2 Baseline definition
	C3 Stacking of services
	C4 Penalties

Module A: Administrative rules

A.1 Technical discrimination: In the market design there might be rules impeding the participation of DER aggregators in the market, or requirements that would imply an excessive burden for their entrance to market. For example, the aggregation of multiple sites can be forbidden by a market rule, connection or metering requirements might not be adapted to aggregation of diffuse resources.

A.2 Interoperability of flexibility platform: There is a wide variety of DSOs in European countries. For example, there is one major DSO in France, Enedis, which supplies 95% of the territory, whereas there are more than 800 in Germany. Each flexibility

⁵NODES has stated that it intends to implement long-term contracts as well to cater for long-term DSO needs.

product will be required for a specific location operated by one DSO only. However, as there could be a potential large number of flexibility requirements (and thus of DSOs involved) in a given country/region, there should be a coherence and common process between these products. A common flexibility platform would benefit aggregators that control assets across several DSO's sites, reducing their learning process.

A.3 Perimeter evolution: The resources controlled in a given location by an aggregator may change over time, such as EV users moving out. Long-term flexibility procurement should allow the evolution of flexibility assets and the consideration of new connections (such as EV charging points that are not yet connected to the grid at the time of the tender process).

Module B: Product definition

B.1 Distance to real-time and availability windows: This characteristic refers to how far ahead of delivery the flexibility products are procured. DSOs might need a long-term assurance of the flexibility availability when planning their grid, as relying only on a short-term markets might be prejudicial to them, but on the other hand aggregators of diffuse resources (such as demand response or EVs) might face high uncertainties on their asset availability ahead of time. To reduce uncertainties for market participants, mid or long term procurement of flexibility may define a specific availability window in which the flexibility should be available for activation. Defining specific availability windows (for example, corresponding to the expected peak-load hours instead of whole days), can help aggregators match their resources availability profiles to DSOs needs. Note that even though flexibility should be available during these periods, they may not be (always) activated.

B.2 Activation time: This refers to the (minimum) amount of time the product (increase/decrease of production/ consumption) is activated. This time will depend on the requirements of DSOs. However, long activation times might put high constraints for aggregators of diffuse resources. For example, an EV aggregator would need to have a higher number of resources to sustain long activation periods, and may face higher operational constraints to ensure the mobility requirements of EV users. Also, since congestion management services are energy-based (instead of capacity-based services like frequency response), long activation times might induce increased battery degradation. Activation times should be maintained at a minimum possible.

B.3 Minimum bid size: The minimum bid size will be linked to how many distributed resource units should be aggregated. Since local flexibility markets are focused on reduced areas, aggregating a high number units might be unfeasible. Low bid sizes will enable the participation of a higher number of flexibility resources and increase liquidity of the market.

B.4 Location: Local flexibility products are different from system-wide flexibility, such as frequency regulation, since the location of the resource is key in the impact it can have in solving a grid constraint. Products should have a well defined location, according to the expected grid constraints, to ensure that the flexibility resources will have a positive impact in grid operation.

Module C: Verification and Payment

C.1 Nature of Payments: For long-term flexibility procurement, both availability and utilization payments are needed. Reservation payments are necessary to ensure the availability of the flexible resources during the required availability windows. They are related to the flexible power capacity (in €/kW for example). These payments may not be needed in close to real-time markets. Activation payments refer to the actual utilization of flexibility, and are related to the energy provided during the flexibility service (thus, a payment is made in €/kWh). Remuneration of flexibility for reservation and activation can be either market-based or a regulated tariff. A combination of market and regulated tariffs can be considered, such as a market-based reservation payment and a regulated tariff for the activation of flexibility. However, ideally both reservation and activation payments are based on declared bids, thus allowing to reflect different cost structures (fixed and variable) of flexibility resources.

C.2 Baseline definition: Baselines are the counterfactual load or generation level of the flexible assets if they had not provided flexibility. The flexibility delivered to the system is measured against this baseline. Adapted baseline methodologies should be used for diffuse resources, which may not respond to the same patterns as conventional, more predictable, resources. This issue has been solved at the transmission level, and services at DSO level should use this knowledge.

C.3 Stacking of services: Local flexibility services are not going to be the only source of revenues for DER aggregators. Participating in DSO services must not be exclusive with other flexibility (system-wide) markets, as long as they do not imply contradictory actions.

C.4 Penalties: Penalties are incurred by a flexibility operator if it does not respond to full extent to a flexibility request by the DSO. While the DSO's need for security is understandable given the limited availability of local flexibility resources, by implementing penalties, they transfer this issue to flexibility operators. Therefore, EV or demand response aggregators have to contend at the same time with high uncertainty on their flexibility availability profiles and high penalties. High penalties can thus prove a barrier to entry for these actors.

We assess the performance of emerging local flexibility tenders using the modular framework shown in Table 5.2. This table shows best practices among the different market designs and allows to identify differences in implementation.

Table 5.2: Assessment of five emerging flexibility implementations' market rules

Rule	Ideal	UKPN	Enedis	GOPACS	Enera	NODES	
A1	Technical discrimination	Adapted connection & metering requirements	+/-	+/-	+/-	N.I.	N.I.
A2	Flexibility platform interoperability	Ample support, open access	+	+	+/-	+/-	-
A3	Perimeter evolution	Allowed evolution & future connections	++	+/- (only evol.)	N.A.	N.A.	N.A.
B1.1	Distance to activation	According to DSO's need	Long	Long	+	+	+
B1.2	Availability window definition ^a	Well defined/shorter	+	+/-	N.A.	N.A.	N.A.
B2	Minimum duration of service	No greater than energy trading period (15-30 min)	+	+	++	+	+
B3	Minimum bid size	Low (<=50kW)	+ / ++	-	-	N.I.	N.I.
B4	Location	Well defined	+	+/-	+	N.I.	+/-
C1	Nature of payments	Adapted to product	+ (Av+Ut)	+ (Av+Ut)	+ (Ut)	+ (Ut)	+ (Ut)
C2	Baseline definition	Adapted to technology	+/-	+	+	+	+
C3	Stacking of services	Possible	+	+	N.A.	N.A.	N.A.
C4	Penalties	Low/Proportionate	+	+/-	+	+	+

^a A clearly-defined availability window is only required for long-term tenders.

+/- indicate positive/negative assessment of implementation.

N.A.: Not Applicable, N.I.: No information available.

Ut: Utilization payment. Av: Availability payment

The main barriers appear on lack of properly defined **connection and metering requirements** for DERs, **high minimum bid requirements** (above 500kW for participants) for most implementations, and poorly defined **baseline definitions**.

Projects that have used V2G technology have found connection requirements too restrictive and time consuming, both in the UK and in France [18][131]. Also, UKPN requires minute-by-minute measurement at each point of connection which do not align with standard smart meter technical capabilities (usually with 15-30 minute time-resolution), thus making an extra barrier for demand-side flexibility. Easing connection process and aligning measurement requirements with standard smart meter capabilities should be considered to allow effective participation of all types of flexibility.

Most implementations set a minimum bid size of 500 kW. This would require the aggregation of a high number of diffuse resources which may prove extremely hard to accomplish in restricted tender areas. Moreover, in the case of Enedis' tender, they have a *full bid* constraint where only one flexibility operator has to satisfy the whole flexibility needs. This imposes a *de facto* greater minimum bid threshold related to the grid flexibility requirement. The opposite case is found in the UKPN tenders, with minimum bid sizes of 50 kW for their MV areas and only 10 kW for their LV areas.

Poorly defined baselines may not reflect real flexibility activation, as they can under-reward or over-reward flexibility. UKPN baseline is defined as the historic average power during the required flexibility window on selected reference days. This baseline presents the benefit of simplicity and certainty of the base levels but it is not adapted to diffuse demand response or long availability windows. Demand profiles from controllable loads, such as water heaters, heat pumps or EVs, can vary widely between hours and days due to weather conditions or usage patterns, and they can get mixed with other uncontrollable loads present in the same buildings. Setting well-adapted baselines is a challenging task, but it has already been addressed for flexibility services for transmission systems, such as explicit demand response [218].

The analyzed projects differ on several aspects of their implementation. On platform interoperability and access, Piclo Flex (the platform used by UKPN), Enedis and GOPACS have the support of most DSOs in their countries, and Enera can employ the Epex Spot platform widely used in Europe, but NODES is a new entrant with only pilot implementations. Trading platforms like Epex Spot (Enera) and ETPA (GOPACS) have utilization fees that could potentially be barriers to new entrants.

Major differences arise from the grid issues they tackle. UKPN's tender deals mostly with load-related grid reinforcements, allowing for well-defined availability windows during expected peak-demand periods, whereas the Enedis tender tackles different investment deferral problems, and thus has a diverse array of availability windows and flexibility requirements. On the other hand, short-term market platforms do not need availability windows, and their technical characteristics (minimum bid size, duration of service, baselines, utilization payments only) are aligned with energy market platforms, which can ease the participation for aggregators already active in these platforms. For example, GOPACS trades 15-minute blocks of energy through the ETPA platform, and baselines are dependent on the aggregators' t-prognosis⁶.

The conditions governing penalties also differ in terms of level and application. UKPN's implementation has a light penalty scheme, with only a reduction of payment for under-

⁶t-prognosis are the self-declared expected profile of the aggregator

delivered flexibility as a way to facilitate the entry for new market participants. UKPN can exclude a participant if they fail to deliver flexibility more than three times [213]. Enedis has aligned its penalties to the TSO balancing mechanism and retain the possibility of banning market participants after repeated default events [219]. Short-term platforms do not yet feature penalties but expect to introduce them in the future [210].

The UKPN tender process is the most mature flexibility market solution, with sustained growth since its beginnings and a highly transparent tender process⁷. It has shown that flexibility for investment deferral can have great value, with strong participation by EV aggregators as flexibility providers.

For the rest of this work, we aim to quantify the potential participation of EV fleets in long-term flexibility tenders. The goal is to identify key parameters that can impact remuneration. The parameters to be analyzed are:

- minimum bid size,
- availability window definition,
- duration of service (as flexibility requirements can run up to 3 hours in the case of a sustained congestion event),
- and the conditions surrounding penalties.

We also identify key EV fleet parameters that affect the provision of flexibility.

3 Methodology and case study

This section presents the model developed to quantify the economics of EV fleet participation in distribution flexibility tenders and the associated case study. We consider both V1G and V2G flexibility.

3.1 Method and modelling

We developed a methodology that mimics the flexibility tender process. In a first stage, we evaluate the potential participation of EV fleets in medium- to long-term flexibility tenders, and in the second stage we evaluate how these fleets perform in terms of effectively delivering the committed flexibility to grid operators, and compute the associated payments and penalties. Each stage has two sub-modules, as summarized in Figure 5.2.

⁷Before the tender, UKPN signals the expected revenue range per tendered zone, informing market participants of the expected value of flexibility at each zone, and after the tender they publish the bids filed under the tender process. Pre- and post-tender reports are available at <https://smartgrid.ukpowernetworks.co.uk/flexibilityhub/>

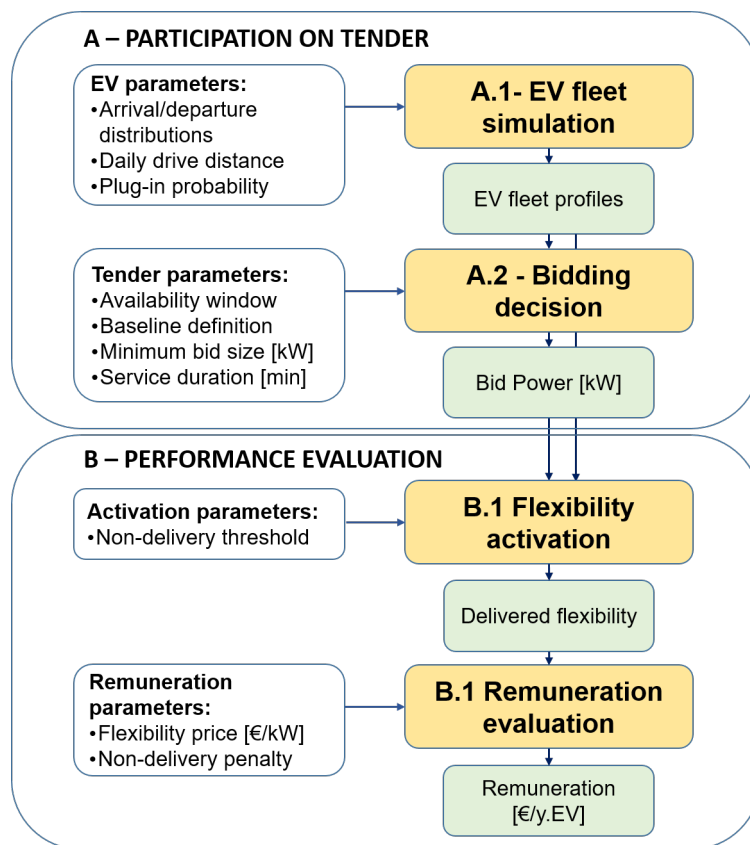


Figure 5.2: Two-stage methodology to quantify EV participation in flexibility tenders.

Stage A: Participation in tender

This stage mimics the bidding decision process to participate in the tender. EV aggregators participating in flexibility tenders commit to delivery flexibility months (or even years) in advance. Flexibility availability depends on EV-user patterns, which can be highly uncertain, as V2G-based flexibility can be only assured when the vehicle is plugged-in. EV aggregators will need to forecast EV usage patterns (sub-module A.1) and then decide on the amount of flexibility they will bid on the tender (sub-module A.2).

A.1 Monte Carlo simulations of EV fleet patterns Here we compute EV charging and flexibility profiles for multiple EV fleets using the agent-based simulation model described in Chapter 3. The simulations consider stochastic arrival and departure times, daily distances driven and non-systematic plug-in behavior. The model is adapted for this case study as it simulates the charging process at one specific location, such as at-home, which is required for local flexibility provision as the location of flexibility is of utmost importance.

The EV simulations provide the availability profiles for each EV (periods during which they are connected), the charging profiles, and the V2G flexibility profiles. V2G flexibility profiles correspond to the maximum flexibility activation that the EV can sustain for a required service duration (for example, injecting power for 30 minutes), at each moment of time, considering technical constraints (minimum SoC and driving requirements) and

a charging trajectory. The equation for the V2G profile for one EV is defined in Eq. 5.1, where $V2Gpr_t$ is the V2G profile (in kW) at time t , for service duration sd (in hours), SOC_t is the state-of-charge in (in pu) (i.e., the charging trajectory), LB_{t+sd} is the lower bound of the accessible storage at time $t + sd$ [kWh] (see Figure 5.3), b the battery size, ν_d the discharging efficiency, and Pch is the charger power (in kW).

Flexibility profiles can be computed for different services durations. An example of the V2G flexibility profiles for 30, 60 and 120 minutes service duration is shown in Figure 5.3.

$$V2Gpr_{t,sd} = \min\left(\frac{(SOC_t - LB_{t+sd}) \cdot b \cdot \nu_d}{sd}, Pch\right) \quad (5.1)$$

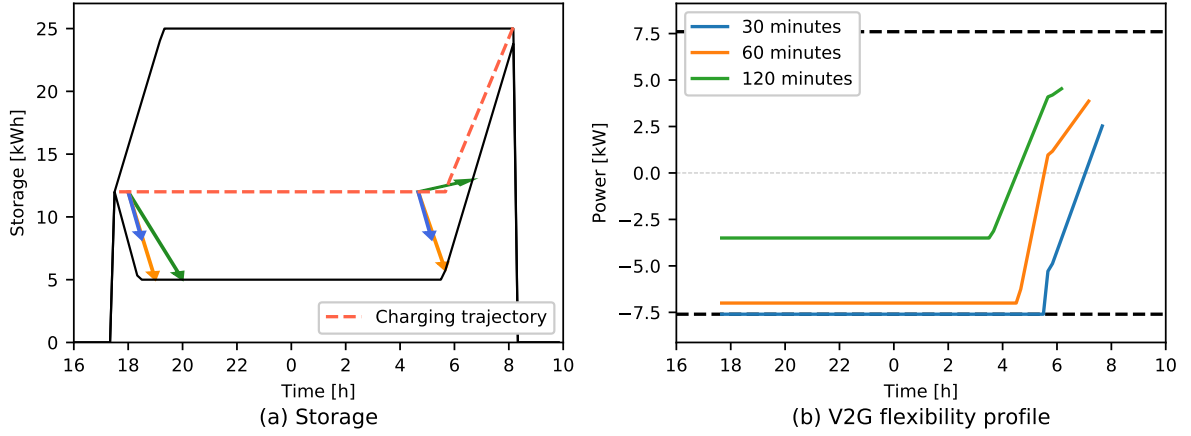


Figure 5.3: Example of 30, 60 and 120 minutes V2G flexibility profiles for one EV. (a) Example of flexibility potential for two instants within the accessible storage capacity, and (b) flexibility profiles.

A.2 Bidding decision Given the expected EV charging, flexibility profiles, and tender rules, we compute the EV fleet bid power (in kW). To achieve this, first we compute the baseline upon which flexibility will be measured from the simulated EV charging profiles. Two baselines are possible: a **unique-value baseline** considered in the UKPN tender, and an **30-minute average profile baseline**, considered in Enedis' tender. The unique-value baseline provides a constant reference value for the whole availability window during which the flexibility might be required, whereas the average profile provides a dynamic profile with a 30 minute time-step. An example of the baselines is shown in Figure 5.4.

The flexibility bid is then computed as the flexibility that can be provided to the system with respect to the baseline, with a given confidence level. Since at each day of simulation the arrival, departure, energy requirements and the number of connected EVs are different, the flexibility profiles provide a range for the amount of flexibility that can be provided to the system. To ensure a high reliability of the delivery of flexibility, we computed the flexibility bid at the 90% confidence level.

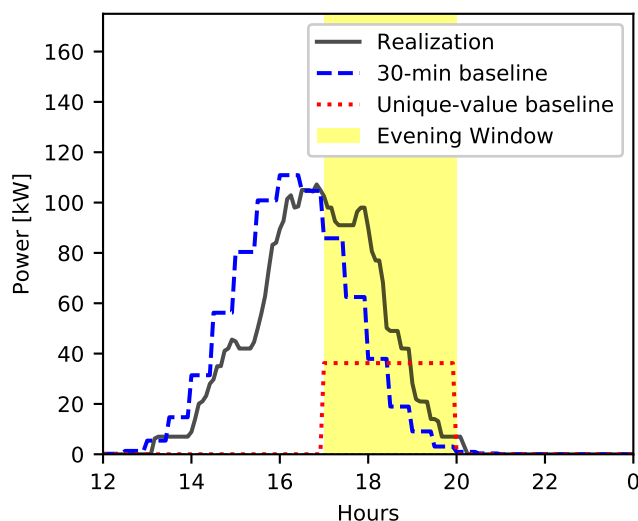


Figure 5.4: Unique-value and 30-minute average baselines for a 20 EV fleet, for an availability window between 5pm and 8pm. A realization of the charging profiles is included.

Stage B: Performance evaluation

Tender participants will be evaluated on their ability to deliver the committed flexibility when required. In case of under-delivery, they can face high penalties and even be banned from the market. We simulate flexibility activation events (sub-module B.1) and then compute payments and penalties (sub-module B.2). Penalties depend on two parameters: the penalty threshold, where delivery of flexibility under this threshold triggers penalties, and the penalty value, in percentage of expected payment.

B.1 Flexibility activation We simulate activation events (n_{act} the number of activations per year) by randomly sampling flexibility events during the availability windows and evaluating flexibility delivery with respect to the penalty threshold. An example of a successful and a failed flexibility activation is shown in Figure 5.5.

B.2 Remuneration evaluation We compute payments and penalties as follows. For one flexibility activation a and flexibility value Γ (in €/kW), if the fleet f is unable to deliver the full amount of the committed flexibility (CF_f) but is still considered a successful flexibility activation (flexibility delivery is above the penalty threshold, i.e., $DF_{f,a} \leq \lambda$, Figure 5.5, (a)), then payments are reduced accordingly. If the delivered flexibility is below the penalty threshold (Figure 5.5, (b)), then no payments are done and penalties (Θ) are applied, as shown in Eq. 5.2. This follows the UKPN de-rating performance factor and the Enedis penalty implementation scheme. Total payments for a fleet will be the sum of each activation payment (Eq. 5.3).

$$ActPayment_{f,a} = \begin{cases} \frac{DF_{f,a} \cdot \Gamma}{n_{act}}, & \text{if } DF_{f,a} \geq \lambda \cdot CF_f \\ -\Theta \cdot CF_f, & \text{if } DF_{f,a} < \lambda \cdot CF_f \end{cases} \quad (5.2)$$

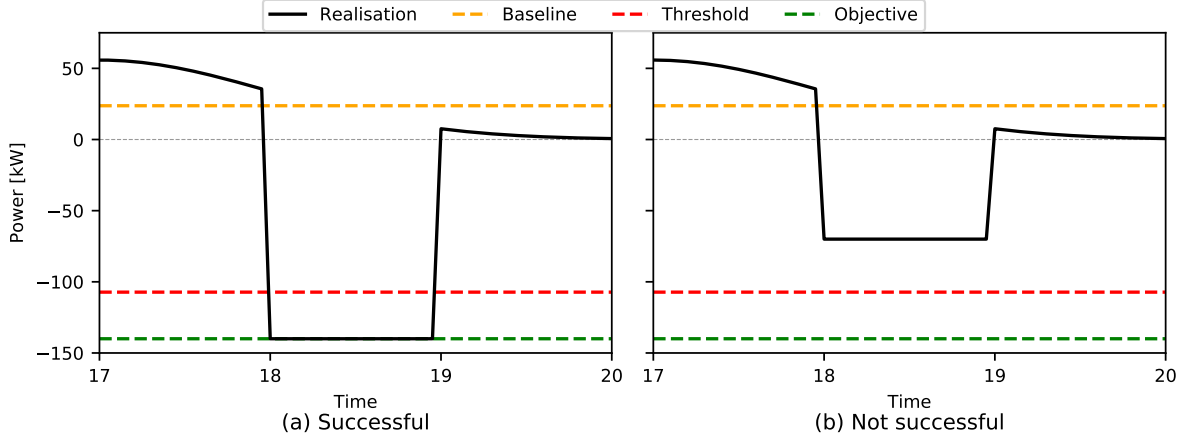


Figure 5.5: Example of (a) successful and (b) failed flexibility activations. Activation for 1 hour between 7pm-8pm, unique-value baseline and penalty threshold of 80% of committed flexibility.

$$TotPayment_f = \sum_{a=1}^{n_{act}} ActPayment_{f,a} \quad (5.3)$$

3.2 Case studies

We evaluate tender participation for **three types of fleets doing uncontrolled overnight charging**: one **company fleet** with consistent travel schedules, and two **commuter fleets** with variable travel patterns and non-systematic plug-in behavior (i.e., not plugging in every day). The three fleets can provide unidirectional (**V1G**) and bidirectional (**V2G**) flexibility with a **7 kW charger** that has 95% charging and discharging efficiency. The EVs have a **50 kWh battery** pack in line with current battery size trends.

The EVs are modeled with stochastic parameters on daily travelled distances and arrival and departure times. Statistical distributions for the company fleet are based on data from the Parker project, shown in Table 5.3, and the EVs are always plugged in after the last trip of the day [220]. The commuter fleets are modeled based on data from the Electric Nation project with arrival and departures following a bivariate distribution (see Fig 3.8). Daily travelled distances follow a log-normal distribution with a mean daily distance of 40.3 km. One commuter fleet has low plug-in probability (Commuter LP), in line with findings from the Electric Nation trial from of Ch. 3 (average plug-in frequency of 2.75 charging sessions per week, $\alpha=1.31$), while the second commuter fleet (Commuter HP) has a higher plug-in ratio averaging 5.32 charging sessions per week ($\alpha = 2.6$), representing the case where the aggregator provides incentives to end-users to plug in. We carry out simulations for 50 weeks and 1000 fleets to capture the variability in end-user behavior.

Regarding tender parameters, we considered **two availability windows**: an **evening window** from 5pm to 8pm, consistent with a majority of zones tendered by UKPN, and a **full-day window**, consistent with one of the Enedis cases. Flexibility should be available

Table 5.3: Stochastic parameters of studied fleets. Data from [220] for company fleets, and [40] for Commuter fleets

Parameter	Type	μ	σ	Shift
Company Fleet				
Arrival time [h]	Normal	13.2	1.82	-
Departure time [h]	Log-normal	1.04	0.53	5.5
Daily distance [km]	Log-normal	2.36	0.79	-
Commuter Fleets				
Daily distance [km]	Log-normal	3.43	0.73	-

for three months, and only during weekdays (a total of 60 days per year). A **30-minute ‘downwards flexibility’** (reducing demand or increasing generation) is required during the availability windows, though **not necessarily activated every day**.

We then consider the **single-value baseline** used in UKPN tenders, computed as the average power (consumed or generated) during the availability window on representative historical days, thus providing a single value for the whole availability window. While this baseline does not correctly capture load profiles, under- or over-rewarding flexibility, it does provide a good trade-off between simplicity and accuracy, especially for short availability windows. To evaluate the performance of flexibility delivery (sub-module B.1), we simulated **10 activations** during the availability period, and considered at most one activation per day.

As shown in Figure 5.1 (Section 2), remuneration can vary greatly according to tender competition and requirements. We considered an equivalent service payment of €50 per firm kW, similar to the fixed price proposed in UKPN 2020 LV tenders and close to the average of bids accepted in the UKPN 2020 HV tender. This represents an availability price of 277 €/MW/h for the evening window (3 hours per day for 60 days = 180 h/y) and 35 €/MW/h for the full-day window (24 hours per day for 60 days = 1440 h/y).

Finally, we considered **three penalty scenarios**: a low case corresponding to penalty parameters implemented by UKPN, a medium case corresponding to Enedis⁸, and a high penalty scenario. Table 5.4 shows the thresholds for successful flexibility activation and the penalty values in percentage of the remuneration price. A penalty of 0% (UKPN case) means that in the event of failed activation, providers get no penalties but no payment either.

Table 5.4: Penalties parameters

Scenario	Tender	Threshold (λ)	Penalty (Θ)
Low	UKPN	60%	0%
Medium	Enedis	80%	35%
High	-	90%	70%

⁸Enedis aligned its penalties to RTE’s (French TSO) balancing mechanism (mécanisme d’ajustement, [221])

4 Results

4.1 Availability profiles and baseline

The three fleets under study present different charging profiles and flexibility potentials, as shown in Figure 5.6. Charging sessions for company fleets start earlier, with peak charging around 3pm, and by 5pm all EVs are usually plugged in, thus offering maximum V2G flexibility potential during the evening availability window. Charging patterns are more variable for commuter fleets, partially coinciding with the evening peak window. Arrivals are more spread out during the afternoon, with peak simultaneous connections occurring after 11pm. Since EVs are not connected every day, the ability of commuter fleets to provide flexibility is greatly reduced in comparison to the company fleet, which can be seen in the reduced V2G flexibility potential curve. Flexibility profiles for commuter fleets also present higher variability, as the number of EVs connected vary each day. This can present a challenge for aggregators that want to make use of EV flexibility.

EVs are not connected all day long, which means there are periods of the day where almost no flexibility is available from the fleets (typically between 8am and 4pm), which leaves aggregators participating in full-day window tenders exposed to high risk of flexibility being activated while the fleet is unable to respond.

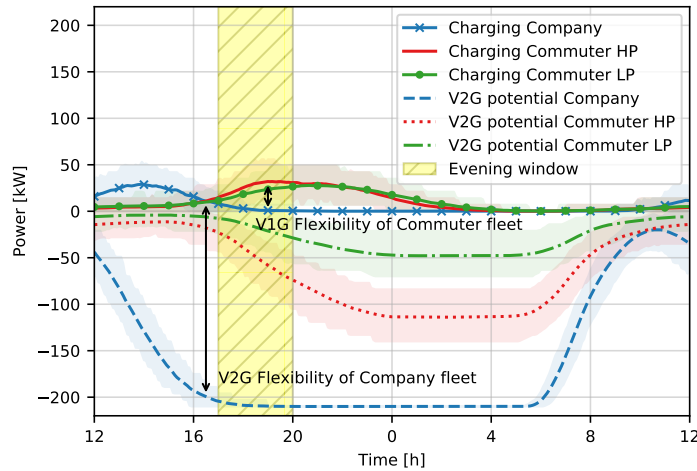


Figure 5.6: Charging profiles and V2G potential for a 30-minute service, and examples of VxG flexibility levels. Fleet size: 30 EVs. Lines represent average profiles and shaded areas represent profiles at 90% confidence level.

Single-value baselines are computed for each fleet and each availability window as the average charging profile. The model simulates a large number of fleets (1000), each with different travel and charging patterns and therefore different baselines. Table 5.5 gives the average baseline value (in kW/EV) for the studied cases. Due to the coincidence of charging with the evening window, baselines for the commuter fleets are higher than for the company fleet, even though they only reach around 1 kW/EV. Thus, the recognized flexibility attainable by V1G-only solutions is therefore limited (maximum delivery of flexibility will mean completely stopping EV charging).

A single-value flexibility window does not provide an accurate baseline for long availability windows. In the full-day window, a single-value baseline means that around 0.3 kW/EV of flexibility will be recognized at any time of the day, even though the fleet does not provide any real flexibility. This problem is less important for shorter availability windows (evening window).

Table 5.5: Average values for the unique-value baseline [kW/EV] for the evening and full-day availability windows. Fleet size: 30 EVs.

Fleet	Evening window	Full-day window
Company	0.31	0.26
Commuter HP	0.98	0.35
Commuter LP	0.76	0.34

4.2 Minimum bid size

In Table 5.6 we show the average bids for a 30-minute service for V1G and V2G cases, considering an aggregator’s 90% confidence on the availability of flexibility. The value of the V1G bid corresponds to the baseline value previously mentioned, as V1G-only flexibility requires to completely stop charging for a required amount of time, which can be done for the studied fleets without compromising user’s charging requirements. V2G can increase the flexibility bids, but only the Company fleet during the evening window can take full advantage of it, increasing flexibility by 7 kW/EV. Commuter HP fleets can provide only 1 kW/EV of additional flexibility using V2G during the evening windows, and Commuter LP only an additional 0.3 kW/EV. In full-day windows flexibility can not be provided reliably by any fleet, limiting the value of V2G.

Table 5.6: Average bids for 30-minute services [kW/EV], confidence level 0.9.

VxG	Fleet	Evening window	Full-day window
V1G	Company	0.31	0.26
	Commuter HP	0.98	0.35
	Commuter LP	0.76	0.34
V2G	Company	7.24	0.45
	Commuter HP	2.02	0.85
	Commuter LP	1.08	0.50

We computed the fleet size required to reach the minimum bid threshold (50 kW or 500 kW) to be able to participate in the tender ($Ne_{bs,f,aw}$), shown in Table 5.7. This was calculated as the bid size (bs in kW) divided by the average V1G/V2G bids (i.e., the committed flexibility $CF_{f,aw}$ for each type of fleet f and availability window aw), as shown in Eq. 5.4.

$$Ne_{bs,f,aw} = \left\lceil \frac{bs}{CF_{f,aw}} \right\rceil \quad (5.4)$$

Having V2G capability allows smaller fleets to participate in the tender, however the effect depends largely on the fleet usage patterns. The company fleet, which is reliable, has a good match to evening availability windows and can take full advantage of the V2G capabilities, requires a reduced number of EVs required to participate in the tender. On the other hand, the Commuter LP, whose variable patterns do not ensure flexibility availability, derives only marginal value from V2G capability and would require high numbers to participate in the tender.

Having small minimum bid size allows a great number of participants to enter the tender, as fleets of only 8 V2G-capable EVs (company fleet) can achieve the threshold of 50 kW. This can be of major importance as these tenders can have limited potential participants due to the local characteristic of the services. Having a 500 kW minimum bid size would probably require V2G-capable fleets, and only be possible in the evening window, as required fleet sizes rise above 500 EVs which can risk to be unfeasible in local conditions (LV grid or MV feeder).

Table 5.7: Minimum fleet size to participate in tender according to minimum bid threshold.

VxG	Fleet	Evening window		Full-day window	
		50 kW	500 kW	50 kW	500 kW
V1G	Company	162	1613	193	1924
	Commuter HP	52	511	143	1429
	Commuter LP	66	658	148	1471
V2G	Company	7	70	113	1121
	Commuter HP	25	248	59	587
	Commuter LP	47	463	100	995

4.3 Minimum service duration

We investigated the impact of minimum flexibility product service duration. UKPN tenders require a minimum service duration of 30 minutes (Enedis require 60 minutes) but also state that requirements can stretch up to 3 hours and that assets capable of providing flexibility for longer periods will be privileged. Fig 5.7 shows the flexibility bid for the three fleets for service run times of 30, 60 and 120 minutes. For the evening window, bids for the three service durations present little difference (under 0.1 kW/EV for the same type of fleet), meaning that EV fleets are capable of providing flexibility services for 120 minutes with the same reliability than for 30 minutes. This is because battery capacities are large enough to sustain a 120-minute service (14 kWh represent only 28% battery capacity) and the flexibility window lies at the beginning of the fleet charging sessions, thus leaving ample time to recharge the battery ahead of next-day departure. The additional cycling induced by this flexibility service can increase battery degradation, but [54] showed that providing 120-minute peak shaving services 20 times a year, similar to our case study, would reduce battery capacity by less than 0.5% over a 10-year period, which is negligible compared to the 31% induced by driving and calendar aging.

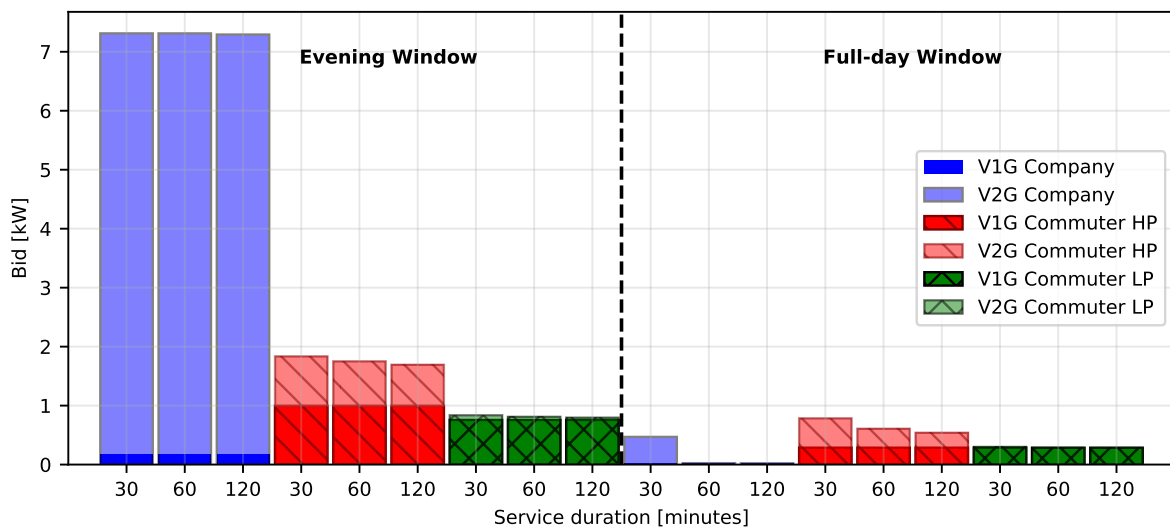


Figure 5.7: Bids [kW/EV] for 30-, 60- and 120-minute service durations. Fleet size: 30 EVs

4.4 Penalties and aggregators' bidding

As shown in Figure 5.6, there is high inter-day (given by variable EV connection patterns from one day to the other) and intra-day (given by varying shares of connected EVs during the day) variability in the flexibility that EV fleets can provide to the system. However, participants in long-term tenders bid a single amount of flexibility (in kW) for a long period in advance. Aggregators can thus decide to bid different levels of flexibility according to the risk they are willing to take. The question we tackle in this subsection is: **what is the optimal bidding level of an EV aggregator that has variable flexibility availability profiles, and how do penalties affect this behavior?**

Figure 5.8 shows the flexibility available for different levels of certainty by the aggregator (a 0.5 confidence level means the aggregator expects to be able to provide that amount of flexibility 50% of the time). If higher confidence is required from the tender process, the aggregator will bid less flexibility, reducing its risk exposure.

Considering V2G, the company fleet can provide high levels of flexibility with high confidence for the evening window, given the good match of the fleet availability to the grid requirements. This is not the case for the commuter fleets, which are less reliable and thus the available flexibility decreases significantly for higher certainty requirements (note that bid level at the 0.9 confidence level is less than 2 kW/EV). The same occurs for the full-day window, as none of the fleets can provide flexibility with high reliability all day long. Therefore, the bid flexibility decreases rapidly for high confidence levels. This means that the added value of V2G with respect to V1G is almost negligible if high reliability for the service is required.

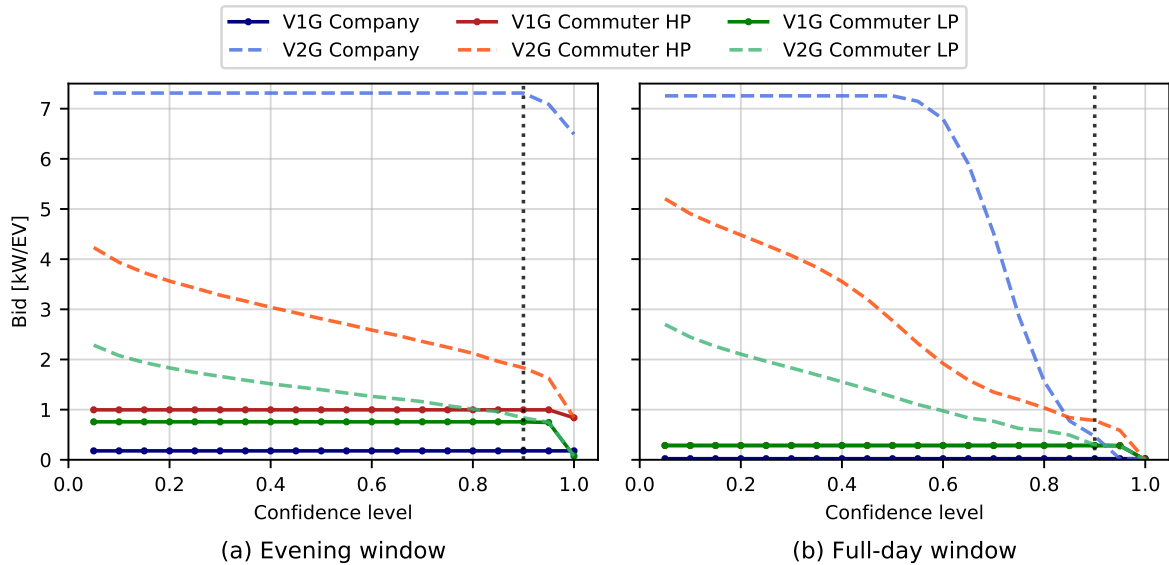


Figure 5.8: Flexibility bids according to aggregator's confidence level [kW/EV]. Fleet size: 30 EVs

To ensure the availability of bid flexibility, the tenders have penalty clauses if the fleet is unable to respond to a flexibility activation. To determine the optimal participation of an EV aggregator (i.e., the bid flexibility), we simulated 500 flexibility activations for varying flexibility reliability levels (from 0.05 to 1), and computed the remuneration

considering different penalty conditions. For each reliability level, we obtain a distribution of remuneration and we computed two indicators: **the expected revenue** and the **risk the aggregator is taking** by bidding at that reliability level. The risk is measured by the **conditional value at-risk (CVaR)** at $\alpha_{CVaR}=95\%$, which represents the expected value of the worst $(1 - \alpha_{CVaR})$ of cases. In this case, it amounts to the remuneration (or losses) of the 5% worst cases [222], as shown in Figure 5.9.

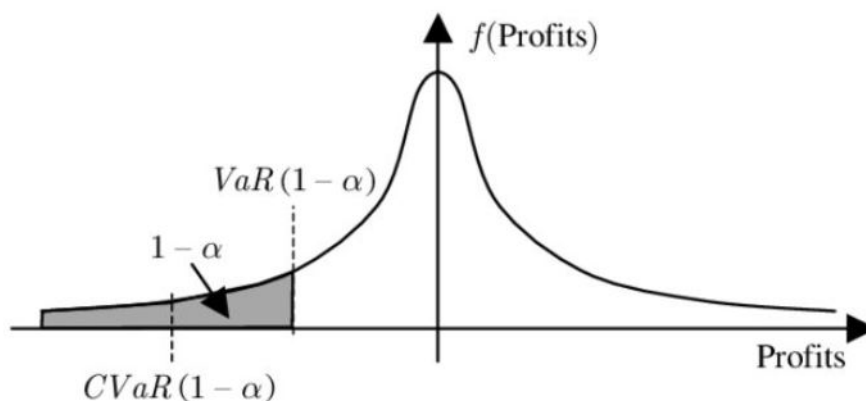


Figure 5.9: Example of risk measures Conditional value-at-risk (CVaR) and Value-at-risk (VaR) of a profit distribution. From [223]

Figure 5.10 shows the remuneration and the risk incurred by the aggregator of V2G-capable fleets⁹ for confidence levels ranging from 0.05 to 1, and for the three penalty conditions in study. We computed optimal participation of the EV aggregator as the reliability level that jointly maximizes the expected revenue and risk, which is indicated in Figure 5.10 for each penalty condition.

Results show that for cases where the aggregator has a high reliability on their flexibility resources, which is the case of the company fleet during the evening window (panel (a) in Figure 5.10), the aggregator can bid the full amount of flexibility and penalties do not impact on the aggregator’s optimal participation. On the other hand, when the reliability of the flexibility resources is variable, penalties have a significant effect on the optimal behavior of the EV aggregator (panels (b) to (f) in Figure 5.10).

The low penalty scenario (blue dots) presents little to no risks for aggregators, as under-delivery of flexibility does not entail any penalties. This makes the optimal confidence level a low value (between 0.3 and 0.4). Increasing penalties reduces average revenue and increases risks of low confidence bids. A risk-averse flexibility operator would logically reduce its bids, bidding only what can be delivered with sufficiently high reliability. Under the medium penalty scenario, the bids correspond already to a 0.7-0.8 confidence level. Under the high penalty scenario, flexibility operators would only bid flexibility with extremely high reliability (0.9-0.95 confidence), which may preclude access to a significant amount of flexibility resources. Note that under this penalty scenario, even if the flexibility operator is able to cover 89% of flexibility request, the activation is still not considered valid, and so penalties would apply.

⁹V1G flexibility (i.e., reducing EV charging) presents almost no risk for the cases studied.

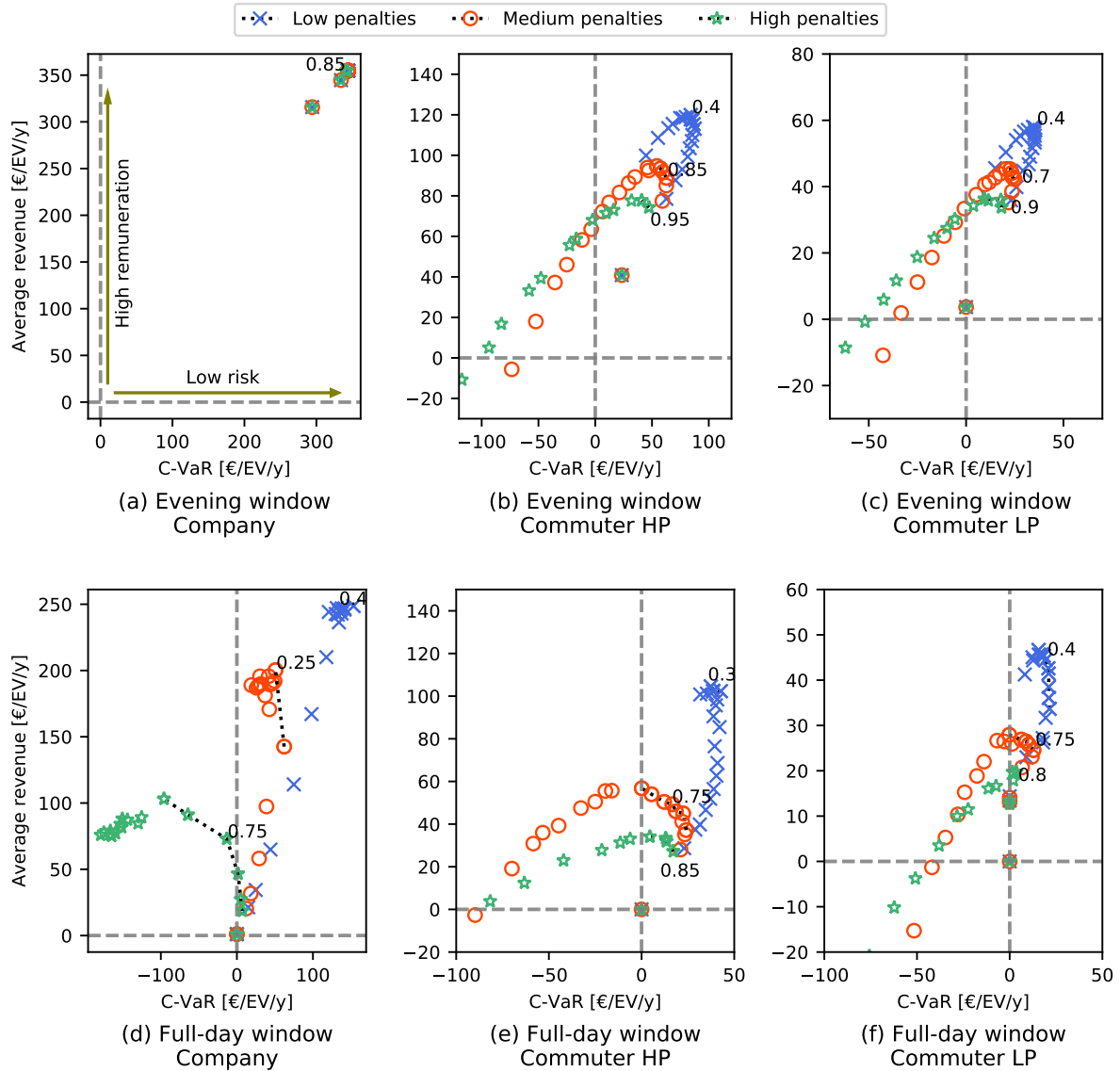


Figure 5.10: Remuneration vs. Conditional Value-at-Risk for V2G-capable fleets. The optimal confidence level is shown for each penalty scenario. Evening window (top) and full-day window (bottom). Flexibility price: 50 €/kW. Note: each plot has different x and y scales.

Table 5.8 show the optimal bid (in kW/EV) and the rate of unsuccessful activations (when the delivered flexibility DF_a is under the penalty threshold λ) for the combinations of penalty scenarios, availability windows and fleets. The low penalty scenario allows for higher bids from EV fleets, but their delivery cannot be ensured. For example, the Company fleet can increase its bid for the full-day window to over 7 kW/EV, allowing to bid the full power of the V2G charger. However, the fleet is not available during a significant part of the day and thus have rate of unsuccessful activations of near 30%. This could potentially ban them from the market and can entail risks for the DSO. Increasing penalties limits the flexibility bid by the aggregators and reduces the rate of unsuccessful activations. Still, for some cases this ratio may remain high (23% for the company fleet during full-day window).

Table 5.8: Optimal bids [kW/EV] and rate of unsuccessful activations (UA) [%] for V2G-capable fleets.

Fleet	Penalty Scenario	Evening		Full-day	
		Bid	UA	Bid	UA
Company	Low	7.3	0.0%	7.3	29.0%
	Medium	7.3	0.0%	7.3	32.3%
	High	7.3	0.0%	2.9	23.8%
Commuter HP	Low	3.0	9.6%	4.1	45.5%
	Medium	2.0	4.4%	1.2	17.7%
	High	1.6	2.9%	0.8	9.8%
Commuter LP	Low	1.5	12.9%	1.6	38.1%
	Medium	1.2	13.4%	0.6	15.2%
	High	0.8	5.4%	0.6	15.6%

DSOs will need to balance the need for flexibility reliability with facilitating development of flexibility resources at local level. If penalties are too high, aggregators might not participate in these markets, which would be a serious issue when these markets are only starting. UKPN strategy follows this logic, reducing penalties as a means to reduce barriers to entry and help build liquid markets. Conversely, if penalties are too low, it can put the provision of the flexibility service at risk. We do think that the right level needs to be addressed case-by-case, taking into account local issues, practices and learning by doing for both sides of the relation.

There are nevertheless alternative solutions to reduce risk exposure for market participants, such as allowing partial participation on the tender (only during certain hours) or defining shorter availability windows that can allow aggregators to better match the availability profiles of their assets to grid requirements. Aggregators can as well, pool different types of resources that can have complementary flexibility profiles to provide flexibility with higher reliability.

4.5 Remuneration

Improving EV participation in flexibility tenders hinges on three factors critical: V2G capability, fleet reliability, and a good availability profiles-to-grid requirements match-up. The V2G-capable company fleet obtains over 350 €/EV with no risk under the evening

window that perfectly matches its flexibility profile (see plot (a) in Figure 5.10). However, unreliable commuter fleets (Commuter LP) obtain much lower remuneration, under 50 €/EV, with most of it coming from V1G. Improving plug-in ratio increases flexibility bids on tenders, thus increasing remuneration from V2G. However, the variability inherent to travel patterns means that the flexibility profile does not match the grid requirements as well as the company fleet (peak availability is reached after 11pm; see Figure 5.6).

Alternative V1G incentives

The revenue that EVs can expect from V1G only remains limited and comes from charging during (and then shifting the charge from) peak demand hours. Given that time-of-use (ToU, peak/off-peak) tariffs are widely applied in the UK and France, the assumption of uncontrolled charging may not hold, as users already have incentives to charge during off-peak periods. Considering a 4.5 c€/kWh price difference between on-peak and off-peak hours¹⁰ and an EV driving 41 km/day only during weekdays¹¹, charging at off-peak hours would save the end-user 91 €/y¹². These savings could be higher, as electricity tariffs aimed specifically at EV users with higher price differentials (such as super-off-peak tariffs) are commercially available¹³. Electricity tariffs thus provide higher incentives for end-users to charge at off-peak hours on a day-to-day basis than flexibility tenders. Therefore, baselines should be adapted to consider off-peak charging if it is indeed the user's behavior.

Sensitivity to flexibility price

The value of flexibility can vary greatly according to tender conditions, as discussed in Section 2. In the UKPN MV tenders, flexibility is valued against the annualized costs of alternative infrastructure reinforcements. The variable price for flexibility (in £ or €/MW/h) can be derived from costs of the grid reinforcements (in €), the expected magnitude of the constraints (in MW) and duration of the availability service (in hours). In the UKPN case, flexibility value ranges from 3.25 to over 4500 £/MW/h (see Figure 5.1). The value of flexibility decreases with increasing grid constraints (in time and power magnitude) as it becomes more cost-efficient to invest in reinforcement. This means that distribution grid services become less attractive compared to other flexibility services such as frequency regulation (i.e., the opportunity cost for a flexibility operator participating in local tenders grows with respect to alternative services).

Given the large flexibility value spread, we carried out a sensitivity analysis of total remuneration per EV for the studied tenders (Table 5.9). Three values of the flexibility price were considered: 12.5, 50 and 200 €/kW of firm flexibility, which are representative of UKPN's low, average and high value areas respectively. It should be noted as well that Enedis-led studies put the value of flexibility for investment deferral in a range between 0–24 €/kW [102], which lies on the lower end of UKPN's tender processes.

¹⁰Tarif bleu, a regulated tariff in France provided by EDF, 2020 [224]

¹¹Average daily distance in France [40]. Similar values are found in other European countries.

¹²Considering EV efficiency: 0.18 kWh/km, EVSE efficiency: 0.95

¹³In the UK, Octopus Energy offers a super-off-peak tariff with 9.7 p/kWh price difference [225]. In France, Engie offers an EV tariff with 7.4 c€/kWh price difference [226].

Remuneration will largely depend on the value of flexibility in each location. In favorable conditions, where grid requirements match fleet availability patterns (company fleet participating in evening window), total remuneration can go from 89 €/EV to over 1400 €/EV/y. This upper bound is in the same order of magnitude than year-round PFC services revenues. [169] showed average revenues of 1322 €/EV/y for providing frequency regulation services 13 hours per day, every day, in Denmark’s DK2 area¹⁴, and [155] showed best-case revenues of 1000 €/EV/y in the FCR cooperation area¹⁵. PFC revenues can be complementary to distribution investment deferral services, as these local services are needed only a few hours a year.

However, remuneration can be significantly reduced for unreliable fleets. Commuter fleets with low plug-in rate (Commuter LP) obtain only 40 €/y in the average case, reaching 158 €/y in a high-value flexibility zone, almost ten times less than the company fleets. If the users have incentives to plug-in, remuneration can more than double (Commuter HP), but still they reach only a fourth of the company fleet revenues.

Table 5.9: Average remuneration per EV [€/y]. Sensitivity analysis on price per firm kW. Low penalty scenario, 0.9 confidence level*

Price [€/kW]	Company		Commuter HP		Commuter LP		
	Evening	Full-day	Evening	Full-day	Evening	Full-day	
12.5	2.2	3.2	12.0	4.3	9.5	4.0	
V1G	50	8.7	12.7	48.2	17.3	38.1	16.0
200	40.8	50.8	192.8	69.2	152.4	64.0	
12.5	88.9	5.3	21.6	9.2	9.9	4.0	
V2G	50	355.8	21.4	86.5	36.9	39.5	16.0
200	1423.2	85.4	346.4	147.5	158.1	56.8	

* Highlighted cells provide the highest remuneration for each type of fleet.

* We considered a 0.9 confidence level to ensure flexibility delivery. As seen in Figure 5.10 and Table 5.8, bids and average remuneration can be increased but at higher risks for DSOs.

Impact of fleet sizes

Fleet size can have affect the amount of flexibility that can be delivered with a given confidence level. Figure 5.11 shows the remuneration obtained for different fleet sizes. As fleet grow in size, the aggregated charging and travel patterns become more reliable, allowing aggregators to bid higher amounts of flexibility on tenders (in kW/EV) and reducing revenue variability. For the evening window, where EV patterns are more reliable, revenues show little change above 30 EVs for the company fleet and 50 EVs for commuter fleets. For the full-day window, the revenues remain relatively stable when pooling above 100 EVs per fleet. Note that attainable revenues are lower for full-day windows than for the evening window, as EVs cannot reliably provide flexibility during the whole day.

¹⁴PFC prices in DK2 area range between 12-60 €/MW/h, much higher than in the UK or Continental Europe.

¹⁵Considering current 4-h FCR products and service provision by EVs every day, both at home (with 7kW charger) and workplace (with 22 kW charger).

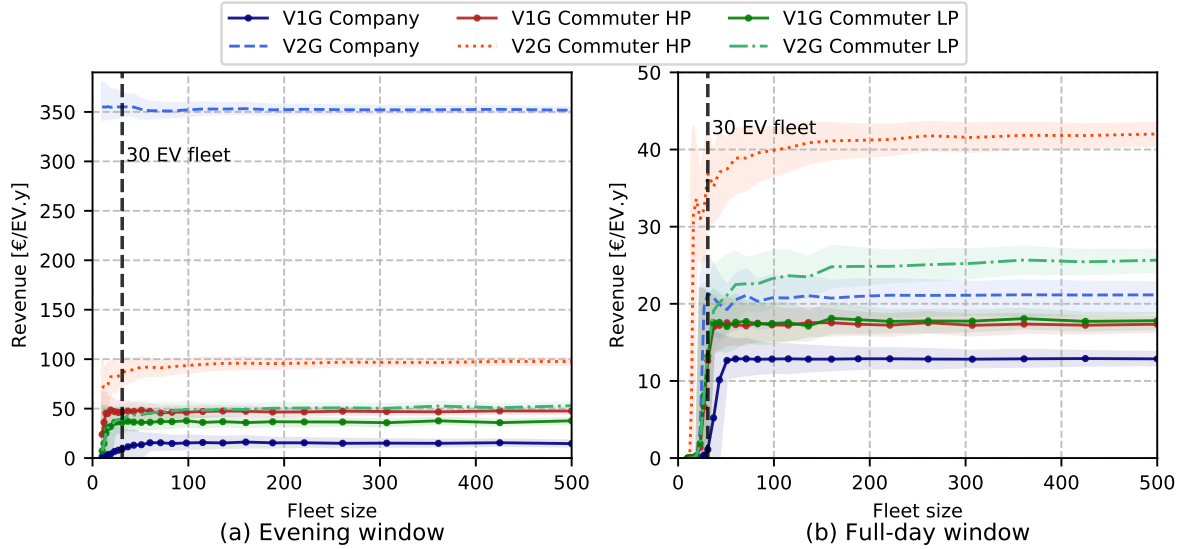


Figure 5.11: Remuneration per EV for different fleet sizes. (a) evening window, and (b) full-day window. Note different scales on remuneration. Flexibility price: 50 €/kW; Low penalty scenario; 0.9 confidence level.

5 Partial conclusions

DSOs are starting to implement market-based mechanisms to use the flexibility offered by DERs. Recent implementations in Europe reflect a wide array of solutions tested, most of which respond to the technical problems encountered in local distribution grids. In zones presenting mainly RES generation-driven congestion, short-term market platforms have been implemented to reduce uneconomic curtailment, whereas in zones expecting load growth, medium- to long-term tenders have been implemented to defer or avoid costly infrastructure reinforcements.

In this chapter we proposed a modular framework to analyze market rules of local flexibility markets (two long-term tenders and three short-term markets) and identify the main barriers to participation of DERs aggregators. We then applied this framework to five emerging flexibility implementations in Europe. The main barriers are on high minimum bid requirements, on connection requirements, and on metering equipment, as most of these solutions are still aimed at medium-size and large customers.

We then presented a model to quantify the participation of EVs in local flexibility tenders. The two-stage model mimics the (ex-ante) tender bidding and activation–settlement processes. We then applied the model to three types of EV fleets based on real-world data from European demonstrator projects. Our case study considered EVs, but our methodology can be applied to other types of DER, such as residential demand response.

Results show that V2G-capable EV fleets with a good match of availability profile to tender requirements can obtain revenues of 350 €/EV/year in average areas, considering flexibility values from UKPN 2020 tender. However, revenues can vary widely depending on the tendered area, going from less than 50 €/EV/year to over 1400 €/EV/year in high-value areas. Unreliable fleets will have reduced revenues, coming mostly from V1G.

Chapter 6

Final conclusions

In this thesis we studied the active integration of electric vehicles (EVs) into distribution grids from **technical, economic, regulatory, and user-behavior** perspectives. This integration takes place against a broader transition towards low-carbon energy system, which includes cross-sector electrification and the massive integration of distributed renewable energy resources. The integration of EVs into distribution grids can pose challenges, as the additional demand can create constraints in the distribution grid, but also create opportunities, as they can provide **flexibility** to the electricity system by means of **smart charging** and **vehicle-to-grid** (V2G) technology. By providing flexibility, EVs can reduce the impact of their integration and create value for different stakeholders in the electricity system. This thesis studied two main aspects related to EV integration:

What flexibility services can be provided to distribution system operators (DSOs) and under which mechanisms?

How does user charging and driving behavior affect EV grid integration?

The remainder of this chapter will present the key takeaways from this thesis, followed by a summary of the works we carried out, and finally recommendations for key stakeholders and for future research.

Key takeaways

- EV fleets can provide three types of flexibility services to the distribution grid: congestion management, voltage regulation and back-up power for fault-restoration. If procured for the long-term, congestion management and voltage regulation services can also be used for investment deferral.
- DSOs have different mechanisms to implement flexibility solutions, including network tariffs, variable capacity connections, short-term local flexibility markets and long-term flexibility tenders. We expect several mechanisms to coexist in the future.
- Long-term tenders, which allow DSOs to procure flexibility for investment deferral and fault-restoration purposes, have had a successful implementation in the UK and are being developed in France. They can ensure DSOs the availability of flexibility

when needed, as well as revenue certainty to EV aggregators, and can be a first step in developing short-term flexibility markets.

- The value of flexibility for distribution services can be significant, but highly dependent on grid conditions (from less than €2 to over €200 per firm kW per year from UK's tenders results). This value can be limited in time, localized in specific areas of the grid, and gets reduced if constraints grow as flexibility will be competing with the costs of alternative grid reinforcements.
- Regular users do not plug-in every day, but between 2-4 times per week. Under these conditions, the flexibility that EV fleets can provide to the system is reduced by at least 50% in flexible time, available power and accessible storage capacity with respect to the case where EVs are plugged-in every day. Large-battery EVs aggravate these issues as they have lower plug-in frequency.
- V2G can increase the flexibility to be provided by EV fleets with respect to smart charging, but only reliable fleets with consistent travel patterns and with high plug-in frequency can fully take advantage of it. EV aggregators should focus on EV fleets with consistent plug-in patterns, such as company fleets, and/or provide incentives to plug-in in a regular basis.
- Local mobility patterns matter when assessing EV grid integration. EV charging dynamics will be different in urban, rural and peri-urban conditions, with higher impacts of EV charging in peri-urban areas of large cities due to higher reliance on car mobility and longer driven distances.

Summary

In **Chapter 2** we carried out a literature review of technical, economic, regulatory and user-related aspects related to the active integration of EVs into distribution grids. We identified the flexibility services that EVs can provide at the distribution level, the associated value frameworks and the remaining barriers for their implementation. We also identify research gaps that will provide the basis of our work.

EVs can provide flexibility services to various stakeholders in the electricity system. For end-users, smart charging and V2G can help optimize their electricity bills and improve self-consumption in a behind-the-meter fashion. EVs can also participate in system-wide services such as frequency regulation and energy arbitrage according to wholesale electricity markets. At the distribution level EVs can provide three main types of services: **congestion management**, **voltage regulation**, and **back-up power for fault-restoration**. If procured for the long-term, congestion management and voltage regulation services can also be used for **investment deferral**, reducing the need for additional grid infrastructure.

We identified four major frameworks for the procurement of flexibility by DSOs: grid codes, network tariffs, flexible connections and market mechanisms. Not all frameworks can be applied to all flexibility services, and each framework presents its strengths and weaknesses.

Grid codes do not remunerate the flexibility provided, thus they should be considered only to requirements to maintain grid security and stability when no other can be framework can be implemented. Its major use-case is reactive power compensation for V2G-capable EVs, as it is already a requirement for power injecting resources (e.g., PV panels) in some countries.

Network tariffs can provide economic signals to incite EV users to shift charging to low demand periods, such as of Time-of-Use (ToU) tariffs. These tariffs are implemented in numerous countries. Studies have shown that people react to these signals, shifting charging to off-peak hours. However they can create higher load peaks at off-peak periods due to a synchronization of EV charging under high EV penetration scenarios. Therefore, network tariffs can be useful for congestion management while EV penetration remains low, but not enough to solve grid issues completely under high EV penetration cases. Also, they are not adequate voltage regulation or fault restoration flexibility services. Network tariffs with higher temporal and/or spatial granularity, or with differentiated off-peak periods per customer to avoid synchronization of EV charging should be developed.

Flexible connections present a move from *firm* capacity connections, where customers can withdraw/inject power from/to the grid up to a fixed level at all times, to *flexible* capacity connections, where the power that can be withdrawn/injected can vary according to system conditions. Flexible connections can be an opportunity to improve system operation by reducing the stress on the grid during peak periods and freeing up capacity during off-peak ones. Interruptible connection can also provide load reduction in unexpected fault events, improving grid reliability. They can also provide a way to value/monetize flexibility, as flexible connections can be accompanied by reduced network fees or faster grid access for new connections. Flexible connections for public charging infrastructure have been demonstrated in real-life projects.

Finally, **market mechanisms** can enable competitive provision of flexibility and have garnered significant attention in latest years. There are two main types of market solutions, short-term local flexibility markets and long-term tenders. For short-term market, the main use case is congestion management, however there have been suggestions of market-based voltage regulation services. Long-term tenders are used to procure flexibility ahead of time, making them suitable for investment deferral and fault-restoration use-cases, as they provide certainty to DSOs on flexibility availability. Market solutions may suffer from a lack of liquidity or high transaction costs at the distribution level due to the highly localized requirements for flexibility.

The ability of EV fleets to provide flexibility services has been proven technically, but the technologies (bidirectional chargers, reactive power control) and communication protocols needed to exploit the full potential of EV flexibility are not yet widespread.

The main barriers for EVs to provide flexibility services to distribution grids are economic and institutional. DSOs have only recently started to change operational and planning practices to move from a "fit-and-forget" approach to an active management of their grids, so there are no widespread value frameworks under which EVs can provide flexibility to DSOs.

We identified some research gaps, which included the consideration of real plug-in behavior and local mobility patterns of EV users when assessing flexibility provision, and the analysis of the participation of EV fleets in emerging flexibility mechanism.

In **Chapter 3** we assessed the impact of plug-in behavior on EV grid integration. We analyzed the plug-in behavior of EV users participating in the Electric Nation project, a residential smart charging trial in the UK. Trends show that **users tend to plug-in their EVs between 2-4 times per week**, albeit with large heterogeneity from users, with larger-battery EVs plugging-in less often, driving more kilometers between charging sessions and requiring more energy to be charged per session.

An agent-based model that considered non-systematic plug-in behavior (i.e., not plugging in every day) was developed and then calibrated using the data from the Electric Nation trial. The model was able to capture the trends observed in the dataset. We used this model to assess how plug-in behavior affects EV charging peak load and the flexibility that EV fleets can provide to the system. This model was used in the other chapters of this thesis as well.

Non-systematic plug-in behavior can reduce the impacts of EV charging on the distribution grid, especially under price-responsive EV charging as it reduces the synchronization of EV charging at low-price hours. Results show as well that increasing charger power can have significant impacts on the distribution grid, especially under price-responsive charging.

Non-systematic plug-in impacts are more important for the flexibility provision of EV fleets, as no flexibility can be provided if the EVs are not connected. **We evidenced a reduction of flexible time, available power, and accessible storage due to non-systematic plug-in behavior.** This is aggravated in the case of large-battery EVs as they have lower plug-in rates. Therefore, current trends towards larger battery sizes may pose a threat to flexibility aggregators, if there is no change in plug-in behavior.

High gains on flexibility can be achieved by improving the plug-in frequency of EV fleets. Small-battery EVs (<25kWh) that are connected every day can provide more flexibility, in flexible time, available power and accessible storage capacity than larger-battery EVs with non-systematic plug-in behavior. This points out to a need to identify fleets with consistent and reliable plug-in patterns which can be better candidates to provide flexibility to the system. Increasing the charger power can improve the flexibility potential as well, but only to a limited amount if it is not accompanied by an increase in plug-in frequency.

In **Chapter 4** we studied how local mobility patterns and the spatial distribution of EVs in the grid affect EV grid integration. From census data we derived mobility requirements at the infra-communal level in France and performed simulations of EV charging for over 2000 primary substations in France.

We showed that **differences in EV charging dynamics arise from urban tissue conditions.** City centers can experience high demand for EV charging during day-time as they attract high number of workers, and relatively lower demand for night-time charging as residents have lower share of car usage for daily mobility and drive shorter distances. On the contrary, peri-urban areas may face high demand for EV charging during night-time, as residents of these areas drive longer distances and have high dependency on vehicle for mobility.

We showed as well that EV charging can be shifted not only at the charging session level, but also at the weekly level. This could be achieved by electricity tariffs with lower prices in the weekend, which are already commercially available in some countries. The ability to shift the charging on a weekly basis will be greater for urban residents, due to

lower daily mobility requirements allowing to need to charge fewer times per week.

Overall, we show that the impact of EV charging, in both additional demand and increase of peak load¹, at the primary substation level will be higher for peri-urban areas of large cities and lower for large urban city centers due to differences in mobility patterns. The impacts of EV charging can be reduced by implementing time-of-use (ToU) tariffs that incite end-users to charge at off-peak hours. However, its effectiveness is limited for substations where the EV demand represents more than 20% of total demand. In substations where EV demand is greater than 20% EV charging can create higher peaks during off-peak hours. Therefore, a need arises to develop *smarter* charging solutions for high EV penetration rates.²

In a second step, we analyzed the joint integration of EVs and PV systems in a mixed urban-rural medium voltage grid that supplies the area around Brive-la-Gaillarde, a city in south-west France. Year-long power-flow simulations were carried out with different combinations of EV and PV integration levels and spatial distribution patterns.

Results from our simulations showed that the MV grid can host even a 100% of EV penetration without facing overloading of grid assets or voltage constraints. **Complementarities may arise between EV charging and PV system integration, but they will depend on the spatial distribution of PV installations and EV charging demand.** Under current trends PV integration, where large-scale ground-mounted PV systems represent around 50% of PV installed capacity, significant voltage and current constraints may arise in the MV grid. This is because ground-mounted PV systems are installed in low-density rural areas supplied by long feeders. EV charging cannot help solve these grid constraints as there is no sufficient local EV charging demand. On the contrary, if high shares of rooftop PV systems are installed in urban areas and coupled with high access to day-time charging, synergies may appear, reducing the integration impacts of both technologies.

Finally, in **Chapter 5** we identified five emerging market-based flexibility implementations in Europe. We used a modular framework to identify best-practices on market design and barriers to entry for distributed energy resources aggregators (DERs, which include EVs, stationary batteries and demand response).

The emerging flexibility implementations included three short-term market platforms and two long-term tenders. Their different approaches are due to the nature of constraints the grid operators face. Short-term market platforms were developed to reduce uneconomic curtailment of renewable energy, providing an alternative for it in the operational time frame. On the contrary, long-term tenders have tackled investment deferral of costly grid reinforcements due to demand-related constraints or flexibility procurement for fault-restoration events. In these cases, DSOs face high risks if they only rely on short-term markets, as flexibility may not be available when needed. Long-term tenders provide valuable certainty for DSOs and flexibility operators and encourage the development of flexibility trading at local level. Therefore, they can be the first step towards building liquid short-term flexibility markets.

We proposed a modular framework for the identification of best-practices on market

¹Increase relative to current levels of demand and peak load.

²Results from this chapter are applicable only for our case study of primary substations in France. The level up to which they can be extended to other countries should be studied, as mobility patterns and grid configuration may differ.

design. It consisted on three levels: administrative rules, product definition, and payment schemes and penalties. The main barriers identified for DER aggregators are on minimum bid requirements, on connection requirement and metering equipment.

Flexibility tenders carried out by UK Power Networks (UKPN, the London-area DSO) have had significant success in recent years and provide insights on the value of flexibility for investment deferral. For this reason, the second part of Chapter 5 was dedicated to a case study of EV participation in long-term tenders.

We developed a methodology to evaluate the participation of EV fleets on long-term flexibility tenders composed by a two-stage model that mimics the (ex-ante) tender bidding and activation–settlement processes. We applied the methodology to three types of fleets: a company fleet with consistent travel patterns and with systematic (every day) plug-in patterns, and two commuter fleets with less consistent travel and plug-in patterns. The case study allowed us to identify the main market rules and EV fleet parameters that affect participation.

Results showed that the main market rules that affect EV participation are **the availability window definition** and the **penalty conditions**. Short and well-defined availability windows can be a way to enter the market for resources with availability profiles that vary along the day, such as EVs, since providing day-long flexibility services can prove to be impossible by these kind of resources. Penalties provide the necessary incentives to ensure flexibility delivery when needed, but too high penalties can limit the flexibility that can be provided to the system. On the other hand, minimum service time has little impact, as EV fleets can provide 2-hour service with almost the same reliability as 30-minute service for the studied cases.

The participation of EV fleets will be mostly dependent on the EV fleet technical characteristics and usage patterns. The three main factors are the **bidirectional capability (V2G)**, the **reliability of the fleet**, and the **availability profiles–tender requirements match-up**. Smart charging provides little participation per EV (less than 1 kW/EV), therefore V2G appears necessary to improve participation in tender. However, only reliable fleets with a good match of connection patterns to grid requirements (in this case the company fleet) can fully take advantage of V2G.

Results from UKPN’s tenders have shown potentially high value of flexibility, but highly dependent on grid conditions. Average flexibility values in UKPN’s area are around €50 per firm kW per year, but they can go as low as 2 €/kW.y to over 200 €/kW.y³. In our case study, a **V2G-capable fleet would obtain an average remuneration of 350 €/EV.y** but ranging from 50 to over 1400 €/EV.y (V2G-capable company fleet with perfect match of connection patterns to grid requirements). This remuneration might increase if higher power chargers are considered, as our study only considered a 7 kW bidirectional charger. On the contrary, **unreliable fleets will have reduced remuneration (<90€/EV.y in average cases), coming mostly from V1G**.

Flexibility services for investment deferral are required only a few hours or months per year (usually during peak load in winter months, in France and the UK). Therefore, this revenue stream can be complementary to other flexibility services such as frequency regulation. However, revenues from distribution services are dependent on grid context: not all grids are constrained, constraints differ in each case (in time, magnitude, duration and frequency), and as constraints grow in time and magnitude, the value of flexibility

³Estimates of flexibility value by French DSO Enedis put in in the range of 0-24 €/kW.y.

diminishes as it becomes more cost-effective to use alternative reinforcement solutions.

Results from Chapter 3 and 5 hint that V2G-based flexibility through aggregators is more likely to be developed in professional-user contexts where company fleets can have higher plug-in reliability and more consistent driving and charging patterns, than for private users where driving and charging patterns are less consistent. Consequently, the volume of accessible flexibility coming from private users, both in energy and power, might be less than expected. However, there can still be significant opportunities for behind-the-meter solutions for *regular* EV users, i.e., vehicle-to-home or vehicle-to-building, and for renewable energy support.

Recommendations and future work

From this work we can derive recommendations which can be of interest to several stakeholders in the electricity and transport ecosystems, including automotive manufacturers (OEMs), DSOs, flexibility aggregators and regulators.

First, EVs suffer from a lack of clear status in the grid and burdensome connection rules, especially when equipped with V2G chargers. In particular, grid codes which are defined at the national level can prove to be particularly problematic for the development of on-board bidirectional chargers, as OEMs sell their vehicles internationally and EVs can travel across international borders. This calls for an uniformization of grid codes (specifically at the distribution level) at a large scale area, such as Europe. The development of flexibility services can also benefit from sub-metering at the EV or charging point level, removing the need for additional metering equipment, and allowing net-metering to avoid double taxation for bidirectional charging.

Second, flexibility aggregators should prioritize fleets with consistent and reliable connection patterns to maximize the value that can be extracted from V2G, or should provide end-users with the incentives to plug-in in a regular basis.

Distribution-level flexibility services can be a great opportunity for flexibility operators, potentially allowing them to obtain high remuneration. However, given the uncertainty and variability (in time and space) of flexibility value and requirements, distribution grid services should be seen as a complement to other flexibility services such as frequency regulation.

Regarding the development of flexibility mechanisms at the distribution level, we have seen that real-life implementations are emerging in several countries. Regulatory frameworks should incite DSOs to implement flexibility solutions as business-as-usual alternative to grid reinforcements, when it proves to be cost-effective.

Different mechanisms can be explored to implement flexibility. Market-based mechanisms should be prioritized, as they allow for flexibility procurement in a competitive manner, but they may not be applicable to all cases. Their limitations should be taken into account when seeking to implement them at the local level. The development of flexible connections for demand resources, like existing offers for renewable generation resources in some countries⁴, can provide an interesting opportunity.

Local flexibility markets are not built overnight; they require strong collaboration between regulators, DSOs and flexibility operators. DSOs should take a proactive ap-

⁴Smart connection agreements, *Offres de raccordement intelligentes* in France.

proach to building these markets, listening to stakeholders and sharing data. In this regard, UKPN has led an open and transparent process, identifying potential tender zones months or years in advance and publishing potential revenues for each tendered zone (willingness-to-pay for flexibility services), which helps flexibility operators identify the value of flexibility. They have shown pragmatism as well, by providing a fixed remuneration fee to all participants in their low-voltage tenders where they may not be sufficient competition for price formation.

Long-term tenders can be a viable option to start market-based flexibility procurement. Tender conditions should be adapted to facilitate the participation of DER aggregators. On the administrative front, easing connection requirements, using existing metering equipment (such as smart meters) and having broad support from local-country DSOs (such as with the PicloFlex platform or the Enedis case, instead of multiple platforms coexisting in the same country) can help reduce barriers to entry for new aggregators. On the product definition front, **a clear barrier is the minimum bid, which should be as low as possible (ideally under 50 kW)** to allow the participation of several aggregators and foster competition. Furthermore, setting short availability windows can help engage participation of assets with variable availability patterns (such as EVs and demand response) to match grid requirements. Finally, on the payments front, long-term contracts should consider both activation and availability payments to secure available flexibility, along with penalties applicable in the event of failure to deliver. However, penalties should not be excessive as to discourage the participation of flexibility aggregators, and should consider local issues, practices and learning by doing for both sides of the relation. If contracts are made with only activation payments, penalties should not be considered.

Finally, we have evidenced that synergies may appear between EV charging and PV generation. However, this requires *spatial* and *temporal* coordination, incentivizing rooftop PV installations in high demand areas and EV day-time charging. Ground-mounted large-scale PV systems which are installed in low-density areas may not allow for these complementarities. A cost-benefit analysis between these alternatives should be carried out.

Perspectives on future work

The interaction of mobility and electricity systems still present many questions which require further study. Here we present some subjects that should be studied in the coming years.

EV integration considering evolutions in mobility patterns: car-sharing, autonomous mobility, modal switching, lasting COVID-19 effects.

In Chapter 4 we showed the differences that local mobility patterns have on EV integration, but these were estimated based on the current (pre-COVID-19) situation and based on fossil-fuel mobility. Future mobility systems may differ radically from the current situation, requiring updated assessments on EV grid integration.

Extended plug-in behavior models and incentives to plug-in.

In this thesis we show the importance of plug-in behavior on the provision of flexibility by EV fleets. Plug-in behavior models would benefit from validation from multiple datasets which may become available with increasing EV adoption. They should consider

different countries, demographic conditions, and EV makes and models.

Additionally, further research is needed to identify the incentives to plug-in. Are monetary incentives sufficient and necessary, or can there be alternative incentives, such as gamification? How will user behavior be modified by such incentives? Are the behavioral changes persistent in time?

Full MV/LV EV integration assessment.

This work analyzed a case study of a medium voltage grid in France, which appeared to be robust in face of high levels of EV integration. However, a full MV/LV analysis should be carried out, as voltage or loading constraints may arise at the low voltage level even when no constraints in the medium voltage grid arise.

Such an analysis should consider the behavioral aspects covered in this thesis: non-systematic plug-in behavior and local mobility patterns. More advanced mobility models can be an advantage.

Flexibility mechanisms for voltage regulation at low-voltage levels.

The highest impacts of EV integration will be borne by low voltage grids, where voltage problems may be solved by only a few well-localized flexibility assets. This service may be required at all times. Market-based mechanisms may not be a cost-effective solution or suffer from a lack of liquidity. What mechanisms can be implemented for voltage regulation and phase balancing? Are grid codes or infrastructure reinforcements the only option?

Grid integration of electric trucks and buses

Research has mainly focused on individual transportation, especially regarding vehicle-to-grid technology. Consistent travel patterns of buses and high-power chargers could make them a valuable asset for flexibility services. Further research should be carried out in this front.

Appendix A

Detailed models for EV charging

We detail here the mathematical model for cost-optimization EV charging and decentralized valley filling.

1 Cost-optimization charging

At each charging session s , an EV that sees variable electricity prices (vector \mathbf{p}), will solve the following optimization model to find the charging power at each time step (vector \mathbf{x}). Implementation was made using the *cvxopt* library in Python.

$$\begin{aligned} & \underset{\mathbf{x}}{\text{minimize}} && \mathbf{p}^T \mathbf{x} \\ & \text{subject to} && \sum_{x_i \in \mathbf{x}} x_i \cdot \Delta t \cdot \nu \geq E_s \\ & && x_i \leq VCC_i \\ & && 0 \leq \mathbf{x} \leq Pch \end{aligned} \tag{A.1}$$

In the precedent Equation, E_s is the required energy to be charged in session s in kWh, Δt the time step duration in hours, ν the charging efficiency, Pch the charging power in kW, and VCC_i the variable capacity limit at time i in kW, if included.

2 Decentralized valley filling

The valley filling strategy is based on a central aggregator that has a base load profile forecast, which is sent to an EV when it is connected. Each EV implements the cost-minimization strategy, where the price vector is the base load profile. This makes the EV to charge during the low demand hours. The EV then sends back the charging profile to the aggregator who updates its base load profile (Eq. A.2). This is repeated for each new EV connection. The algorithm is shown in Figure A.1, where the $netload_n$ is the updated load profile after n EVs have connected and sent back their charging profile to the aggregator.

$$netload_n = netload_{n-1} + \mathbf{x}_n \tag{A.2}$$

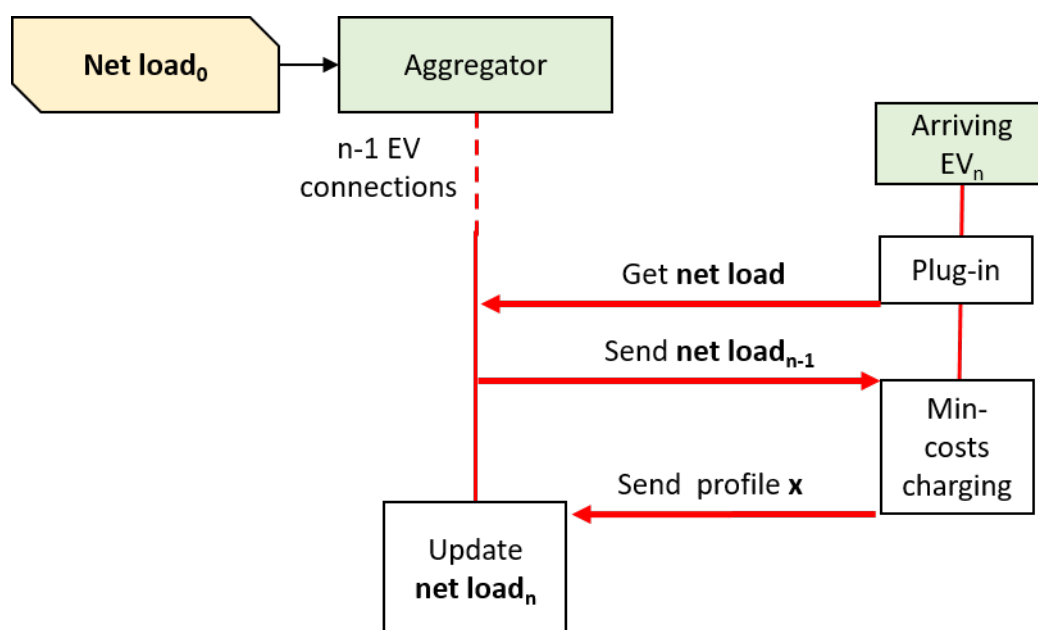


Figure A.1: Flowchart of the decentralized valley filling strategy

Appendix B

Grid reconstruction from GIS data

We detail here the methodology used to build realistic MV grid test cases from GIS data.

1 Datasets

We use three main datasets to reconstruct the MV grids:

- Cartography of grid assets.
- Demand profiles by customer classes at the regional level.
- Demand at the infra-communal level by customer categories.
- Census data at the infra-communal cell.

The cartography of Enedis' network is publicly available [here](#) [197]. It contains the positions of the main network elements: HV/MV substations, MV lines, MV/LV transformers, and LV lines. However, no connectivity among the grid elements nor any technical information of lines (only whether it is an underground cable or overhead line) or transformers is given. An example of the MV network data can be seen in Figure B.1.

The demand profiles by customer classes and region with a 30-minute time resolution are published by the DSO in [227]. There are 18 customer classes grouped in four main categories: Residential (RES), professional (PRO), small industry (ENT \leq 36 kVA) and big industry (ENT $>$ 36 kVA), as shown in Table B.1.

The annual demand is provided for five main customer categories: residential (RES), professional (PRO), agriculture (ENT-S1), industry (ENT-S2), and tertiary (ENT-S3) at infra-communal (IRIS) [228].

The regional profiles per customer classes and the annual demand by infra-communal cell allows us to obtain a load profile at the infra-communal level that considers local demand patterns. To achieve that, at each region, we group the demand profiles into the five categories¹, and create a per-unit profile for each customer class (RES, PRO,

¹We group the six RES customer classes into a single RES category, the same for PRO classes. Agriculture, Industry and Tertiary categories have the customer classes ENT-S1, ENT-S2 and ENT-S3 respectively

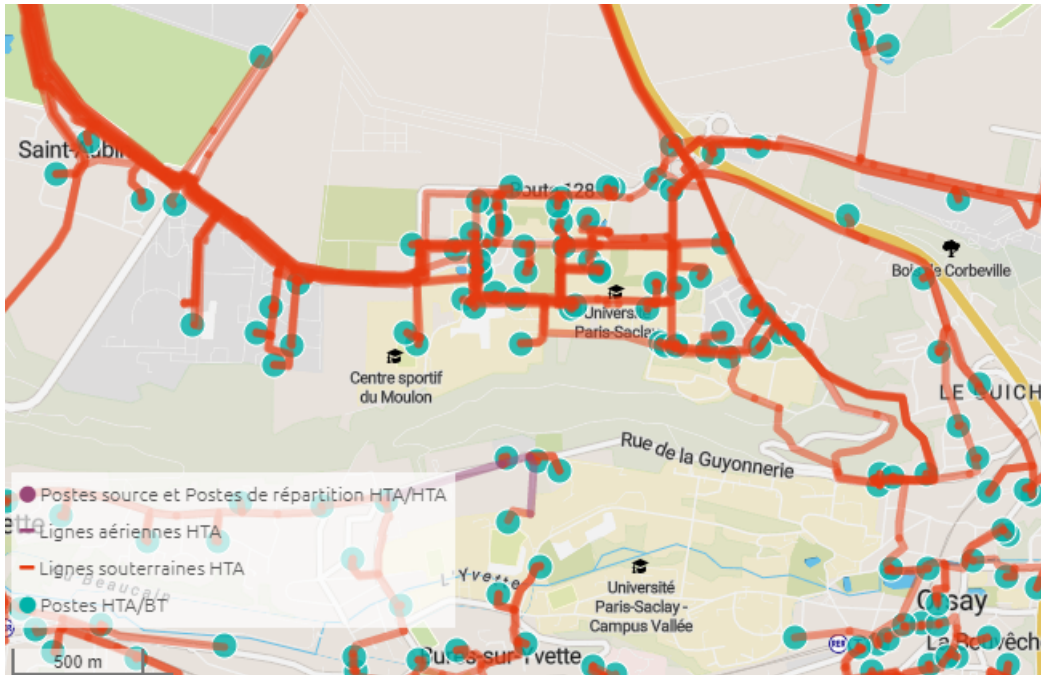


Figure B.1: Distribution grid around the CentraleSupélec campus, including MV lines and MV/LV transformers. Screen capture taken from Enedis’ network cartography tool [197].

Table B.1: Customer classes and demand in 2018 at the national level in France.

Level	Profile	Type	Demand 2018 [TWh]	Share 2018 [%]
<=36kVA	RES1	Residential Base <= 6 kVA	32.84	9.46 %
	RES11	Residential Base >6 kVA	14.02	4.04 %
	RES2	Residential off-peak	95.76	27.58 %
	RES2WE	Residential off-peak + WE	0.38	0.11 %
	RES3	Residential Mobile Peak (6-22h)	2.17	0.62 %
	RES4	Residential Mobile Peak (7-01h)	3.06	0.88 %
	PRO1	Professional Base <= 6 kVA	21.03	6.06 %
	PRO2	Professional HP/HC	13.30	3.83 %
	PRO3	Professional Mobile Peak (6-22h)	1.73	0.50 %
	PRO4	Professional Mobile Peak (7-01h)	1.02	0.29 %
>= 36 kVA	PRO5	Public Lighting	4.3	1.26 %
	ENT1+2	Industry Low Voltage (400 V)	0.11	0.03 %
	ENT3+4+5	Industry Medium Voltage (20 kV)	0.41	0.12 %
	ENT – S1	Agriculture	3.51	1.01 %
	ENT – S2	Industry	56.88	16.38 %
	ENT – S3	Tertiary	95.43	27.48 %
	ENT – S4	Non Affected	1.18	0.34%

Agriculture, Industry and Tertiary) at the regional level. Then, we obtain the load profile at the infra-communal level ($Load_i$, in MW) by scaling each customer profile of the corresponding region ($Profile_{p,r}$, for p the type of profile and r the region) to match the annual demand of the cell ($D_{i,p}$, in MWh), as shown in Eq. B.1.

$$Load_i = \frac{\sum_{p \in P} Profile_{p,r} \cdot D_{i,p}}{8760} \quad (\text{B.1})$$

Finally, we obtain from census data the number of single-dwellings per infra-communal cell from [229], and we derive the number of large buildings per infra-communal cell from the data on [230].

2 Grid reconstruction methodology

To be able to perform power flow simulations, we require:

- **A network model** composed of transformers, lines, buses. This should include their connectivity and the technical parameters (impedances, nominal voltages, rated capacities).
- **A set of loads.** The loads should be assigned to certain buses in the grid model, and should have a profile to perform time-series simulations.
- **A set of generators** (if required). The generators should be defined by their technical parameters (installed capacity), profiles (time series of generation), and position in the grid.

A methodology was developed to reconstruct the MV grid served by a HV/MV substation from the position of network elements. The main steps are:

1. **Determine grid connectivity.** Here is determined how each line segment or transformer is connected to each other, defining all grid nodes. An algorithm was developed for this purpose.
2. **Define service area of a HV/MV substation.** This step determines the area served by the substation under normal operation conditions, by defining open/closed lines considering that the network is operated in a radial fashion, without closed loops or loads being alimented to two or more HV/MV substations at the same time. This step mimics operational processes of distribution grids [191].
3. **Include loads at MV/LV transformers.** Using annual electricity demand per customer type (residential, commercial, industrial) at the infra-communal level, a demand time-series is generated for each infra-communal cell. This load is distributed among the MV/LV transformers.
4. **Determine technical characteristics of lines** (resistance, reactance and capacitance). An algorithm defines the smallest conductor section for each line segment from a set of possible conductor types, considering thermal and voltage drop constraints during peak-load hours.

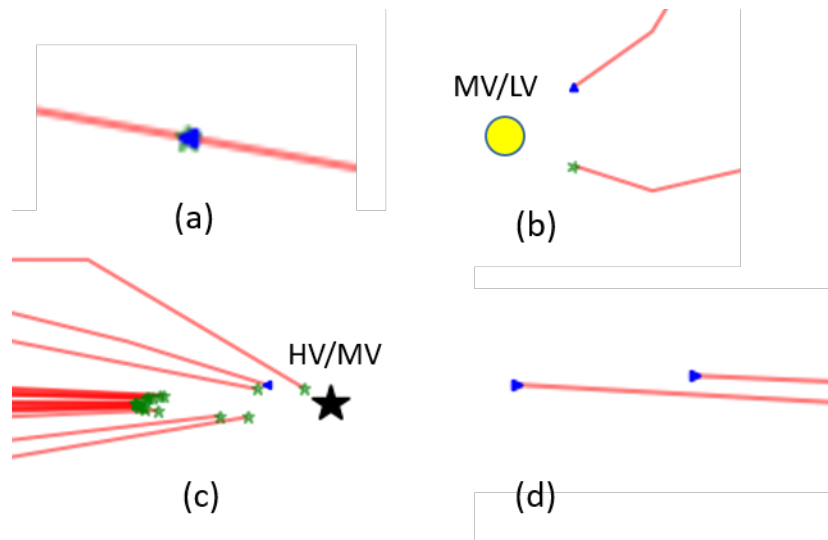


Figure B.2: Examples of connectivity in cartography data. (a) two lines for which ends coincide, (b) two lines supplying a MV/LV transformer, (c) HV/MV substation and its feeders, and (d) two lines that could be connected.

5. **Include generators.** We considered the integration of PV systems, requiring the identification of locations and installed capacity.

At the end of the methodology, we obtain the necessary files required to perform power flow simulations for a base case without the integration of renewable energy or EVs.

2.1 Determine grid connectivity

The cartography of network assets is composed of a set of geo-referenced points (HV/MV substations, MV/LV transformers) and lines (underground cables or overhead lines). The connectivity is not easily determined, as end of lines do not necessarily correspond to a transformer or other line, as shown in Figure B.2.

We developed an algorithm that defines the connectivity of the assets, defining all *grid buses*. The algorithm is carried out in three steps:

- Define a list of all the *potential buses* of the grid: line ends, MV/LV transformers, HV/MV substations.
- Define *grid buses* for all *potential buses* whose position perfectly coincide. Remove these *potential buses* from the list.
- For the remaining *potential buses*, grouping all within a 3m radius², creating new *grid buses*. Remove the assigned *potential buses* from the list.
- For the *potential buses*, grouping all within a radius of 7m, creating new *grid buses*. Remove the assigned *potential buses* from the list.

²The radius is a parameter of the algorithm, it was determined by experience.

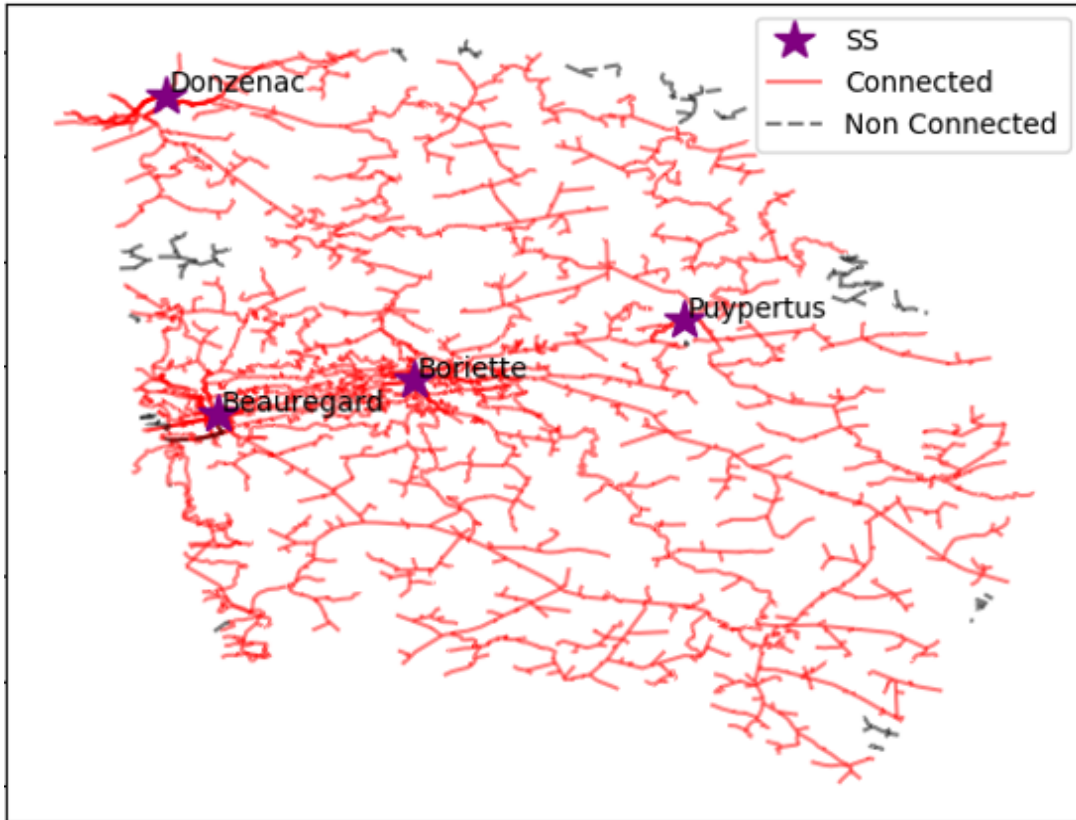


Figure B.3: Example of connectivity reconstruction for *La Boriette* substation area. Four substations are shown, all red lines are electrically connected to *La Boriette* substation. Grey lines are not electrically connected to the substation.

- Define *grid buses* for remaining (unconnected) *potential buses*.

At the end of the algorithm we obtain graph composed of a set of *grid buses* (vertices) to which each line is connected. An example of the connectivity reconstruction is shown in Figure B.3

2.2 Defining service area of the substation

Most MV grids are operated in a radial topology, where each connection is supplied by only one substation and from only one unique feeder. However, as seen in Figure B.3, the HV/MV substations present connections between each other (redundancy) and between its own feeders (loops). The meshing of the network is used to improve reliability of supply under fault conditions.

We define the service area of the HV/MV substation under normal operating conditions, considering that the network is operated using a radial topology for the MV feeders. This requires to define line switches and their connection state, i.e., normally closed or normally open³.

³The positions of switches are not defined in the data, so we consider any segment of the data as a possible switch.

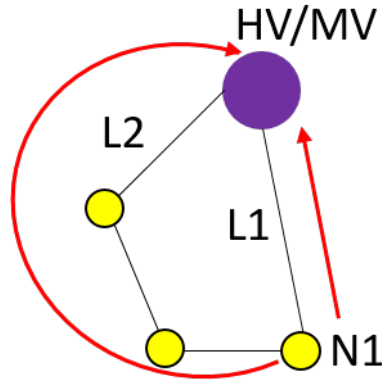


Figure B.4: Example of untangling internal loops. The path of connection of N1 towards the HV/MV substation that passes through L1 is shorter than the path that passes through L2. Therefore, N1 will be assigned to be supplied by L1.

We developed an algorithm to *separate* the service areas of neighboring substations, and to *untangle* feeder loops within the same substation. It follows three steps:

- Separate substation areas based on distance of each node to each substation. For this we compute the minimum distance of each node to each substation⁴ using the dijkstra algorithm⁵. Then, we assign each node to the substation to which it is closest.
- Untangle internal loops to define unique radial feeders. Similarly, we define the distance of each node to the studied substation, but forcing the path through each one of the initial lines segments connected to the main HV/MV substation. We then define the a feeder for each node in the supply area. This is exemplified in Figure B.4
- Manual correction. A graphic user interface was implemented, to verify and modify the *open* and *closed* switches.

The result of the service area separation and feeder untangling for the *La Boriette* case is shown in Figure B.5.

2.3 Assigning loads

In this step we assign the infra-communal loads to the grid. We consider that all loads will be connected to the MV/LV transformers. We distribute the load of each infra-communal cell evenly among the number of LV/MV transformers located in the cell.

⁴The distance is computed 'through the network', using lines length and graph structure.

⁵We use the NetworkX library in Python. It provides several functions for networks/graph studies, including the minimum distance computation in a graph using the dijkstra algorithm.

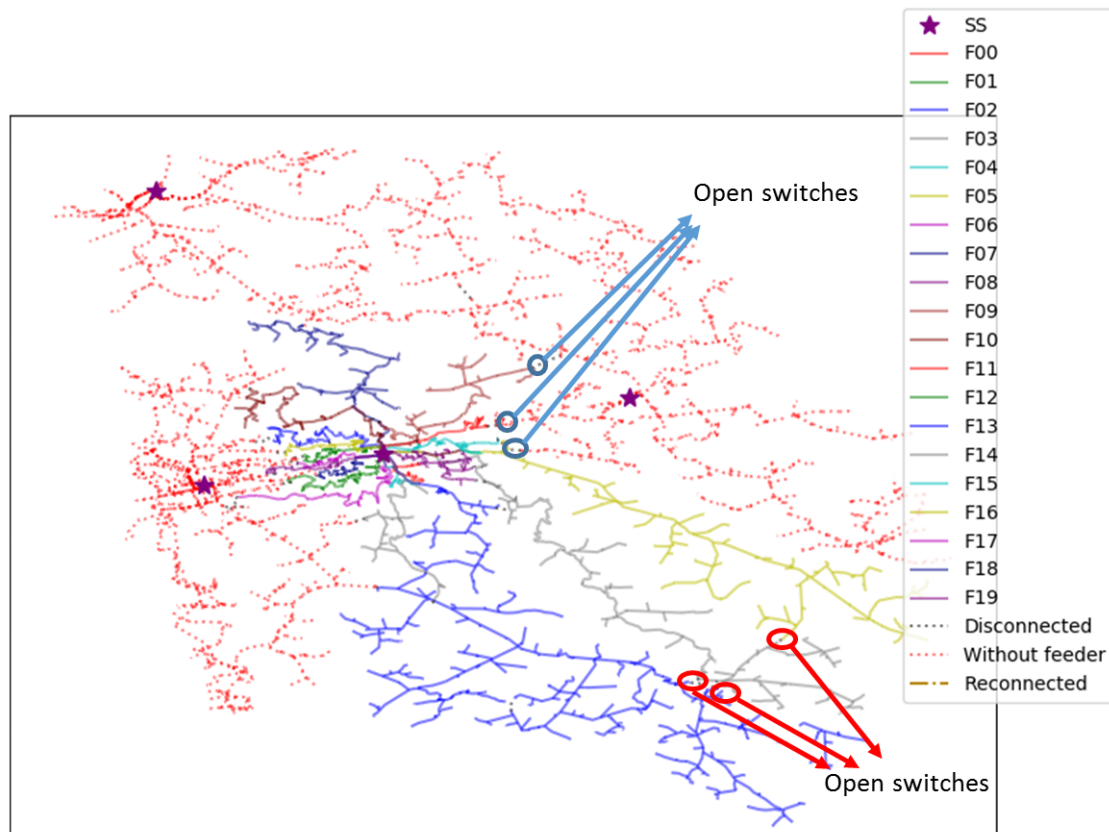


Figure B.5: Example of the separation of services areas and untangling feeder loops for *La Boriette* substation. The final grid supplied by the substation has 20 independent feeders, each plotted in a different color. The dotted red lines are not served by *La Boriette* substation.

2.4 Determining line technical characteristics

In this step we determine the resistance, reactance and ampacity of each line segment, based on standard conductor types typically found in French grids. The considered conductor types are shown in Table B.2.

Table B.2: Conductor types

Line type	Type	Section [mm ²]	Rated current [A]	R [Ω/km]	X [Ω/km]	C [nF/km]
OH_148	Overhead	148	365	0.223	0.35	5
OH_75	Overhead	75	240	0.438	0.35	5
OH_54	Overhead	54	195	0.606	0.35	5
OH_34	Overhead	34	145	0.962	0.35	5
UG_240	Underground	240	495	0.125	0.11	320
UG_150	Underground	150	370	0.2	0.12	269
UG_95	Underground	95	280	0.316	0.13	230

To determine the type of conductor of each cable, we considered that the feeder complies with two criteria in normal operating conditions:

- There are **no overloadings** in any asset.
- **Limited voltage deviations** at the end of the feeder.

We evaluate these two conditions at peak load (as we know the loads positions and profiles) considering a demand of reactive power given by the power factor $\tan\phi$. We determine the active power flow that pass through each segment (P_j) and evaluate the no-overloading condition at nominal voltage (V_{nom}) considering a security factor >1 (Eq. B.2, where I_{max_c} is the rated current of the conductor, and κ the security factor). This defines a constraint on the rated current of the conductor.

$$I_{max_c} \geq \frac{P_j \cdot \kappa}{\sqrt{3}V_{nom}} \quad (\text{B.2})$$

To define a maximum voltage deviation within a feeder (ΔV_{max}), Knowing the distance of the further bus of each feeder (L_{max_f}), we compute a maximum voltage deviation per km ($\Delta V_{km,f}$) that each segment in a given feeder f must comply with (Eq.B.3).

$$\Delta V_{km,f} \leq \frac{\Delta V_{max}}{L_{max_f}} \quad (\text{B.3})$$

We consider a linear approximation for the voltage drop per km in each segment ($\Delta V_{km,j}$), shown in Eq. B.4 and R_c, X_c the resistance and reactance per km of the conductor.

$$\Delta V_{km,j} = \frac{P_j(R_c + X_c \cdot \tan\phi)}{V_{nom}} \quad (\text{B.4})$$

From Eq. B.3 and B.4 we can derive a constraint on R and X of the conductor, shown in Eq. B.5, dependent on the maximum length of the feeder, the accepted voltage drop and the peak load that passes through the segment.

$$(R_c + X_c \cdot \tan\phi) \leq \frac{\Delta V_{max} \cdot V_{nom}}{L_{max_f} \cdot P_j} \quad (\text{B.5})$$

To select the type of conductor in each segment, we choose the conductor with the smallest section that can comply with the two conditions, on current (Eq. B.2) and on voltage drop (Eq. B.5).

We apply the methodology to *La Boriette* case considering a $\tan\phi$ of 0.3, a maximum voltage drop per feeder of 0.04 pu and a security factor on line overload of 1.5. The conductor assignment shown in Figure B.6 and Table B.3, showing that most segments get assigned the smallest available section, which is in line with data from the area.

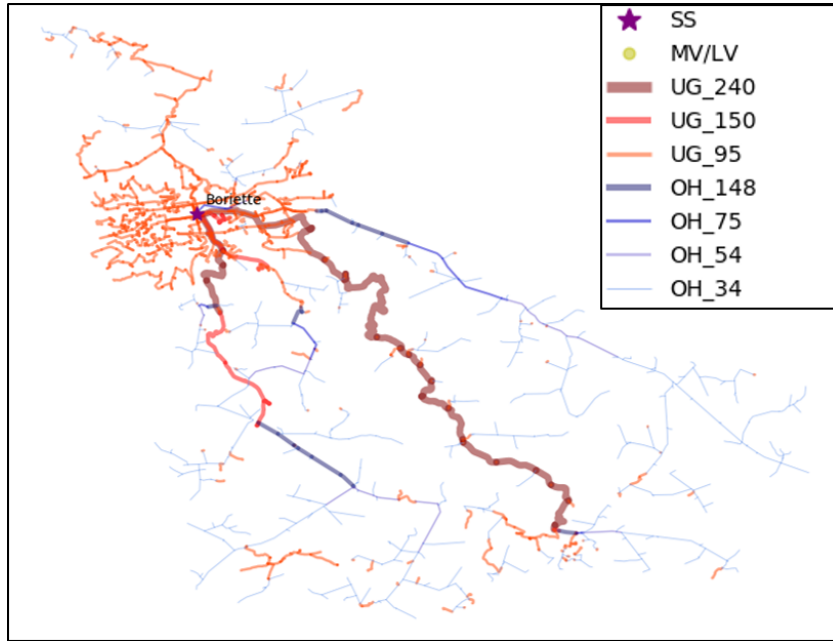


Figure B.6: Conductor assignment for *La Boriette* substation.

Table B.3: Number of segments for each type of conductor in *La Boriette* service area.

Code	Type	Section [mm ²]	# lines
OH_148	Overhead	148	17
OH_75	Overhead	75	12
OH_54	Overhead	54	27
OH_34	Overhead	34	567
UG_240	Underground	240	22
UG_150	Underground	150	12
UG_95	Underground	95	442

2.5 PV assignment

To include PV generation into the grid we need to define two aspects: how much PV should be installed, and where (i.e., in which nodes of the grid).

Types of PV installations

We considered three types of PV installations:

- **Small-scale rooftop PV**, corresponding to residential PV systems with a mean capacity of 4 kW.
- **Medium-scale rooftop PV**. Corresponding to larger installations that can be found in large buildings' rooftops, with a mean capacity of 120 kW.
- **Large ground-mounted PV**. Corresponding to large-scale farms with a mean capacity of 3 MW⁶.

Each type of PV installation will be included in a different fashion into the grid.

Small-scale rooftop PV will be installed based on the number of single dwellings of each infra-communal cell (Nsd_i) considering a residential PV diffusion parameter δ_{PVres} and the average installation size S_{res} (4 kW), as shown in Eq. B.6. The total installed capacity ($PVres_i$) is then equally distributed among the MV/LV transformers of an infra-communal cell.

$$PVres_i = Nsd_i \cdot \delta_{PVres} \cdot S_{res} \quad (\text{B.6})$$

Medium-scale rooftop PV will be installed based on the number of large buildings of each infra-communal cell (Nlb_i) considering a mid-scale PV diffusion parameter δ_{PVmid} , and an average installation size S_{mid} (120 kW) as shown in Eq. B.7. We obtain the number of installations which are then distributed randomly (each with a size S_{mid} in the nodes of the infra-communal cell.

$$NPVmid_i = \lceil Nlb_i \cdot \delta_{PVmid} \rceil \quad (\text{B.7})$$

Finally, large scale PV installations of a size of 3MW are distributed randomly among among the nodes of rural infra-communal cells. The number of large-scale installations to include can be determined by fixing an objective of PV installed capacity.

PV installed capacity following current trends

We determine a scenario of PV installation based on current trends in France. We assume that the shares of PV installations per region and per PV type (small, medium and large scale) remain constant. We then derive the PV residential and commercial diffusion at the regional level

Objectives from the French government expect over 70 GW of PV installed capacity by 2035. In the Nouvelle Aquitaine region (region where is located La Boriette substation) which concentrates 19% of France's PV installed capacity, this would translate in 13.6

⁶Mean installed capacities are derived from the current installed capacity, shown in Table 4.2

GW by 2035. The PV installed capacity in Nouvelle Aquitaine would be composed of 1.7 GW in small-scale, 3.2 GW in medium-scale and 8.7 GW in large-scale PV.

We compute the PV diffusion for small and medium-scale PV based at the regional level (Eq. B.8 and B.9, obtaining a residential PV diffusion of $\delta_{PV_{res}}=19.9\%$ and a medium-scale PV diffusion of $\delta_{PV_{mid}}=93\%$). For large-scale installations, we consider that they will be evenly distributed among rural infra-communal cells, obtaining a mean of 0.78 large-scale PV installations per rural infra-communal cell.

We apply these factors ($\delta_{PV_{res}}$, $\delta_{PV_{mid}}$, and mean large-scale PV per rural cell) to the *Boriette* case, obtaining 11.8 MW of small-scale PV, 15.1 MW of medium-scale PV and 42.1 MW of large-scale PV.

$$\delta_{PV_{res_{region}}} = \frac{PV_{res_{region}}}{Nsd_{region} \cdot S_{res}} \quad (\text{B.8})$$

$$\delta_{PV_{mid_{region}}} = \frac{PV_{mid_{region}}}{Nlb_{region} \cdot S_{mid}} \quad (\text{B.9})$$

Appendix C

Computational times

The EV model presented in Chapter 3 was fully implemented in Python 3, with the optimization library *cvxopt*. Simulations presented in this thesis were carried out in a laptop with an Intel i5 processor and 16 GB of RAM.

Computing times for 2-week simulations with a 30-minute time steps for 1,000 EVs doing uncontrolled or off-peak charging take around 1.8 seconds. Simulations for the same parameters for fleets implementing the decentralized *valley-filling* strategy take around 30 seconds. The increase in time in the valley filling strategy is due to the fact that each charging session (i.e., each day for each vehicle) requires to solve an (small) optimization problem and calling a solver each time.

The simulations carried out in Chapter 4, Section 3, to study the impacts of EV charging on 2,000 primary substations (in each substation, between 1,000 to 25,000 EVs were simulated) took around 10 hours of computing time for each studied charging strategy.

The power flow simulations of the *Boriette* case study in Chapter 4, Section 4, were implemented using the *pandapower* library in Python 3. The studied grid consisted of 1096 nodes, 1095 lines, and included a voltage controller on the HV/MV transformer to maintain the voltage between 0.99 and 1.01 pu at the MV side and Volt-VAR controllers for ground-mounted PV farms. Each year-long simulation with a 30-minute time-step took around 2 hours of computing time.

Appendix D

Complementary results from *La Boriette* case study

1 Spatial distribution of EVs and PV installations

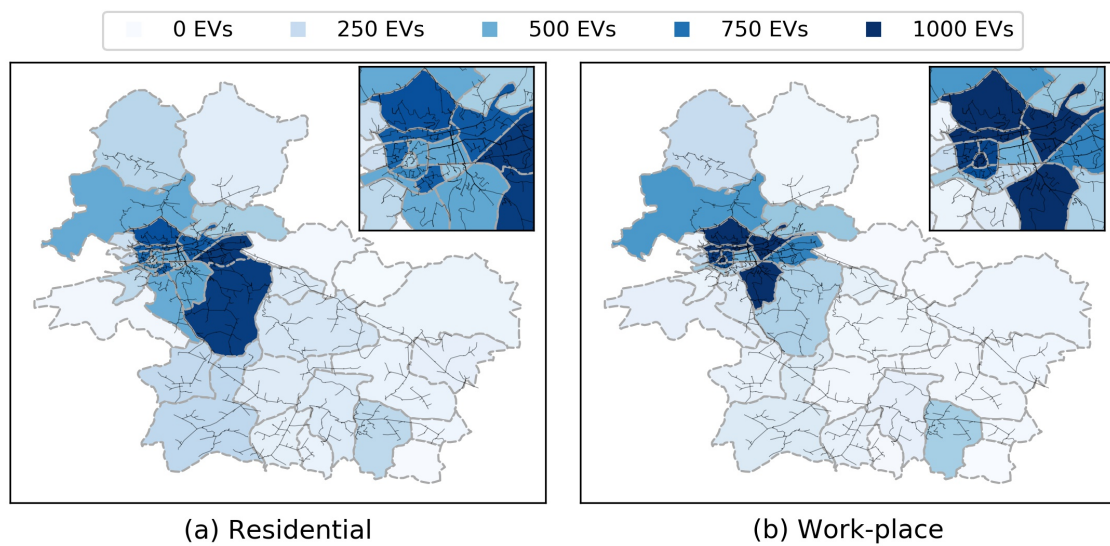


Figure D.1: Spatial distribution of EVs per infra-communal cell, Synergies scenario. EV diffusion=100%, Work-place charging access=50%. Zoom on Brive-la-Gaillarde city center on top right corner of each plot.

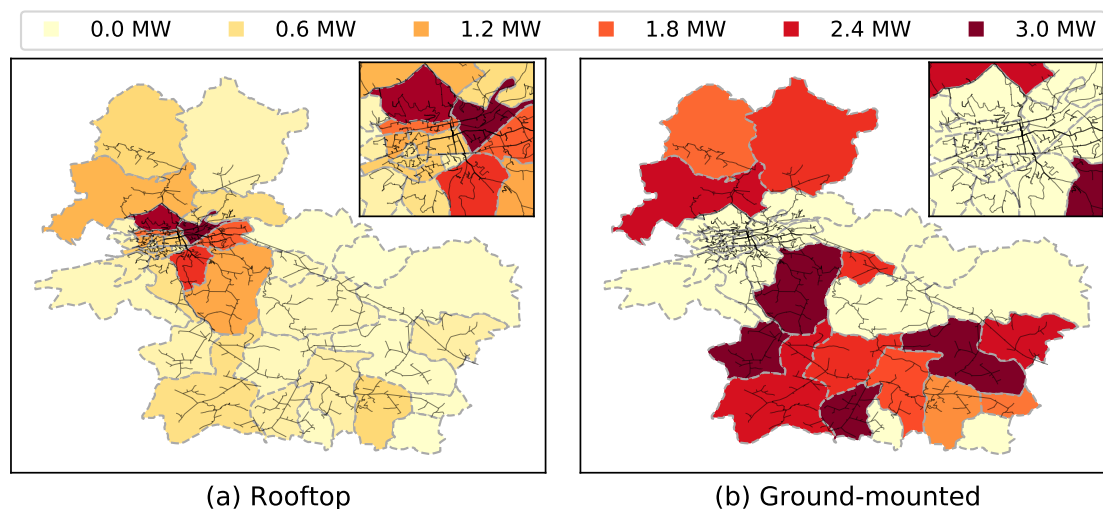


Figure D.2: Spatial distribution of PV installed capacity per infra-communal cell, EV-only and Continuity scenarios 60.5 MW of rooftop PV and 9.3 MW of ground-mounted PV. Zoom on Brive-la-Gaillarde city center on top right corner of each plot.

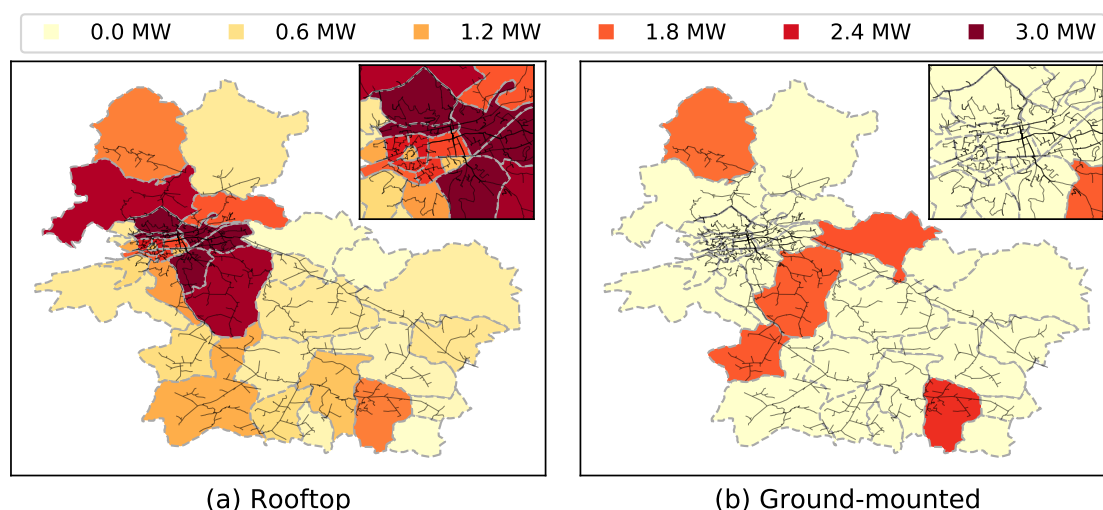


Figure D.3: Spatial distribution of PV installed capacity per infra-communal cell, Synergies scenario. 60.5 MW of rooftop PV and 9.3 MW of ground-mounted PV. Zoom on Brive-la-Gaillarde city center on top right corner of each plot.

2 Maximum line loading

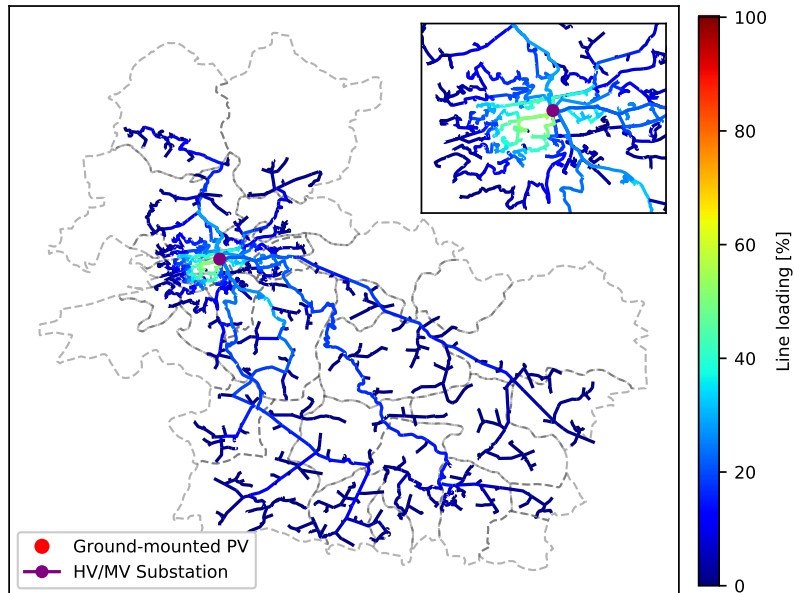


Figure D.4: Maximum line loading in the EV-only scenario.

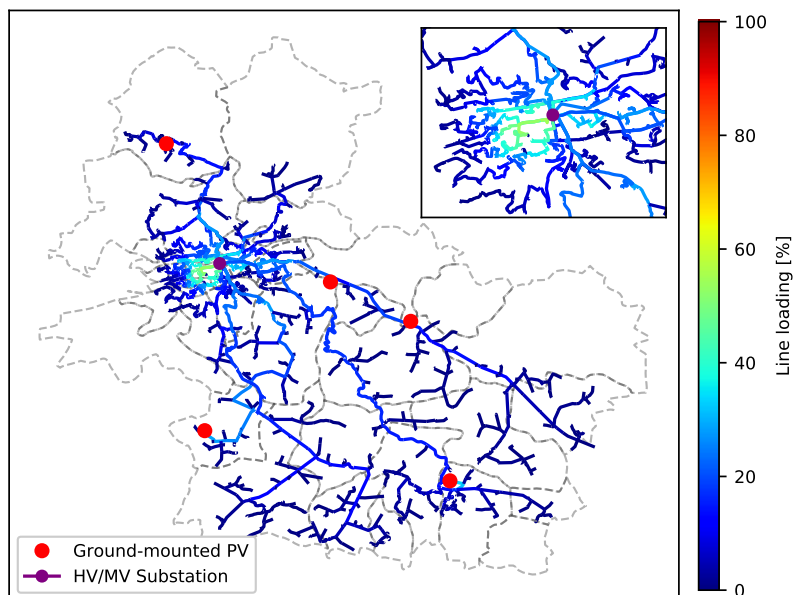


Figure D.5: Maximum line loading in the Synergies scenario.

Appendix E

Résumé en français.

Le développement de la mobilité propre, dont les véhicules électriques (VE) sont un des axes principaux, s'inscrit dans la politique globale de la transition énergétique. Néanmoins le déploiement massif de VE présente des enjeux pour leur intégration aux réseaux électriques. La recharge simultanée d'un grand nombre de VE risque d'entraîner des surcharges dans les équipements électriques ou des chutes de tension en dehors des limites établies. Inversement, les VE peuvent être une source de flexibilité pour l'opération des réseaux électriques en implémentant des stratégies de recharge intelligente, et aussi comme unités de stockage distribuées avec la recharge bidirectionnelle (vehicle-to-grid, V2G), tant au niveau globale (équilibre offre demande) comme au niveau locale (résolution de contraintes sur le réseau moyenne et basse tension). Cette thèse a étudié deux questions principales:

Comment les habitudes de recharge (quand et avec quelle fréquence les VEs sont connectés) et de mobilité locale des utilisateurs (urbain vs rural) affectent l'intégration des VE sur les réseaux de distribution.

Quels services de flexibilité peuvent être fournis aux gestionnaires des réseaux de distribution (GRD) par des flottes des véhicules électriques et avec quels cadres de valorisation ?

Chapitre 2 : Intégration active des véhicules électriques dans les réseaux de distribution

Ce chapitre présente une revue de littérature des aspects techniques, économiques, réglementaires et comportementaux qui affectent l'intégration des VE dans les réseaux de distribution d'électricité (réseaux moyenne et basse tension où sont connectés la plupart des utilisateurs finaux). On a identifié les services de flexibilité qui peuvent être proposés par des flottes de VE et les cadres de valorisation pour leur implémentation. On a aussi identifié des espaces de recherche qui guideront le reste de cette thèse.

Les VE peuvent apporter des services de flexibilité à différents acteurs des systèmes électriques. Pour les utilisateurs finaux, la recharge intelligente ou le V2G peuvent réduire leurs factures d'électricité et améliorer le facteur d'autoconsommation de génération renouvelable *derrière le compteur*. Les VEs peuvent aussi participer à des services au niveau

global du système électrique comme la régulation de fréquence ou l'arbitrage en énergie. Au niveau de distribution, les VE peuvent fournir trois types de services : gestion des congestions, régulation de tension et puissance de secours en cas de défaut sur le réseau. Si la flexibilité est procurée pour le long terme, les services de gestion de congestion et la régulation de tension peuvent être utilisés pour le report d'investissement dans des nouvelles infrastructures de réseau (transformateurs, câbles).

Quatre cadres de valorisation existent pour la fourniture de flexibilité aux GRDs : codes de réseau, tarifs réseau, connections intelligentes et approches marché. En particulier, des solutions basées sur des connections intelligentes et des marchés locaux de flexibilité ont été testés avec des flottes de VEs dans des projets démonstrateurs Européens. Cela montre une grande diversité pour l'implémentation des solutions de flexibilité au niveau de distribution.

On a identifié des barrières pour le développement des solutions de flexibilité au niveau de distribution. Des barrières techniques existent, notamment car les technologies nécessaires pour le V2G (chargeurs bidirectionnels, control en réactif, standards de communication) ne sont pas encore étendues massivement, mais le seront dans les années à venir. Au contraire, les barrières principales sont économiques et réglementaires, car les GRDs ont récemment commencé à changer leurs pratiques opérationnelles et de planification pour inclure des solutions de flexibilité. Cela fait qu'il n'existe pas des cadres de valorisation matures pour ces services.

Des espaces de recherche ont été identifiés, notamment (i) la considération des comportements de recharge dite *non-systématique* (pas tous les jours) et des besoins de mobilité au niveau local dans l'évaluation de la capacité de flexibilité des flottes de VE, et (ii) l'analyse de la participation des flottes de VE dans des mécanismes de flexibilité émergents au niveau Européen.

Chapitre 3 : Comportements de recharge des utilisateurs de VEs : modélisation et impacts pour leur intégration au réseau.

Dans ce chapitre on a évalué l'impact des différentes habitudes de recharge sur l'intégration des VE au réseau. Pour cela on a analysé des données de recharge issus du projet Electric Nation au Royaume Uni. Les observations montrent que les utilisateurs chargent leur VE entre 2 à 4 fois par semaine, en moyenne, mais avec une grande hétérogénéité des utilisateurs. Les VEs avec des batteries de grande taille (>50 kWh) se connectent moins souvent, conduisent plus de kilomètres entre sessions de recharge et ont de besoins de recharge (en énergie) plus élevées à chaque session.

Un modèle multi-agent pour simuler la recharge des utilisateurs de VE a été développé. Ce modèle considère les habitudes de recharge non-systématiques et a été calibré avec les données du projet Electric Nation. Le modèle permet de retrouver les tendances de recharge observées et sera utilisé dans le reste de la thèse. On a évalué l'impact des habitudes de recharge non-systématique, par rapport aux cas de recharge systématique, dans la demande de pointe qui génèrent des flottes de VE. Les habitudes de recharge non-systématiques peuvent réduire les impacts de la recharge sur le réseau électrique, en

particulier pour des cas des stratégies de recharge en fonction des prix, car elle réduit la synchronisation de la recharge en heures creuses (moins de VE sont connectés au même temps).

Les impacts des habitudes de recharge non-systématiques sont plus importants pour la fourniture de flexibilité, car si les VE ne sont pas connectés ils ne peuvent pas offrir de la flexibilité au réseau. La recharge non-systématique réduit les trois indicateurs de flexibilité considérés : le temps disponible pour la flexibilité, la puissance disponible et la capacité de stockage accessible. Ces effets sont d'autant plus importants pour les flottes de VE avec des batteries de grande taille, en raison de leur faible taux de connexion.

Des gains importants de flexibilité peuvent être atteints en améliorant le taux de connexion des VE. Des flottes de petite taille (<25 kWh) qui se rechargent tous les jours peuvent apporter plus de flexibilité (même en stockage) que des flottes avec des tailles de batterie plus importante mais avec une recharge non-systématique. L'identification des flottes avec des habitudes de connexion au réseau fiables est à envisager. L'augmentation des puissances de chargeurs peut aussi améliorer la flexibilité disponible, mais pas de façon significative si elle n'est pas accompagnée par une augmentation du taux de connexion.

Chapitre 4 : Evaluation de l'intégration des VE dans les réseaux de distribution, une approche basée dans les données

Dans ce chapitre on a étudié comment les besoins de mobilité au niveau local, ainsi que la distribution de la recharge des VE dans l'espace, impactent l'intégration des VE au réseau. On a dérivé des besoins de mobilité au niveau infra-communal à partir des données du recensement de la population en France, et réalisé des simulations de recharge de VE pour plus de 2000 postes sources en France.

Des différences dans les courbes de recharge des VE agrégées au niveau poste source apparaissent selon le type de tissu urbain. Les centres des grands pôles urbains peuvent éprouver des besoins de recharge élevés en journée, car ils attirent un nombre important des travailleurs, et des besoins relativement modérés en soirée, car leurs résidents ont moins recours au véhicule pour leurs déplacements et conduisent des distances moins élevées par jour. Au contraire, des zones péri-urbaines auront des demandes de recharge de VE beaucoup plus élevées en soirée, car leurs résidents ont une dépendance plus importante à la voiture pour les trajets quotidiens et parcourent des distances plus élevées.

Globalement, l'impact de l'intégration des VE au niveau poste source sera plus importante, tant en demande additionnel en énergie comme en puissance de pointe, dans les zones péri-urbaines des grands pôles urbains, et moindre dans les centre villes de grands pôles urbains, en raison des différences dans les besoins de mobilité dans chaque zone. Ces impacts peuvent être réduits en implémentant des stratégies de recharge type *heures creuses*, où les utilisateurs rechargeront leur VE en dehors des heures de demande de pointe. Cependant, ces stratégies ont un impact limité quand la recharge des VE représente une proportion trop élevée de la demande du poste source (autour de 20%). Au-dessus ce seuil, la recharge des VE commence à créer des nouvelles pointes de demande pendant les heures creuses. Il apparaît donc nécessaire de développer des stratégies de

recharge plus avancées pour gérer l'intégration d'une pénétration élevée des VE dans ces postes source critiques, par exemple des stratégie *valley filling*.

Dans une deuxième partie du Chapitre 4, on a étudié l'intégration conjointe des VE et des systèmes de génération photovoltaïque (PV) dans un réseau moyen tension (HTA) alimentant la ville de Brive-la-Gaillarde. Le réseau a été reconstruit utilisant des données publiques de cartographie des réseaux. Des simulations de flux de puissance pour une année complète avec différentes combinaisons de taux de diffusion et de distribution spatiale des VEs et PV ont été réalisées.

Les résultats montrent que le réseau étudié est robuste face même à des niveaux de diffusion de VE de 100%. Des complémentarités peuvent apparaître entre la recharge de VE et la génération PV, mais elles dépendront de la distribution spatiale des installations PV. Avec les tendances actuelles, autour d'un 50% de la puissance installée comprend des installations de grande taille posées au sol, qui sont localisées dans des zones rurales à faible densité de population, et donc une absence de VEs pour absorber la puissance générée de façon locale. Au contraire, une diffusion prédominante du PV sur toiture, couplée avec un taux d'accès à la recharge en journée élevé, peut réduire les impacts d'intégration des deux technologies.

Chapitre 5: Participation des flottes de VEs dans des appels d'offres de flexibilité. Analyse des barrières à l'entrée et solutions possibles.

La première partie de ce chapitre est consacrée à l'analyse des règles de marché des solutions de flexibilité émergents au niveau Européen. On a identifié 5 implémentations au niveau commercial en Europe, trois marchés locaux de flexibilité à court-terme (intra-day) et deux appels d'offres de flexibilité pour des besoins à moyen- long-terme. Les différences en approches viennent de la nature de contraintes réseau auxquelles elles répondent. Les plateformes court-terme ont été développées pour la gestion de congestion en cas d'excès de génération renouvelable, permettant une alternative au niveau opérationnel à l'effacement. Au contraire, les appels d'offres de flexibilité ont abordé des problèmes liés au report d'investissement ou à la provision de flexibilité en cas de défaut. Dans ces cas d'utilisation, les GRDs peuvent faire face à des risques élevés s'ils utilisent seulement des solutions de marché court-terme, car la flexibilité peut ne pas être disponible au moment requis. Les appels d'offre peuvent donner l'assurance de disponibilité de la flexibilité aux GRDs, nécessaire pour la planification et le maintien de la sécurité opérationnelle des réseaux, et aussi garantir des revenus aux agrégateurs de flexibilité.

On a analysé les règles de marché des 5 solutions de flexibilité à travers 3 niveaux : règles administratives, définition des produits de flexibilité, et schémas de rémunération et pénalités. Même si ces solutions ont été conçues en considérant la participation des agrégateurs de ressources distribuées (dont des VE, mais aussi des batteries distribuées ou demand response), des barrières existantes à l'entrée pour ces acteurs persistent, notamment avec des seuils minimaux de participation trop élevés pour des mécanismes au niveau local (500 kW) et des exigences en matière de connexion et mesure contraignants pour des ressources distribuées.

Entre les 5 cas étudiés, le plus mature est le cas d'appels d'offres de flexibilité réalisés par UK Power Networks (UKPN, le GRD de la zone de Londres). Pour cette raison, dans la deuxième partie du Chapitre 5 on s'est centré sur la participation des flottes de VE dans les appels d'offres long-terme.

On a développé une méthodologie en deux étapes pour qui reproduit les processus de réponse à l'appel d'offres (ex-ante) et d'activation de la flexibilité en temps réel. On a évalué la participation dans des appels d'offre par trois types de flottes : une flotte d'entreprise qui est connecté au réseau tous les jours et deux flottes des utilisateurs *réguliers* avec des habitudes de connexion au réseau non-systématiques. Ce cas d'étude a permis l'identification des règles de marché et des caractéristiques des flottes de VE qui ont le plus d'impact pour leur participation aux appels d'offres.

Les principales règles de marché qui affectent la participation des VE sont : la définition des fenêtres de disponibilité et les conditions de pénalités. Des fenêtres de disponibilité courtes et bien définies permettent la participation aux ressources qui ont des profils de disponibilité variables au cours de la journée, comme les VEs, pour qui assurer la fourniture de flexibilité à toute heure de la journée n'est pas possible. Les pénalités sont nécessaires pour assurer la livraison des services de flexibilité contractés, cependant des pénalités trop élevées peuvent dissuader la participation des volumes importants de flexibilité.

La participation des flottes de VE sera surtout déterminée par ses caractéristiques techniques et leur usage. Les trois facteurs principaux sont la capacité de recharge bidirectionnelle (V2G), la fiabilité de connexion de la flotte, et la bonne correspondance entre les besoins de flexibilité du réseau et le profil de disponibilité de la flotte. La recharge intelligente (unidirectionnelle) permet une participation réduite aux appels d'offres ($<1\text{kW/VE}$), rendant le V2G nécessaire pour augmenter la participation des flottes de VE. Cependant, seulement les flottes avec une grande fiabilité de connexion au réseau (la flotte d'entreprise dans notre cas d'étude) peuvent saisir pleinement les bénéfices du V2G.

Les résultats des appel d'offres 2020 de UKPN ont montré une valeur potentielle élevée de la flexibilité pour des besoins de report d'investissement, mais très variable selon les conditions du réseau. La valeur moyenne de la flexibilité dans les zones contractualisées atteint 58 £ per kW de flexibilité idéal par an, mais qui peut varier entre £2 à plus de £200/kW.an¹. Dans notre cas d'étude, cela représente une rémunération de 350€/VE.an en moyenne (variant entre 50-1400€/VE.an) pour les meilleurs cas². Au contraire, des flottes avec des habitudes de recharge non systématique atteignent une rémunération en dessous 90€/VE.an, provenant principalement de la recharge intelligente.

Les services de flexibilité pour le report d'investissement sont demandés pendant quelques heures/mois par an (en générale pendant les périodes de demande de pointe en hiver). Alors, cette source de revenu peut être complémentaire avec d'autres services de flexibilité qui peuvent fournir les flottes de VEs, comme la régulation de fréquence. Cependant, les services de flexibilité pour le réseau de distribution sont limités et dépendent des conditions du réseau : seulement quelques portions du réseau ont des contraintes à lever

¹Des estimations d'Enedis posent la valeur de la flexibilité entre 0-24€/kW

²Cas de flotte d'entreprise connectée au réseau tous les jours avec un chargeur bidirectionnel de 7kW, et une très bonne correspondance entre les besoins de flexibilité du réseau (activation entre 17h-20h) et la disponibilité de la flotte)

par de la flexibilité, les contraintes diffèrent dans chaque cas (en temps, ampleur, durée et fréquence d'occurrence), et quand les besoins de flexibilité augmentent, la valeur de la flexibilité se voit réduite car elle rentre en concurrence avec les solutions d'investissement réseau.

Les résultats des Chapitres 3 et 5 pointent vers un développement préférentiel du V2G dans des milieux professionnels que dans des cas des utilisateurs *réguliers*. Des flottes d'entreprise qui ont des habitudes de connexion au réseau plus fiables et consistantes dans le temps sont des meilleures ressources de flexibilité que des flottes moins fiables. En conséquence, le volume de flexibilité accessible provenant des utilisateurs *réguliers* peut être limité. Cependant, il peut y avoir des opportunités pour le développement des solutions de recharge bidirectionnelle *derrière le compteur* pour lesquels le besoin de fiabilité est moins importante, telle que le véhicule-to-home ou l'autoconsommation de génération renouvelable.

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Titre : Intégration des véhicules électriques dans les réseaux de distribution. Considérations des comportements des utilisateurs et mécanismes d'implémentation de flexibilité.

Mots clés : Véhicules électrique, Réseaux de distribution d'électricité, Recharge intelligente, Vehicle-to-grid

Résumé : L'intégration massive des véhicules électriques (VEs) dans les systèmes électriques peut créer des contraintes si la recharge n'est pas gérée de façon appropriée. Cependant, les VEs peuvent apporter de la flexibilité opérationnelle aux systèmes électriques en adoptant des stratégies de recharge et de décharge intelligente.

Cette thèse étudie l'intégration des VEs aux réseaux de distribution d'électricité en considérant des aspects techniques, comportementaux, économiques et réglementaires.

Premièrement, les cas d'utilisation de flexibilité des VE les barrières associées pour leur déploiement sont identifiés. Ensuite, on étudie le comportement de recharge des utilisateurs de VE et son impact sur les réseaux de distributions et le potentiel de flexibilité.

Après, on a développé une méthodologie pour évaluer l'impact des VEs sur les réseaux moyenne tension qui exploite des données à granularité fine. On met en évidence les impacts des schémas de mobilité local (urbain vs. rural) sur la recharge des VE et sur le réseau de distribution, et les possibles de complémentarités avec la génération renouvelable distribuée (photovoltaïque).

Finalement, on analyse des mécanismes de flexibilité implémentés par des opérateurs de réseau de distribution en Europe. Un cas d'étude numérique permet d'identifier les principales règles de marché qui impactent la participation des VE à ces mécanismes et le niveau de rémunération qu'ils peuvent atteindre. Des recommandations de réglementation sont formulées.

Title : Electric vehicle integration into distribution systems. Considerations of user behavior and frameworks for flexibility implementation.

Keywords : Electric vehicles, Electricity distribution systems, Smart charging, Vehicle-to-grid, Flexibility

Abstract : The massive integration of electric vehicles (EVs) can pose challenges for electricity systems if charging is not appropriately managed. However, EVs can provide flexibility, improving system operation, by using smart charging and discharging strategies.

This thesis studies EV integration into distribution systems through technical, behavioral, economic, and regulatory aspects. First, the use-cases for flexibility at the distribution level are identified, along with the remaining technical, economic, and regulatory barriers for their deployment.

Second, an assessment of the impact of plug-in behavior (i.e., users not plugging in every day) in EV integration studies was carried out. For this, an agent-based model was developed and calibrated with real-world data. The impact of EV charging and EV fleets' potential to provide flexibility are evaluated

and consequences of current trends towards larger battery sizes are derived.

Third, a framework to assess EV charging impact in realistic medium voltage grids that considered granular open-source datasets was developed. We evidenced the impact that local mobility patterns (rural vs. urban) and spatial distribution of EVs have on EV grid integration and its coupling with distributed renewable generation.

Finally, we studied market mechanisms to procure flexibility at the local level implemented by European distribution system operators. Using a regulatory analysis framework, barriers to entry for EV aggregators were identified, and a case study to assess the potential revenues of different types of EV fleets participating in these schemes was carried out. Policy recommendations for market design were derived.